ANALYSIS AND EVALUATION OF THE IMPACT OF ARTIFICIAL INTELLIGENCE ON VALUE CREATION IN THE SUPPLY CHAIN

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Abstract

Problem Statement: Significant increase of applying artificial intelligence (AI) will substantially change the way supply chain (SC) entities and their subsystems consisting of human experts and technical agents collaborating in the 2020s and beyond to create sustainable competitive advantages. However, the literature review has revealed that insufficient coverage of appropriate conceptual frameworks (CF) for adequately assessing the performance of future SC scenarios in the context of AI and its contribution to competitive value creation (VC). Research focus has been primarily placed on the ability of isolated AI applications to contribute with natural language processing (NLP), computer vision, machine learning (ML), or rational decision-making to increasing SC effectiveness. However, there is more need to assess the mutual interoperability of these AI abilities and other SC descriptors across the entire SC which will contribute with new knowledge to interdisciplinary academic research and practitioners' strategic, tactical, and operational evolvement. So far, there is the lack of a CF which can be used to build propositions on the impact of AI on inter-organisational SC structures and the ability of AI to support emergence in the SC. Therefore, the overall aim of this thesis is to analyse and evaluate the impact of AI on VC in the SC.

Research Methodology: Based on a critical realism ontology, the thesis applies an abductive research approach using mixed methods for data collection and analysis. The research design has the following stages: (1) semi-structured interviews and Delphi Study, (2) cross-impact balance (CIB) analysis, (3) propositions and theory building, (4) verification with cooperative game theory.

Main Achievements: (1) Literature review allows to contextualise the application of AI in SC and reveals SC mechanisms as a foundation to develop an appropriate CF. (2) Gaps of the existing research are identified. (3) A CF is developed for proposing a network of relationships between relevant SC descriptors in this research. (4) Relationships between these SC descriptors are evaluated and analysed with the purpose to identify future SC scenarios and their performance. (5) Exploring these SC scenarios allows for establishing propositions on future SC mechanisms and their ability to create value. (6) A theory about the impact of AI on VC in the SC is developed. (7) Verification of the proposed CF and the developed theory.

Results: (1) The theory based on the CIB-analysis proclaims that AI creates value for the SC through improving ordinary and dynamic SC capabilities. (2) Sustainable competitive advantages will only be achieved with the combination of widely implemented use of AI in forecasting and fully adopted autonomous planning techniques along the entire SC. This combination of knowledge creation and knowledge distribution is the only feasible future concept to leverage sufficient value through the inevitable data-centric approach across the SC. (3) Isolated application of AI-enabled descriptors of the CF leads to the unavoidable long-term demise of SC. (4) The recommended inter-organisational structure to support controlled self-organisation is built on clusters

that connect the inter-organisational subsystems at the interfaces between SC entities. (5) AI applications only indirectly contribute to emergence of new SC structures but create value by strengthening the collective behaviour of human experts to find a new equilibrium. (6) Self-learning AI ability in combination with big data allows for improved SC responsiveness and SC efficiency by turning demand-driven SC into forecast-driven SC. (7) AI creates value through keeping SC resources valuable, imperfectly imitable, and non-substitutable.

Contributions:
The main contribution of this PhD project from the theoretical perspective is the development of a theory that allows academics to evaluate the impact of AI on VC in the SC in a fact-based manner. The system-theoretical structure of the underlying CF allows academics to explore the aspect of SC learning by extended Resource-based View (RBV) and to explain phenomena of the SC reality by scientifically justified propositions.
From practical application perspective, practitioners can apply the CF to derive logical dependencies beyond the proposed descriptors to decide on SC resource mix and to initiate studies and practical projects to synchronise process-orientation, decentral coordination, and decision autonomy to leverage first-mover competitive advantages.

Limitations: Due to the resource and time constraints of this PhD project, the findings and results of this thesis are only as good as the knowledge and the experiences of the participating experts and the deductive capabilities of the author of this thesis.

Declaration

I declare that, except where noted and credited, the content of this thesis is my work. I further declare that this PhD thesis was created in accordance with the guidelines and regulations of the University of Gloucestershire. I affirm that this thesis has not been submitted to any other educational institution in the United Kingdom or abroad or as part of any other academic award. All views and opinions tendered in this PhD thesis are solely mine and not, in any way, those of the University of Gloucestershire.

Signed………………………………………….. Date…31 July 2021………………………

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To my dearest wife Eva and my beloved children

Yannick and Matilda for their patience!

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The journey would not have been possible without the great support of people who have accompanied and inspired me in the past years.

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List of Abbreviations

Abbreviation	Meaning
AI	Artificial Intelligence
ABM	Agent-based Modelling
AGV	Autonomous Guided Vehicles
ANN	Artificial Neural Networks
ASI	Artificial Superintelligence
B2B	Business to Business
CAS	Complex Adaptive System
CF	Conceptual framework
CIB	Cross-Impact-Balance
COGS	Cost of Goods Sold
DCF	Discounted Cash Flow
EDI	Electronic Data Interchange
GST	General Systems Theory
GT	Game Theory
IA	Impact Analysis / Impact Analyses
ICT	Information and Communication Technology
IoT	Internet of Things
IT	Information technology
KPI	Key Performance Indicators
KBV	Knowledge-Based View
ML	Machine Learning
MRP	Material Requirement Planning
NIE	New Institutional Economics
NIP	Natural Image Processing
NLP	Natural Language Processing
NPV	Net Present Value
NT	Network Theory
PAT	Principal-Agent-Theory
P-ID	Personal Identification Number of study participants
PPIM	Process and Performance Indicator Matrix
PoS	Point of Sales
PwC	PriceWaterhouseCoopers
RBV	Resource-based View
RCT	Rational Choice Theory
RPA	Robot Process Automation
RWH	Regional Warehouse(s)
RO	Research Objective
R&D	Research and Development
SC	Supply Chain / Supply Chains
SCOR Model	Supply-Chain-Operations-Reference-Model
TC	Transaction Costs
UC/APP	Use Cases and Applications
VC	Value Creation
WIP	Work in Progress

Chapter 1 Introduction

1.1 Project Background

A supply chain (SC) is defined as a complex adaptive system (CAS) consisting of adaptive entities coordinating interorganisational dependencies with the purpose to efficiently and effectively plan, and organise upstream and downstream material, information and finance flow (Aitken, 1998; Mentzer et al., 2001; Vitasek, Manrodt, & Abbott, 2005). Conflicting goals of high service and low costs (Stevens, 1989) are SC inherent. Body of literature reveals that contemporary SC are predominantly coined by trust-based win-win-oriented interorganisational collaboration (Cao & Zhang, 2011; Whipple & Russell, 2007) and cooperation (Aitken, 1998) as a result of social negotiation processes between distributed decentral decision-making units (Schneeweiss & Zimmer, 2003) within a system of rules safeguarded by formal contracts, incentive structures and social relationships (Halldórsson, Hsuan, & Kotzab, 2015). In current SC, operational, tactical, and strategic decisions are mainly based on so-called bounded rationality which means most of the decisions are made by human beings with unclear criteria. In recent years, some of the executives in SC have tried to apply artificial intelligence (AI) and AI-enabled multi-agent systems to support their future decision-making (Kirschstein, 2015; Kuntze, Lal, & Seibert, 2020). In fact, only a few decisions in contemporary SC are made using intelligent agents (machines, computer-based applications) and the decisions are mainly limited to intra-logistics applications such as autonomous guided vehicles (AGV) or visual recognition of material characteristics during production as described in Memmesheimer (2015) or Zhang, Lim, and Han (2019). Meanwhile, based on literature it is believed that self-learning intelligent agents would be widely applied in future SC (Brynjolfsson & McAfee, 2016; Chui et al., 2018; Shoham et al., 2019).

Referring to the principle of system theory (Bertalanffy, 1972; Gell-Mann, 1994a), the SC as a system is composed and orchestrated by subsystems which consist of an interplay between bounded-rational (human beings) and rationally-deciding intelligent agents (Russell & Norvig, 2016). The future SC must be seen as a system with an increasing number of AI-enabled technical subsystems that executes and operates SC business processes (Hengstler, Enkel, & Duelli, 2016; Memmesheimer, 2015) integrated in a real-time platform (Ali & Nishikant, 2015; Kuntze et al., 2020), often with adaptive objective function to maximise the expected value (Bringsjord & Govindarajulu, 2020; Wolchover, 2020). For the aforementioned reason, the future SC will complete the evolutionary process from a socio-ecological system (Gruner & Power, 2017) to a socio-technical system (Ropohl, 2009) with a significant percentage of self-learning technical subsystems independently acting and reacting to the environments. It is believed that these significant applications of algorithm-based rational decision-making systems will tremendously impact future SC mechanisms. A new balance of a lower number of human experts and a significantly higher number of AI agents will coin future SC. This new balance of agents will change coordination principles, a collaboration between subsystems, the mode of communication, and decision-making and will affect the way how learning and knowledge building contribute to value creation (VC) in future SC. It has been explored that AI in general impacts VC (Brandenburg, 2016; D. Q. Chen, Preston, & Swink, 2016; Hammervoll, 2009; Zhu, Krikke, & Caniëls, 2018). However, the literature review reveals that it has not been sufficiently analysed and evaluated to what extent these AI-enabled rational decision-making units will change the behaviour and composition of contemporary SC mechanisms and how these changes will impact VC in future SC.

Not only shareholders shall benefit from the created value of the entire SC as proposed by the shareholder value concept (Koller, 1994) but other stakeholders such as employees, suppliers, and consumers etc. The value in this thesis is defined as the financial benefits through investments and revenues such as cost reduction through more efficient equipment or more sales through better delivery services. Their shares are materialised through the positive cash flow of the entire SC for all relevant SC entities (Hofmann & Wessely, 2013). SC mechanisms create both tangible as well as intangible value (e.g. brand value, patents, knowledge, customer relations, firm credibility, or innovations (Kalafut & Low, 2001; Wendee, 2011)). However, the literature review provides only limited concepts to explore how intangible value created by investments in AI-enabled applications can be expressed in the resulting net present value (NPV) of these business cases.

Services and products only create cash flow if they create value for consumers to stimulate buying process. The value created through revenue of AI-enabled applications shall be maximised for all SC entities by optimal pricing of services and products (Lieberman, Balasubramanian, & Garcia-Castro, 2018) and fairly allocated to the SC entities. Thun (2005) informs about the potential of cooperative game theory (GT) to allocate profit among SC partners. However, there is limited literature for appropriately exploring optimal allocation of created value in the SC so that cooperative GT is applied to test a fair coalition approach.

It is observed that current SC are still characterised by SC concepts which have been established during the last decades such as the ‘lean SC’ (Vitasek et al., 2005), the ‘integrated SC’ (Stevens, 1989), or the ‘agile SC’ (Christopher, 2000). Prevailing technologies supporting these SC concepts such as Enterprise Resource Planning (ERP), electronic data interchange (EDI) connectivity, Advanced Planning and Scheduling (APS), or modular platform concepts in production or to connect suppliers and customers with focal companies have been developed and established for some years (Battaglia et al., 2004; Chandrashekar & Schary, 1999; Esch, 2013; Hvolby & Steger-Jensen, 2010; Penthin, 2012). Nevertheless, the predominantly common opinion of practitioners and academics is that AI has the potential to be an emerging technology of the future for SC management (Anonym, 2017b; Brynjolfsson & McAfee, 2016; Chui et al., 2018; Shoham et al., 2019; Toy, Gesing, Ward, Noronha, & Bodenbenner, 2020). Indoor and outdoor autonomous driving (Anonym, 2018; Toy et al., 2020) or Natural Language Processing (NLP) of chatbots (Kreutzer & Sirrenberg, 2019, p. 25; Shoham et al., 2019) are only two of the most popular AI applications which are expected to tremendously change patterns of future ecosystems in general and SC in particular. These prospective mechanisms will be coined by AI-enabled big data analytics fed by IoT sensor technology (Calatayud, Mangan, & Christopher, 2019; Sanders & Swink, 2020) which is supposed to enormously improve the simulation and forecasting capabilities of SC entities (Anonym, 2021b; Campuzano-Bolarín, Frutos, Ruiz Abellón, & Lisec, 2013; Kersten, Von See, Lodemann, & Grotemeier, 2020; Mahdi, Saeid, Bijan, & Kaveh Izadi, 2019). Scientific as well as professional journals already report for years the benefits and advantages of AI-enabled concepts and models in the context of predictive and prescriptive analytics (Anagnostopoulos, 2016; Anna & Stefan, 2018; Chalmers, Hill, Zhao, & Lou, 2015; Gast, 2018; Lepenioti, Bousdekis, Apostolou, & Mentzas, 2020; Poornima & Pushpalatha, 2020; Punia, Singh, & Madaan, 2020) with the expectation of sustainable competitive advantage of the entire SC for early movers (Laney, 2018; Wodecki, 2019). As a consequence, it should be supposed that a tendency might be recognised that SC business processes are guided significantly more and more by forecast-driven instead of demand-driven approach in downstream and upstream flow from manufacturer to consumer. However, although some applications of big data analytics can be observed, actual mainstream behaviour is still to primarily avoid forecast-driven planning. Prevailing current SC concepts are mainly built on linear extrapolation of available demand and historical data. Most of the decision-makers still hesitate to fully believe in the accuracy of AI-enabled forecasting and therefore prefer to wait for guidance and standards through convincing research.

Future SC will integrate a large number of AI-enabled decentral decision-making agents into a common platform with the purpose to establish reliable operational and tactical autonomous SC planning (Kuntze et al., 2020) and the most accurate forecast on future demand. Autonomous SC planning connects SC execution with SC planning and requires permanently exchanging and assessing (near) real-time data across the entire SC to establish real-time transparency on the performance of SC agents to immediately react to disturbances and re-plan the physical material flow (Calatayud et al., 2019). The most accurate forecast of future demand is a vague promise for prospective change of established SC concepts putting decoupling points and postponement strategies in the centre (Fisher, 1997; Mason-Jones, Naylor, & Towill, 2000). On the one hand, the prediction of future behaviour of consumers is one key argument for AI-enabled forecasting. But on the other hand, SC managers still hesitate to bet on anticipatory material flow strategies as depicted by (Gast, 2018) and Spiegel, McKenna, Lakshman, and Nordstrom (2013). Various articles have been reviewed and existing conceptual frameworks (CF) have been analysed and evaluated. It turned out that none of the proposed frameworks are suitable to provide an appropriate instrument for analysing and evaluating future SC. Hence, the literature review indicates an inconsistent conclusion of the belief on VC through AI-enabled operating applications, planning capabilities, and forecast strategies. These findings indicate a gap in the literature to be addressed by this thesis. This gap will be closed with abductive reasoning to develop explaining propositions embedded in a mixed-methods approach. Expert interviews and a Delphi Study deliver both quantitative and qualitative data which are examined together with a cross-impact balance (CIB) analysis. The creative process of developing hypotheses is conducted with a strict methodological foundation by Grounded Theory methodology and results in a theory about the impact of AI on VC in the SC.

1.2 Motivation of the Project

On the one hand, motivation is fed by the strong wish to contribute new knowledge to the academic and practitioner SC community. It would be a deep satisfaction to develop durable hypotheses about future SC mechanisms which might be confirmed by testing through other researchers with implemented business cases. The author of this study would feel grateful if the belief in the findings led to subsequent implementations of the recommendations. On the other hand, this research is motivated by the strong interest of the author of this study to understand how a SC will successfully perform in the future with the wide application of AI-enabled technology. The interpretation of the notion ‘successfully’ has different aspects: It is of interest how a SC achieves sustainable competitive advantage through permanent improvement of SC performance. It is also interesting to what extent competitive advantage and/or performance improvement actually create value and to whom in the SC this value is allocated. A strong drive for this research is to investigate how adjusted SC mechanisms triggered by changes in consumer behaviours or changes of market players establish a stable structure to ensure an appropriate equilibrium in the SC. Contemporary academic discussion sees a paradigm shift from principal-agent-related top-down concepts of cooperation (Williamson, 1975) to more positive and intrinsically motivated agents with the need for mutual and decentral information exchange (Blomqvist, Hurmelinna, & Seppänen, 2005; Schneeweiss & Zimmer, 2003). Therefore, especially emergence through AI-enabled self-learning applications and self-organisation by employees in an increasing multi-agent system is worthwhile to be analysed and evaluated. The aforementioned explanation shows that a situation of change is recognised and this change is sufficiently significant to explore its impact on VC in the SC.

1.3 Overall Aim and Research Objectives

1.3.1 Overall Aim

Concerning the identified research gap and the significance of changes in strategic factor markets through emerging technologies and changes of behaviours and demand patterns in consumer markets, the overall aim of this thesis is to propose, design, and develop a new framework for analysing and evaluating the impact of AI on VC in the SC to find new rules and even a theory to predict future mechanisms for sustainable competitive advantages.

1.3.2 Research Objectives

The application of system theoretical concepts underpins that parallel or simultaneous activities of adaptive SC entities are interlinked in a complex socio-economic network of relationships. For that reason, it is insufficient to just explore the direct relationship between a few numbers of dependent and independent variables. Therefore, it is necessary to review established technologies and concepts for improving SC performances with the purpose of evolving and improving current SC mechanisms. The understanding of these mechanisms feeds the preparation of data collection to develop the targeted CF appropriately. The CF serves to conduct a cross-impact analysis on the complex network of relationships. However, the assumption that AI-enabled applications will take up a large proportion of future SC processes leaves no room for reference to justified belief what makes it necessary to explore how far these future mechanisms will create value for involved SC entities.

Thus, the research objectives are:

RO1: To review, analyse, and evaluate the technologies for improving SC performance especially VC in SC as well as CF leading to sustainable competitive advantages.

RO2: To develop a CF with the purpose to explore, analyse, and evaluate the impact of AI on VC in the future SC.

RO3: To build a theory on the findings from exploring the CF.

RO4: To verify the proposed theory and the identified AI applications through case studies.

1.4 Contributions to the New Knowledge Generation

This research will advance existing knowledge of the impact of AI on VC in the SC. It is important for both academics and practitioners because it provides a theory with which possible future SC scenarios can be explored from both perspectives. It is anticipated that the following contribution to the new knowledge generation will be made:

The contribution to the new knowledge generation for theoretical advancement:

1. Analysis and evaluation of the state of research in the interdisciplinary field of AI, VC, and SC management.
2. Identification, analysis, and evaluation of the major issues with the evaluation of creating and allocating value in the SC.
3. Development of a CF which can be used by academics to evaluate the impacts of AI in the SC in a fact-based and competent manner.
4. Exploration of the aspect of SC learning by extended Resource-based view (RBV) with the proposed CF.

5. The development of a theory about the impact of AI on VC in the SC, which is consist of a system of six scientifically justified propositions that explain phenomena of the SC reality and underlying laws. This theory. This theory allows to convince academics that regard forecasting with extensive scepticism from the value created by significantly improved predictability through AI-enabled forecasting.

The contribution to the new knowledge generation for practical applications:

1. Practitioners can apply the CF to derive logical dependencies beyond the proposed descriptors to decide on SC resource mix.
2. This theory provides an initial starting point to initiate studies and practical projects to synchronise process-orientation, decentral coordination, and decision autonomy.
3. The proposed method is a strong argument for companies to convince SC partners for value-creating collaboration in the SC.
4. Practitioners are enabled to correctly assess the significance of AI for specific investment fields.
5. The CF presents the benefits of creating and leveraging first-mover knowledge pools.

1.5 Thesis Structure

This thesis is structured and presented in eight chapters. In **Chapter 1**, “Introduction”, the researcher’s motivation to conduct an abductive approach is explained and the research aim and objectives to contribute to new knowledge generation are derived. In **Chapter 2**, “Literature Review”, a foundation for the subsequent chapters by critically reviewing the literature for identifying the research gaps in the area of the SC and its VC potential, AI and the impact of AI application on VC in SC. In **Chapter 3**, “Research Approach and Methods”, the researcher’s ontological stance as a critical realist is outlined and evaluated. Epistemological assumptions on the Grounded Theory approach to be useful in association with scenario analysis in an open system environment are elucidated. Methods of data collection analysis and presentation are demonstrated, and it is reasoned why a mixed-method approach is decided. The approach, how rigour and validity is established, and ethical research issue are respected. In **Chapter 4**, “Data Collection, Presentation, and Analysis”, a Three-poll Delphi Study is applied to collect and present experts’ opinion. In **Chapter 5**, “Design and Development of Conceptual Framework”, the Delphi Study results are investigated and the descriptors and their variants for the CF are determined and described. The correlations between the descriptors are outlined. In **Chapter 6**, “Evaluation and Findings AI of Application to the Future Supply Chain”, CIB-analysis is applied to identify appropriate scenarios based on the descriptor variants of the CF. The direct and indirect correlations of these scenarios are explored. The analysis is underpinned by SC-related theories and identified hypotheses are discussed. In **Chapter 7**, a theory about the impact of AI on VC in future SC is established. In **Chapter 8**, testing of the theory is conducted. Finally, in **Chapter 9** , “Conclusion and Further Work”, the key results are summarised, and future applications of the CF are proposed. The limitations of this thesis are explained. Figure 1-1 illustrates the thesis structure.

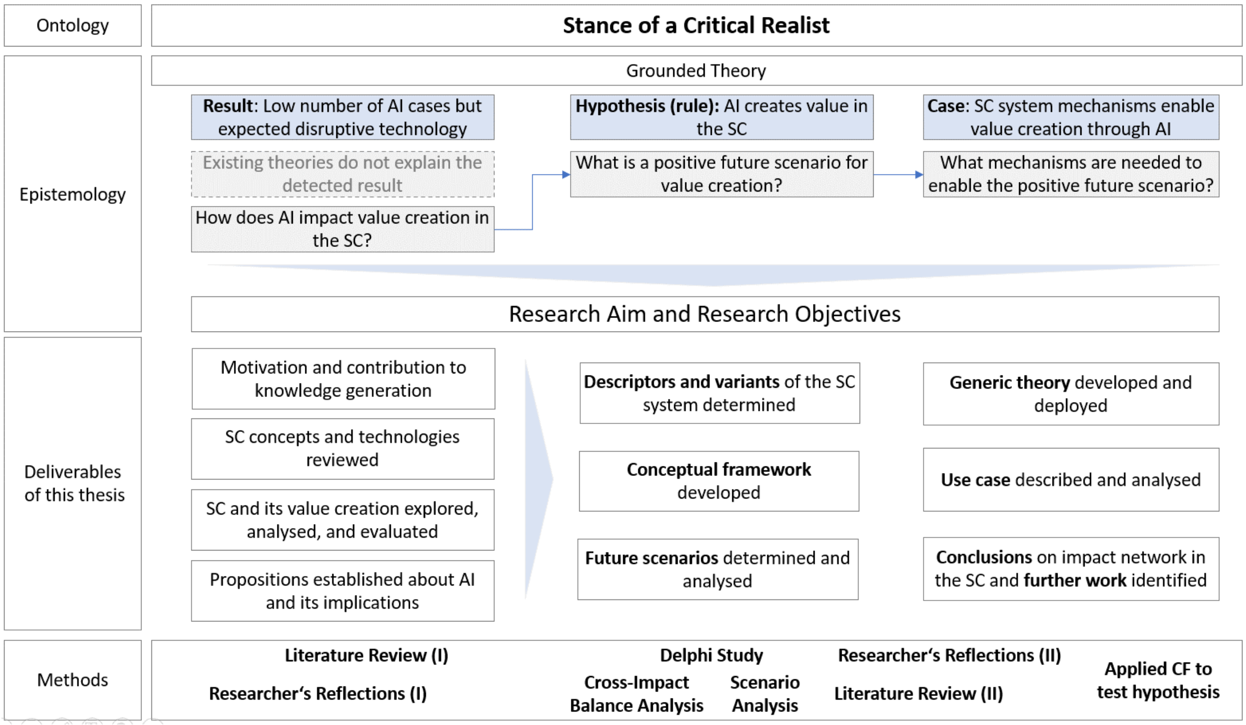


Figure 1-1: Thesis Structure

Chapter 2 Literature Reviews

2.1 Introduction

This chapter is to critically review literature in the areas that are relevant to the topics of this thesis. It starts with exploring the SC as the context in which the CF to be designed is embedded. Then it continues with reviewing existing work about AI and its contribution to performance and VC in the SC. Impact analysis and systems modelling as the applied methodologies of the CF are elucidated. This chapter concludes to argue the relevance of this research by identifying the problems associated with the VC of SC.

2.2 Supply Chain Definitions and Performances

SC definitions are reviewed to find information about the nature of the SC to constitute the foundation of the CF to be designed in this thesis. It is observed that an important element of SC nature is the endeavour of its decision-making entities to achieve competitive SC performance (Chandak, Kumar, & Dalpati, 2019; Petersen, Ragatz, & Monczka, 2005; Porter, 1985; Struebing, 1997). Banbury (1975) and Burns and Sivazlian (1978) firstly link ‘supply chain’ with performance goals both in academic or practitioner journals. However, both papers do not discuss the conflict between divergent performance goals. Later, Stevens (1989) catches up with this issue by pointing out “*the conflicting goals of high customer service, low inventory investment and low unit cost*”. In these early definitions, the fundamental SC performance goal of delivering on-time and in-full goes in line with cost-reducing aspects of the physical material flow and the inventory situation in the SC.

Chandak et al. (2019) integrate the measurement of SC efficiency and SC effectiveness. However, these two performance dimensions do not represent all aspects of SC performance so that Werner (2017) as well as Beamon (1999) state that the dimension of agility (flexibility) should be considered. But it seems critical that these authors only find the purpose in striving to achieve existing performance goals. This is why Mason - Jones and Towill (1999) add the purpose of SC activities in an improvement, even maximisation of SC performance. However, these papers of the 1980s and 1990s define the SC from the perspective of focal companies which operate their businesses logistically as closed systems. This is also observed by Aitken (1998, p. 19) which is why he assumes the nature of an SC in coordinating interfaces between partners in a multi-echelon network. Whilst Aitken (1998) expands the dyadic integration to the network between suppliers and buyers based on a supplier association, Mentzer et al. (2001) provide a collection of existing SC definitions and emphasise the coordination of SC organisations across interfaces of the entire vertical SC referring to the downstream flow from the manufacturer to the customer as well as the upstream flow from supplier to manufacturer. Forrester (1961) with his findings about the so-called ‘Bullwhip Effect’ (Forrester Effect) of amplifying forecast on inventory volume, significantly coins SC research across decades in this direction (Burns & Sivazlian, 1978; Domański, Hadaś, Cyplik, & Fertsch, 2009; Metters, Conference, Nh, & Jun, 1996; Nguyen, Adulyasak, & Landry, 2019). This viewpoint of an entire SC has been considered as an important improvement on SC definitions. Mentzer et al. (2001) add the important aspect of finance flow in their SC definition. Another SC concept is defined by Frischkorn et al. (1993) and Vitasek et al. (2005) as the ‘lean supply chain’. The lean SC concept continuous the path of performance improvement by mainly focusing on cost reduction aspects. Other scholars consider the nature of the SC from additional viewpoints and differentiate the general SC concept by developing extensional SC definitions such as the ‘integrated SC’ (Stevens, 1989), the ‘virtual SC (Chandrashekar & Schary, 1999), the ‘agile SC’ (Christopher, 2000), the ‘leagile SC’ (Naylor, Naim, & Berry, 1999) or the ‘sustainable SC’ (New, Green, &

Morton, 1997). It is obvious that the SC is challenged by increasing diversity during the 1990s. This diversity leads to increasing complexity and uncertainty due to demand and market volatility in the SC which is intensified by starting globalisation. Significantly more product variants through mass customisation (Kotler, 1989; Mueller - Heumann, 1992), shortening product life cycles and customers' reduced brand loyalty (Christopher, 2005, p. 45) in line with rigorous service level requirements such as just-in-time deliveries or precise time slot and gate allocation characterise the SC until today. Therefore, most of these SC concepts are relevant for the CF of this thesis, except the virtual SC concept. Both, Christopher (2005) and Chandrashekar and Schary (1999) assume that a virtual SC utilises a formal physical network structure, and operates through a network of separate organizations. This is possible because of available information and communication technology (ICT). However, it should be considered that the flexibility of adapting to changes in the business environment depends not only on technological aspects, but also on contracts and boundaries of legal companies. The limitation of the virtual SC concept appears when testing it against the market or hierarchical coordination in the sense of Williamson (1975). It is obvious that the concept of 'virtual SC' is replaced in the upcoming decades: The aspect of modularisation is met by multiple sourcing. 'Segmentation' is a more common term to discuss modularised production and customer needs. The technological aspect is overlapped by the terms and concepts of 'digitalisation' and 'platform' (Battaglia et al., 2004). The concept of fragmentation was taken up by the concept of 'agents' and continued to the concept of 'digital twins' (Rienk & Daan, 2018). The concept of 'virtual supply chains' is occasionally taken up by papers but mostly with the technological focus. Thus, note that the extensional definition 'virtual SC' as a product of its time could not prevail as performance improving SC concept up to now. Therefore, the virtual SC concept is not further considered for the CF of this thesis. However, the idea that ICT improves collaboration between legally separated firms is still valuable for further reflection. From the literature review in this thesis, it can be noticed that various SC definitions are given for individual researcher's purposes, which suggests that elements of SC nature are only partly, or not at all part of SC definitions. However, missing elements could contribute a strong relevance to the CF of this thesis. Therefore, available SC definitions are mapped against SC-specific buzzwords and double-checked according to completeness and relevance for the CF of this study. Whilst inventory optimisation and cost-reduction are mirrored in the first decade of emerging SC definitions, Figure 2-1 illustrates that each decade has its specific SC topics contributing to SC performance improvements over time.

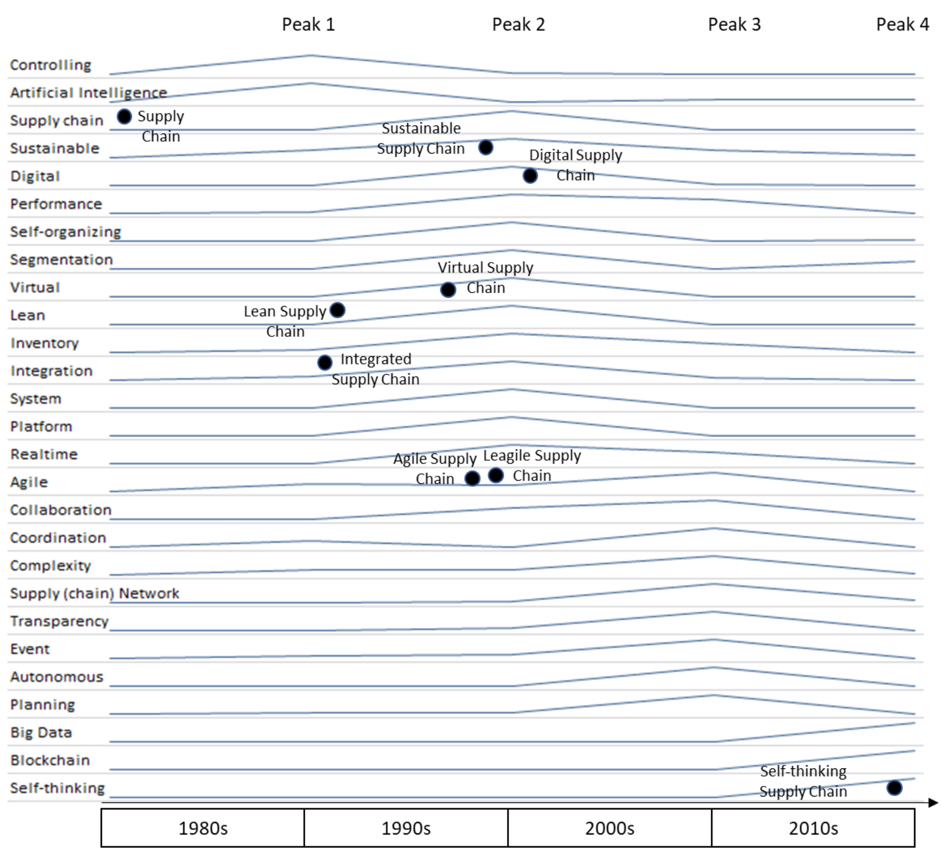


Figure 2-1: Chronological Development of Search Terms and Entry of Extensional SC Definitions (Author's illustration)

However, ‘autonomous SC’ or ‘transparent SC’ are not found as definitions. This recognition is different to corresponding search terms such as ‘lean’ or ‘agile’ discussed in the available literature. It seems that ‘transparency’ is related to a sustainable SC in the sense of social performance ("Transparent Supply Chain Is Goal," 2012) or to an agile or lean SC in the IT-related sense to create visibility at the various stages in the chain (Srivastava, 2006). Especially the ‘sustainable SC concept’ as defined by Fan and Zhang (2016, p. 144 et seq.) seems to integrate different performance-related aspects by referring to “*three pillars of sustainability, namely, environment performance, economic performance, and social performance*”. The observation here is that the definition of sustainable SC paves the way to contemplate the SC as a socio-economic system. This perspective is supported by the definition of Heylighen (2001) who orientates his SC definition on system theories including the striving of the SC to an equilibrium. With the entrance of system thinking, the SC-centric viewpoint comes in the centre. The assumption is here, that the interplay of SC entities in one system competes against other systems.

The definitions in Figure 2-1 show, that there is a progressing evolution of performance improving topics along the decades. Each topic contributes in its decade to a competitive advantage according to SC performance improvement. But it is found that after having introduced and implemented respective tools and methods through a significant number of competing companies, the effect is exhausted, and new concepts are introduced to add methods and tools for the next step of performance improvement. On the one hand, as shown by several authors (Borgstrom & Hertz, 2011; Braziotis, Bourlakis, Rogers, & Tannock, 2013; Stevens & Johnson, 2016), the need of improving the SC performance comes from changes in the environment. On the other hand, it is also an SC-inherent impulse that forces the continuous development of new SC concepts. Referring to Getto (2016) as well as Brynjolfsson and McAfee (2016) another impact comes from technological developments through web-based real-time communication, steadily increasing bandwidth, and increasing computational power. It is observed that these technological developments enable SC decision-makers to either improve SC performance with existing SC concepts or to apply additional SC concepts which are fully enabled by these new technologies. This evolutionary aspect of the SC is also underpinned by papers outlining different models of phases or types referring to time-related or chronological development (Borgstrom & Hertz, 2011; Braziotis et al., 2013; Cecere, 2006; Chandrashekar & Schary, 1999; R. E. Miles & Snow, 2007; Potter, Towill, & Christopher, 2015; Stevens & Johnson, 2016). It is comprehensible to consider all of these papers as a 'snapshot' of the SC evolution from the perspective of the time of their creation. However, common to all these evolutionary SC models is that they elaborate cooperation as the nature of the SC.

For that reason, Esper, Clifford Defee, and Mentzer (2010) state with their SC definition that each view on an SC *"emphasizes coordination and collaboration with suppliers and customers*." The authors distinguish the pure managing of dependencies between activities (Malone & Crowston, 1994) and the trust-based win-win-oriented joint collaborative behaviour (Whipple & Russell, 2007) of SC entities. In regard to SC performance, Eltantawy, Paulraj, Giunipero, Naslund, and Thute (2015) or Soroor, Tarokh, and Shemshadi (2009) confirm the improvement potential of inter-organisational coordination with their empirical studies. These papers locate a key lever in the application of cross-company information technology (IT). But they only figure out marginally that one of the game-changing aspects lies in the communication direction and the role of decision-making in the SC. Top-down communication from a central decision-making unit in the SC turns to decentral decision-making units and the communication becomes mutual information exchange from principal to agent as Schneeweiss and Zimmer (2003) state. The term-combination ‘principal’ and ‘agent’ points out that traditional Neoclassical Economics viewpoint in the field of SC management is enhanced by the New Institutional Economics (NIE) position. This is, why the SC definition of Halldórsson et al. (2015) fits well in that evolution. Halldórsson et al. (2015) confirm that “*the SC is viewed as a system of rules [...] which rewards cooperation-compliant behaviour and sanctions counteraction [...] and their acceptance is safeguarded by [...] formal contracts, incentive structures and social relationships [...] so that a more or less close cooperation evolves*”. Clearly this definition underlies the x-theory idea of man. However, the evolution from the coordination to the collaboration perspective is only possible because the human idea has changed to the y-theory, explained by Schein (2004, p. 173 et seqq.).

The current state of SC evolution is defined by Katz (2000) and Sanders and Swink (2020) through the ‘digital SC’. However, Sanders and Swink (2020) criticise that there is little agreement on what it means. It is found that new opportunities such as predictive or prescriptive analytics based on Big Data with applied AI and IoT characterise the ‘digital SC’ (He, Xue, & Gu, 2020). It is also observed that these technologies open the door to rethink and reassess the agile and leagile SC concepts with their constraints of market mediation costs. In this connection, Calatayud et al. (2019) take up the discussion on AI in conjunction with autonomous agents and dare an outlook to a next stage of SC evolution by referring to the SC as a self-thinking system. This SC definition is mainly characterised by IoT sensor technology connected through Blockchain-enabled Cloud solutions. Calatayud et al. (2019) only isolate their focus on technological changes instead of including the changing SC structure, changing coordination and collaboration models which are affected by these technological changes. To conclude the observation of the digital SC, it has to be stated that none of these authors find answers to quantify the impact of these technologies on SC performance. In contrast, Straub (2017) makes a significant point by referring to the fact that these new technologies are also applied to attack and significantly interrupt cooperative work of the entire SC. This is why cybersecurity is recently made a subject of discussion (Simon & Omar, 2020). However, papers referring to SC resilience (e.g. Christopher & Holweg, 2017) or SC risk management (e.g. Christopher & Holweg, 2017) of the last few years do not sufficiently attract attention to this kind of SC disturbances.

With the purpose to clarify the distinction between supply chains and supply networks (SN), Braziotis et al. (2013) elaborate on the contrast between the SC concept and SN concept. However, as shown by Braziotis et al. (2013, p. 647) the SN concept plays only a subordinated role whilst the majority of papers subsume the attributes of the network under the term 'supply chain'. For that reason, Albert (2009) states that the corresponding term "supply net" or "supply network" failed to take off and Christopher (1998) as well as Melnyk, Lummus, Vokurka, Burns, and Sandor (2009) integrate the SN concept in their SC definition. However, these authors neglected to further detail the structure of SC topologies. They describe different supply chain topologies as evolving from a supply wheel into a supply chain network but omit to mention self-organising SC clusters -so-called 'distributed SC' as added by Fiedler, Sackmann, and Haasis (2019, p. 62). Houlihan (1988), Halldórsson et al. (2015, p. 576) as well as Halldórsson, Kotzab, Mikkola, and Skjøtt-Larsen (2007) do not take into further consideration the SC topology but emphasise the aspect of an SC as uniform flow of material and services, information and finances. It seems that these authors give a general SC definition. However, Fisher (1997) redefines the uniform viewpoint of the SC and distinguishes between a 'physically efficient supply chain' and a 'market responsive supply chain' mainly aiming towards the different predictability of demand of required products. However, the middle range between both poles of functional and innovative products is not clearly defined. For products that do not fit the threshold values of both poles, the derivation of an SC strategy is not outlined. In the end, it should be stressed, that Fisher (1997) operationalises Porter's competitive advantage concept for the SC to either position as cost leader or follow a differential strategy (Porter, 1985). An SC built for functional products follows a cost leadership strategy whereas the responsive SC is represented in the focus strategy (smaller group of affluent customers accept longer lead times to get one particular -in this case customised- product or service). Nevertheless, segmentation principles and the adequate positioning of the decoupling point is a significant element of the CF to be designed. However, in the 1990s as Fisher elaborated the SC segmentation principles and other authors derived agile and leagile SC concepts, predictive and prescriptive analytics on consumer behaviour to improve the forecast accuracy of primary demand were not applicable due to missing technological innovations. But especially AI-based Big Data analytics might shed new light on these segmentation principles and the residual uncertainty of forecast inaccuracy as recently shown by Spiegel et al. (2013) as well as Gast (2018) and their anticipatory shipping concepts based on predictive analytics.

Table 2-1: The Summary of the Existing SC Definitions

No.	Supply Chain Definitions	Authors and Year	Key Features	Thesis relevance
General Definition				
1	SC is linked with an economic and continuous supply […] in the quantities and at the time required […] and with a minimum of disturbance.	(Banbury, 1975)	Seamless material flow on-time and in-full.	Yes
2	The very purpose of a SC is to disseminate goods from the source to a vast number of sinks who are geographically dispersed. The final purpose is to provide a steady flow of goods while simultaneously avoiding the added cost of excessive inventories in the system.	(Burns & Sivazlian, 1978)	Inventory-optimised material flow	Yes
3	A SC is defined as a set of three or more entities (organizations or individuals) directly involved in the upstream and downstream flows of products,	(Mentzer et al., 2001)	Upstream and downstream flow of material,	Yes

	services, finances, and / or information from a source to a customer.		information and finances.	
4	The SC encompasses all activities associated with the flow and transformation of goods from raw materials stage to the end user, as well as the associated information flows. Material and information flow both up and down the SC.	(Seuring & Müller, 2008b)	Flow and transformation of goods and associated information flow.	No
5	A SC is defined by the entire network of firms and activities involved in designing a set of products or services and related processes, acquiring and covering inputs into these products and services, distributing and consuming these products or services, and disposing of these products and services	(Melnyk et al., 2009)	Network of firms and activities. Covering the whole product life cycle.	No
6	SC, the network of firms that contributes both inbound and outbound products and services along an industry value chain.	(R. E. Miles & Snow, 2007)	Central organising unit in global industries.	No
Lean Supply Chain				
7	A set of organisations directly linked by upstream and downstream flows of products, services, finances, and information that collaboratively work to reduce cost and waste by efficiently pulling what is needed to meet the needs of the individual customer.	(Vitasek et al., 2005)	Collaboration of firms to reduce cost and waste. Efficiently meet customer needs.	Yes
Integrated Supply Chain				
8	The connected series of activities which is concerned with planning, coordinating and controlling material, parts and finished goods from suppliers to the customers. It is concerned with two distinct flows through the organisation: material and information. The scope begins with the source of supply and ends at the point of consumption. It extends much further than simply a concern with the physical movement of material and is just as much concerned with supplier management, purchasing, materials management, manufacturing management, facilities planning, customer service and information flow as with transport and physical distribution. The objective of managing the SC is to synchronise the requirements of the customer with the flow of material from suppliers in order to affect a balance between what are often seen as the conflicting goals of high customer service, low inventory investment and low unit cost.	(Stevens, 1989)	Conflicting goals of high service and low costs. Synchronise demand and supply. Planning, coordinating and controlling of material and information flow.	Yes
9	A network of connected and interdependent organisations mutually and co-operatively working together to control, manage and improve the flow of materials and information from suppliers to end users.	(Aitken, 1998)	Network character of a SC. Mutual cooperation to improve flows.	Yes
Virtual Supply Chain				
10	A chain (or network) connected through electronic links. A virtual SC represents an organization structure that facilitates efficient and effective flows of both physical goods and	(Chandrashekar & Schary, 1999)	Electronic connectivity of SC entities.	No

	information in a seamless fashion. The distinction between virtual chain and traditional SC is its inherent flexibility to quickly adopt and adapt to changes in the business environment. As a result, new members can be continually added and old members deleted or have roles reassigned to them. Consequently, the ability to reconfigure organizational structures (sometimes on a real-time basis) provides the chain the capability to customize solutions for different segments of customers or keep up with changes in customer requirements.		Inherent flexibility to re-configure the organisational structure of the SC. Competition of supply chains.	
Agile Supply Chain				
11	The agile SC basically refers to the use of responsiveness, competency, flexibility, and quickness to manage how well a SC entity operates on a daily basis. Unlike the lean SC, the agile SC uses real-time data and updated information to leverage current operations and real-time data against demand forecast, which helps to improve the overall efficiency and productivity of the given entity.	(Christopher, 2000)	Responsiveness and flexibility through use of real-time data.	Yes
Leagile Supply Chain				
12	Leagility is the combination of the lean and agile paradigm within a total SC strategy by positioning the decoupling point so as to best suit the need for responding to a volatile demand downstream yet providing level scheduling upstream from the decoupling point.	(Mason-Jones et al., 2000)	Combination of lean and agile principles. Best positioning of decoupling point.	Yes
Sustainable Supply Chain				
13	Material, information, and capital flows as well as cooperation among companies along the SC while taking goals from all three dimensions of sustainable development, that is, economic, environmental, and social, into account which are derived from customer’s and stakeholder’s requirements.	(Seuring & Müller, 2008b)	Sustainable SC encompass economic, environmental, and social sustainability.	Yes
New Institutional Economics SC definition				
14	Arrangements between economically independent but mutually connected business entities whose decision makers try to harmonize an individual company’s courses of action. SC are multistage and multidirectional structures of autonomous decision makers and can be seen as the result of a social negotiation process. Managing SC often refers to the setup of specific norms and standards, which rewards cooperation-compliant behaviour and sanctions counteraction. The SC, as an institution, is viewed as a system of rules that govern and control behaviour or action systems that are controlled by these rules. SC are arranged by human interaction in terms of a guiding system and as such, they are valid for a longer period of time and for a larger group of individuals and their acceptance is safeguarded by	(Halldórsson et al., 2015)	Network of mutually connected entities. Course of action as a result of social negotiation process. System of rules – an institution. Acceptance safeguarded by formal contracts, incentive structures and social relationships.	Yes

	different means, both formal contracts, incentive structures and social relationships.			
Digital Supply Chain				
15	Makes maximal use of digital technologies to plan and execute transactions, communications and actions.	(Sanders & Swink, 2020)	Use of digital technologies.	No
Self-thinking Supply Chain				
16	A new SC model with autonomous and predictive capabilities.	(Calatayud et al., 2019)	Autonomous and predictive capabilities.	Yes

2.3 Theories for Supply Chain Entities and Their Interactions

Entities in the SC include in general suppliers, manufacturers, logistics service providers, and retailers (Chia & Goh, 2009). However, authors determine SC entities following their purposes and industry specifics e.g. as equipment or service providers, contract manufacturers, purchasers, OEMi, or consumers (e.g. P. Reyes, Raisinghani, & Singh, 2002, p. 54). In general, it is found that SC entities are mapped as the nodes in an SC network, vertically and horizontally connected and represented by agents in a CF. The CF in this thesis is applied to simulate the nature of the SC with the objective to predict the behaviour and the interaction of SC entities. For that reason, theories provide insights and assumptions about how SC entities behave and act so that the agents in the CF can be correctly mapped (Defee, Williams, Randall, & Thomas, 2010, p. 404).

Defee et al. (2010, p. 407), Swanson, Goel, Francisco, and Stock (2017), Gligor, Bozkurt, Russo, and Omar (2019), and Yang and Xu (2019, p. 191) provide a comprehensive overview of theories related to logistics and SC management. All four papers conclude that transaction costs (TC) Economics and Resource-Based View (RBV) are by far the most applied theories in SC management. However, it is found that both theories only represent a limited view on SC. TCE contributes to the CF of this thesis with the theorisation of efficient boundaries of the firm in the SC and provides choices between hierarchy and market access (Williamson, 1985) whilst RBV turns the view primarily on the bundling of inter-firm resources. This is why the viewpoint of Halldórsson et al. (2015, p. 578) is also considered which highlights the four complementary theories RBV, TC Economics, Principal-Agent-Theory (PAT), and Network Theory (NT) as most important. Equal to all four theories is their behavioural assumption of 'bounded rationality'. This is considered more realistic to explore decision-making processes of SC entities instead of the principles of rational agents underlying the (neo) classical economic theory. Obviously, PAT is useful to close conceptual gaps with its insights on division of labour and the alignment of incentives in dyads embedded in networks. However, NT is only of minor relevance for this CF to explore the interplay of SC entities due to its primary focus on providing a framework for multiple other theories dealing with socio-economic relationships or structures of networks and systems. In contrast to the classification of theories Halldórsson et al. (2015, p. 578) applies for their argumentation, it could even be stated, that NT can be classified as a grand theory encompassing other middle range theories instead of being applied as middle-range theory defined in that paper as "trying to explain inter-organizational phenomena".

Defee et al. (2010) but especially Kor and Mahoney (2004) locate the RBV in the papers of J. Barney (1991), Penrose (1959), and Wernerfelt (1984). J. Barney (1991) turns the view of sustained competitive advantages on firm-internal sources and sees the firm's resources with their attributes to be valuable, rare, imperfectly imitable, and non-substitutable as the major factor. The three categories of resources defined by J. Barney (1991) are enhanced by Steinmann, Schreyögg, and Koch (2013) to five types of resources to be combined in resource bundles: financial resources (e.g. creditworthiness), human resources (e.g. managers), organisational resources (e.g. IT systems), physical resources (e.g. real estates) and technological resources (e.g. quality standards, brand names or research know-how). But neither the proposed bundling of the five types of resources nor the three resource categories of J. Barney (1991) considers the power structure between SC entities. This aspect of the CF is seen to be explained and solved in the PAT resp. agency theory (Coase, 1937; Jensen & Meckling, 1976). Halldórsson et al. (2007) find in the RBV a theory which informs SC management about the coordination of assets. The paper argues with the access to another firm's core competencies through cooperative arrangements and with inter-organisational relationships to facilitate and advance learning processes of individual firms. However, RBV is not sufficient as the foundation for inter-organisational relationship simulation of this CF. Amongst other reasons, Hoopes, Madsen, and Walker (2003) moan about the insufficient competitive heterogeneity such as the market as organisation form is underrepresented. They state that RBV only focuses on hierarchical cooperation in the sense of Williamson (1975). It also appears that that RBV only applies organisation theories. Social theories are not included. Due to the publishing date in the early 1990s, the Internet is not considered a resource to access nearly free-of-charge information or at least as a source of data and information exchange between cooperating firms. In addition, the initial assumption of J. Barney (1991) that differences of resources distributed across firms are stable over time is questioned by papers later published (e.g. Chandrashekar & Schary, 1999; Surana, Kumara, Greaves, & Raghavan, 2005). Further development of the RBV is the Knowledge-based View (KBV) postulated in the papers of Kogut and Zander (1992) and Grant (1996) which leads to SC learning conceptualised through the 'extended RBV' by Lavie (2006) and Lewis, Brandon‐Jones, Slack, and Howard (2010) including an inter-organisational resource viewpoint. However, extended RBV takes up Relational View (Dyer & Singh, 1998) and (social) NT (Hearnshaw & Wilson, 2013; Wasserman & Faust, 1994) which is already complementary to RBV (Halldórsson et al., 2015, p. 578) so that extended RBV might be considered as a consolidation and further development of both related theories. Nevertheless, a recent call for papers by Elsevier for their Journal of Business Research (Anonym, 2020g) underpins the relevance of further developing RBV and KBV due to new digital and disruptive technologies such as AI, Blockchain, augmented reality and 5G with the intelligence-based view to emphasise targeted competitive advantages of specific insights (Lichtenthaler, 2019) with the combination of these technologies. These findings underpin the initial intention for research in this thesis. In the course of these new technologies, the theory of stigmergy might come into play. These new technologies might strengthen or even enable a mechanism of indirect coordination of communication through the environment between agents or actions (Marsh & Onof, 2008). Referring to Elliot (2007), integrative and regulatory processes may emerge, leading to social regulation. Especially the idea that self-organised re-establishing of an equilibrium without planned, controlled, or direct communication through mass collaboration might be an interesting research focus with only a few papers (Kumar & Anbuudayasankar, 2019; Soni, Jain, Chan, Niu, & Prakash, 2019) undertaken for SC management as far as reviewed literature shows. However, middle-range theories based on bounded rationality as proposed by Halldórsson et al. (2007) to be applied to simulate and predict behaviour of human beings are not sufficient for the research objective of this thesis. As illustrated in Table 2-2, there is also the need to apply GT and Rational-Choice Theory (RCT) as part of Decision Theory (DT) with their assumption of rational agents to determine and predict outcomes of actions of technical devices.

Table 2-2: Theories Relevant for the Conceptional Framework of this Research

Theory related to SC Entities and their Interactions		**Authors and Years**	**Contribution to Conceptual Framework**
New Institutional Economics			*Assumption of bounded rationality*
KBV (Knowledge-Based View)		(Kogut & Zander, 1992)	Contributes to insights on SC learning
PAT (Principal-Agent theory / Agency theory)		(Jensen & Meckling, 1976)	Theorises the hierarchical relationship of SC entities
RBV (Resource-based View)		J. Barney (1991)	Induces resource-based competitive advantages
RV (Relational View)		(Dyer & Singh, 1998)	Includes inter-organisational dependencies
ST (Stigmergy Theory)		(Elliot, 2007)	Ideates to visionary thinking through considering mass collaboration with swarm intelligence
TCE (Transaction Cost Economics)		(Williamson, 1985)	Defines boundaries of SC organisations
Neoclassical Economics Theory			*Assumption of rational agents*
GT	Game Theory	(Thun, 2005)	Enables modelling of situations of choice
RCT	Rational-Choice Theory	(Marwala, 2017)	Stimulates simulation of AI-supported decision-making

This is because a technical device is seen as a rational agent with clear preferences, modelling uncertainty via expected values of variables or functions of variables, and always choosing to act with the optimal expected outcome of itself from among all feasible actions (Visser, 2010). Visser (2010) outlines two aspects: the rationality assumption with full market transparency and immediate information availability and the utility maximisation or margin optimisation assumption. The first aspect of neoclassical rationality is critically argued by J. Levin and Milgrom (2004), and Fumagalli (2020). In contrast to the pure teaching, J. Levin and Milgrom (2004) see RCT as already fertilised and inspired by bounded rationality theories. They recognise the shortcomings of RCT and propose a concept which still retains the utility function but under the assumption to rationalise agents' situational and contextual real preferences through empirical analysis so that the problem of rational choice can be represented as one of maximising a real-valued utility function. Another objection raised against RCT is that its assumptions on choice are not underpinned by empirical studies or miss the link to neuropsychological hypotheses. Fumagalli (2020) goes in that direction by stating that RCT already implies explanatory potential and defends RCT against bounded rationality critics. However, his refutations of arguments from opponents of the RCT appear to come from an intensive philosophical viewpoint so that his arguments appear to a certain extent artificial and constructed and less convincing to economists. However, both authors do not question the maximising assumption versus satisfactory solutions to agent's choice problems.

In contrast, referring to the latter aspect, Vetrò, Santangelo, Beretta, and De Martin (2019) critically point out that it is not enough for AI-supported technical devices to be able to carry out their functions driven only by narrow, task-oriented, optimisation goals but it is also necessary to make decisions "respectful of humans principles". This aspect is a good starting point to further be considered in the CF of this thesis. However, this general understanding should be discussed in a more differentiated way to elaborate on the nature of the SC. Vetrò et al. (2019) primarily focus on social aspects such as discrimination towards specific population groups. Note that in the sense of SC management, the 'human principles' shall more turn to the simulation of cooperative planning and the avoidance of arbitrary and biased profit or margin accumulation so that all SC entities return their fair benefit according to their individual contribution to the SC performance.

GT is considered as an important theory in SC management by the above-mentioned literature reviews although neither Halldórsson et al. (2007) nor Halldórsson et al. (2015) consider GT as relevant due to their strict focus on bounded rationality. But GT is applied in cases that decision-making units include in their decision-making process the behaviour of their counterpart as explored, modelled, or described by Leng and Parlar (2009), Hennet and Arda (2008), Jabarzare and Rasti-Barzoki (2020), or Thun (2005) and gives, therefore, additional opportunities to evaluate SC reality. However, GT is supposed to claim unrealistic requirements towards cooperating entities. It is criticised that often simple utility functions are applied because it is challenging to map all relevant parameters of reality in a CF. Nevertheless, GT achieved to establish computer-based agents which are superior to human beings (Bamberg & Coenenberg, 2008; Bitz, 1981; Zintl, 1995) and therefore, it might be an adequate instrument to assume the choices of SC entities. Therefore, this thesis applies RCT as an instrument to heuristically determine practicable solutions.

As a conclusion, it is followed the assumption of Alexander, Walker, and Naim (2014, p. 506) that rational normative and contextually biased behavioural decision-making can be brought together as prescriptive decision analysis.

2.4 Supply Chain as a Complex Adaptive System

Caddy and Helou (2007) inform about the general systems concept of decomposition where systems are constructed of sub-systems which are themselves constructed of sub-systems (Bertalanffy, 1972). They comprehensively argue that an SC is a collection of tangible and intangible sub-systems. Their reasoning is underpinned by supplementing tests against general systems theory (GST) principles mainly of Ackoff (1971), Bertalanffy (1972), as well as Yourdon (1989) and therefore prove evidence that an SC can be considered and treated as a system. Caddy and Helou (2007) also recognise that SC systems are complex and that GST contributes to a deeper and more informed understanding of the management of such complex SC systems. However, there are two important aspects of a system that are not further explored by Caddy and Helou (2007) with general systems theory, namely the feedback loop in a quasi-equilibrium and the sub-systems themselves with their constituting components. Moreover, in recent years GST is attributed to a lack of adaptation and co-alignment instruments (Pathak &

Dilts, 2002) so that the system behaviour at “the edge of chaos” (Lansing, 2003; Turner & Baker, 2019) and the behaviour of individual agents -understood as the elements of the sub-systems as referring to Bertalanffy (1972)- are not sufficiently respected. Therefore, these aspects are reviewed through papers applying CAS theory to the SC. CAS are supposed to self-regulate by positive or negative feedback loops based on parallel or simultaneous activities of their entities (Anderson, 1999; Holland, 2006; Mingers & White, 2010). This is why Choi, Dooley, and Rungtusanatham (2001) discuss the right balance of controls versus autonomous actions in the SC. Their underlying assumption is that “controls act as a form of negative feedback” through rules and regulations or institutional and budgetary restrictions. Obviously, Choi et al. (2001) refer to perceptual control theory in their reasoning that control through negative feedback stabilises the SC system after having received environmental or system-inherent disturbances. They agree with the GST, but state that bringing the SC system back in the initial stable equilibrium to regain its lost efficiency is only beneficial in the case of incremental disadvantages. Instead, CAS theory sees positive feedback to allow for autonomous action which is supposed to be the driver for emergence in the system. Choi et al. (2001) argue that only the ability of a SC system to create emergence makes this SC resilient against so-called ‘quantum changes’ which requires moving the SC system to a new equilibrium for sustainable competitive advantages. However, their strict distinction between these two antagonistic pairs of controls/negative feedback and autonomous actions/positive feedback might be limited in regard to disruptive theory (Christensen, 1995; Christensen, Raynor, & McDonald, 2015) which claims for the application of management instruments inducing controlled and ordered changes of business models to defend but also include disruptive services and technologies. It might appear that also controlled and ordered activities evolve the SC system to a new meta-stable equilibrium.

The second aspect noted by Caddy and Helou (2007) refers to the sub-systems themselves with their constituting components. Again, Choi et al. (2001, p. 358) frame the description of CAS with comprehensible illustrative SC examples. Besides already discussed CAS attributes assigned to the SC as a system, interest shall be pointed to internal mechanisms of agents and schema. Choi et al. (2001, p. 358) convincingly expound that individual SC entities who work together through alliances based on shared norms and economic incentives are represented by agents that share a common schema. They inform that the higher the shared schema is the higher will be the level of fitness for each of these SC entities. Fitness maps the performance of SC entities through delivery time, cost, quality, or flexibility and contributes to reduced TC and increased efficiency. These mutual dependencies of agents' schema and fitness lead to learning of single agents. Choi et al. (2001) comprehensibly underpin that learning is represented through adaptiveness of each agent.

To learn more about SC as CAS, the research results of authors who all apply CAS theory to SC are reviewed with the purpose to test whether the assumption that an SC can be considered as a CAS can be confirmed. Relevant papers are Pathak and Dilts (2002), Changrui et al. (2002), Surana et al. (2005), and Barrientos and de la Mota (2016). All these authors refer in their basic assumptions on the SC as a CAS to Choi et al. (2001). Obviously, these papers are mostly informed about CAS by the concepts of Holland (1992), Gell-Mann (1994a), or Gell-Mann (1994b) so that a strong agreement prevails what characterises SC as CAS. Authors apply CAS theory with the purpose to model SC. A model is a simplified depiction of reality and enable authors to simulate the behaviour of an SC (Stachowiak, 1973). The CAS theory provides the systems' inherent attributes of this model.

Pathak and Dilts (2002) prove evidence that SC mapped as CAS in simulation models form new structures and that an SC emerges with additional tiered nodes in case that overcapacity is subcontracted. The results of this well-established simulation provide learning input for the CF of this thesis. Agent strategies lead to adaptable and emerging SC structures and form a new equilibrium what is a key attribute of a CAS. However, the underlying rational choice parameters and the utility maximisation assumption might limit the application in CF with bounded rationality assumptions. The same limitation might appear with the evolutionary GT-based modelling approach of Barrientos and de la Mota (2016). However, their conclusion that the "*proportion of cooperative companies… evolves positively over time… when their benefit obtained by cooperating is maximum*", seems profane compared to the complexity of the explanatory model, the underlying effort assumed, and other papers already tested cooperative behaviours in the SC. Changrui et al. (2002) intend to find a new research approach on agile SC modelling using the CAS-inherent bottom-up concept of individual agent strategies leading to desired collaborative behaviour. The authors describe the setup of the simulation model. However, the paper does not map a coherent concept of the nature of agile SC. It is not fully clear what makes the difference to modelling e.g., the lean SC concept. It might be interesting to learn about the decoupling point in the model, an important element of agile SC. It should be explained how the specific product attributes such as low predictability to which an agile SC should respond, affect the SC system. No management strategies are found which might be used to apply in an agile SC to deal with SC equilibrium. The model does not consider control aspects; thus, the modelled agile SC is only supposed to find a new stable equilibrium, but can the model be generalised with this limitation so that it proves the SC as a CAS? As learning input for this thesis, the results are only of minor interest.

Surana et al. (2005) discuss the opportunities for the SC provided by new technologies. They explore whether it is possible for managers to control with these new technologies the entire SC although the SC is a CAS and as such, it emerges and self-organises new structures. From the perspective of scholars in 2005, they conclude that technology is not yet sufficiently developed to do so. However, during the last 15 years after this well-argued paper has been published, technologies progressed so that their research might be revised and updated. Nevertheless, the key challenge Surana et al. (2005) identify -determining what agent strategies lead to the desired collective behaviour in the sense of CAS theory- might be the same as 15 years ago and therefore, their findings are beneficial to build the CF of this thesis.

The first conclusion of this part of the literature review is, that available literature convincingly informs that the nature of an SC can be presented as a CAS. With new technologies arising in the last few years, the second conclusion is that there is still the need to explore how management strategies can be applied to achieve collective behaviour in the SC system. Therefore, this thesis builds a CF that treats SC as CAS.

2.5 Information Technology Applied to Supply Chains

Over the last years, several authors confirmed that the use of IT significantly improves SC performance (Aysenur & Hikmet, 2017; Oh, Ryu, & Yang, 2019; Thöni & Tjoa, 2017; Vanpoucke, Vereecke, & Muylle, 2017). IT is assumed to improve strategic and tactical SC management as well as SC execution and monitoring (Thöni & Tjoa, 2017). IT is applied to improve different elements of the SC flow such as transportation and coordination between companies. On a strategic and tactical level, network planning or business to business (B2B) e-procurement can be designed more efficiently (Oh et al., 2019). It is found that especially the potential of IT-enabled 'Internet of Things (IoT)' in the SC is addressed in respective literature (e.g. Thöni & Tjoa, 2017; Varma & Khan, 2014). Chandrashekar and Schary (1999) deduce the IT development in the SC from the 1970s to the late 1990s from stand-alone applications to coordinated interfaces among all suppliers, focal companies, and customers with SC management software and the internet. ERP systems in SC are applied with a high maturity degree to enable digitalised transactions within one SC entity. Referring to Battaglia et al. (2004), platforms facilitate more and more inter-company communication and data exchange between SC entities and between SC entities and their environment. Thus, today's SC is more and more characterised by IT providing (near) real-time visibility as exemplarily illustrated by use cases from diverse papers and websites (e.g. Anonym, 2019b; 2020f, 2020m; Dreyer, Strandhagen, Romsdal, & Hoff, 2010; George, Subramoniam, Krishnankutty, & International Conference on Green Technologies Trivandrum, 2012; Mejjaouli & Babiceanu, 2018).

However, Section 2.4 informs that the SC is a CAS. Referring to Calatayud et al. (2019), from the viewpoint of IT, the SC of the future which will tackle such a CAS will be coined by the requirement to be autonomous and to have predictive capabilities. This is why Fiedler et al. (2019) explore how decentralised multi-agent systems can be applied in all areas of the SC to approximate this autonomous management. But referring to Miloslavskaya and Tolstoy (2016), it appears that agents becoming enabled to autonomously manage SC activities inevitably need access to heterogenous data sources, fast data, and data lakes. However, Calatayud et al. (2019) find out that interface layers of traditional IT such as material requirement planning (MRP), advanced planning and optimisation (APO), warehouse management systems (WMS), or customer service management (CSM) have only limited capability of sharing on-time and accurate data throughout the entire SC. Miloslavskaya and Tolstoy (2016) underpin this viewpoint by explaining that data-centric or data-driven approaches are not efficiently feasible for traditional IT due to their way of processing requests which ends up in an infinite growth of queues or useless storage of infinitely increasing volumes of raw data. This is why Calatayud et al. (2019) and Mandal (2019) state that what is lacking are the technologies for collecting and processing big data, sharing it with SC partners, processing machine-enabled decision-making through drawing meaningful conclusions from data with application of statistics, mathematics, econometrics, simulation, optimisation or other techniques with minimum or no human intervention. Calatayud et al. (2019) and Marr (2019) inform that this is where AI comes into play.

2.6 Artificial Intelligence (AI)

2.6.1 AI Definitions

It is expected that authors defining a notion or term with a strong technological association, focusses on its determining salient attributes and the innovative impact that technology has on socio-technical environment. However, a significant portion of the papers reviewed to find definitions of AI, firstly gives a brief historical overview of how AI technology evolved (Brynjolfsson & McAfee, 2017; Feldt, Kontny, & Wagenitz, 2019; Russell & Norvig, 2016; Simmons & Chappell, 1988; Tredinnick, 2017). These papers commonly name John McCarthy as the person who originally introducing the term ‘Artificial Intelligence’ (AI), and Alan Turing with his ‘Turing machine’ and his ‘Turing Test’ as two of the most influential scholars in this field. This is often a limited illustration of scholars who have significantly contributed to AI progress. A more comprehensive depiction is given by Nilsson (2009) who provides an in-depth historical description of AI and relates their contributions to other acknowledged scientists such as Marvin Minsky, Allen Newell, Herb Simon, Bruce Buchanan and Joshua Lederberg. It can be found that AI is an interdisciplinary science which interlinks experts from the field of logic, mathematics, engineering, neurology, psychology or cognitive science.

Comparing two definitions of AI given by prestigious dictionaries, the two divergent viewpoints and expectations on AI become obvious: On the one hand, AI is interpreted as "[…] computer systems that can copy intelligent human behaviour" (2020b) and on the other hand as "machines that have some of the qualities that the human mind has, such as the ability to understand language, recognise pictures, solve problems, and learn" (2020c). The first definition can be related to 'strong AI', a term critically discussed from the philosophical viewpoint in Searle (1980) but to a certain extent expected within the next three decades by Kurzweil (2013). In contrast, Tredinnick (2017) is noncommittal to a specific point in time but sees the general machine intelligence at least as a long-time goal. The second definition refers to so called 'weak AI', which serves only to solve specific expert problems in specific fields (Kreutzer & Sirrenberg, 2019, p. 87; Nilsson, 2009; Simmons & Chappell, 1988). These controversial viewpoints show that discussions on AI are led from different perspectives and with different technological insight. An often-raised criticism towards scholars like Kurzweil, that their visionary assumptions on future AI scenarios are closed to science fiction is shared by scholars who are more interested on solutions, which are feasible with their understanding and imagination of the conservative evolution of current technology. Wahlster (2016) e.g. argues that AI should not try to copy or imitate human intelligence so that human intelligence is the aim of AI engineers. AI-enabled capabilities should complement human capabilities. From the opinion of Wahlster (2016), expert systems already compensate a lot of humans' weaknesses but with technological approaches, different to humans' approaches. Nevertheless, humans combine and unite their capabilities (sensor fusion) to a uniform and consistent picture and their emotional and social intelligence is managed by the interplay of hormones and chemical processes. This is why Wahlster (2016) convincingly argues that this will not be feasible to implement in AI-enabled agents. This viewpoint is more comprehensible to be applied in this thesis, than the belief in AI which represents an embodiment of a robot mind in the phenomenological sense (Sharkey & Ziemke, 2001). Nevertheless, Searle (1980) as well as Sharkey and Ziemke (2001) see weak AI's 'intelligent machines', as to derive meaning only from their designers and observers. On the one hand, this gives the interpretation that weak AI still remains in the 'von Neumann architecture' (Nilsson, 2009, p. 393 et seqq.) and that interpretation of information processing only depends on human beings. On the other hand, it opens the door to discuss to what extent AI-based expert systems still depend on the programming and coding of their developers. Simmons and Chappell (1988, p. 39) put it in a nutshell that none of the approaches using the 'von Neumann architecture' provide an adequate solution to work with partial information. But it is found that developers are no longer able to code the complexity of the required solutions in their programmes. Therefore, computer systems must be able to explore presented knowledge and derive, as well as create tacit knowledge in the sense of Polanyi (1966) and apply on organisational knowledge management by Nonaka (1994) to supplement available partial knowledge. Simmons and Chappell (1988, p. 39) conclude that this is possible with "neural net machines", better known in the meanwhile as artificial neural networks (ANN) related. Thus, the definition of AI as referred to in this thesis primarily frames AI applications, which are ANN-related to solve problems. This is due to the fact, that ANN are seen as the technology which most significantly expresses the capability to act like human behaviours and to learn, although being a machine. This aspect of ‘learning’ leads to the often-used term ‘machine learning’ (ML) in the context of AI. However, the term ML is not consistently differentiated from the term AI. Feldt et al. (2019) confirm this perception, it appears as though both are different concepts on the same level but miss the opportunity to explain and argue their viewpoint to close this gap. In contrast, other authors prefer to consider ML as one technology of the superior AI concept (Brynjolfsson & McAfee, 2017; Korn, Zubovic, Czaika, & Aksi, 2019; Kreutzer & Sirrenberg, 2019; Moroff & Sardesai, 2019; Tredinnick, 2017). Tredinnick (2017) distinguishes the AI clusters NLP, ML, intelligent agents and rational decision-making and defines ML as “the ability to improve at performing tasks on the basis of iteration”. At least two critical issues are found with this distinction. Firstly, reducing ML only on its ability to perform tasks iteratively withheld the nature of ML which is better illustrated by Samuel (1959) or Brynjolfsson and McAfee (2017), who emphasise the self-learning aspect of ML. Secondly, these clusters are not mutually exclusive and collectively exhaustive. Intelligent agents are defined through attributes like performing action or a learning process. This is why Panayiotopoulos and Zacharis (2001) state that ML techniques are used for managing these tasks of intelligent agents. The same can be said with NLP (Kreutzer & Sirrenberg, 2019, p. 83). ML is the procedure which defines NLP or intelligent agents. Additionally, if counting NLP as one cluster, then computer vision (natural image processing (NIP)) is worth being counted as another cluster.

Syam and Sharma (2018) consider ML as prerequisite to the development of AI and argue with the substantial amounts of data (big data) to run through algorithms provided by ML to make a machine ‘intelligent’. It appears that authors relate ML with the technical aspect of learning. These authors often underpin the methods of how to run data through different types of algorithms and how the process of learning is applied and progresses by classifying learning techniques such as ‘supervised learning’, ‘unsupervised learning’, ‘reinforcement learning’ or ‘deep learning’ (e.g. Kreutzer & Sirrenberg, 2019; Schmidhuber, 2015). In contrast, it seems that authors striving to define AI are more concerned with discussing the philosophical aspects of learning.

Helm et al. (2020) describe AI as ‘*the simple theory of human intelligence being exhibited by machines*”. This raises the question on how to define intelligence in general and especially human intelligence. Korn et al. (2019) answer with referring to cognitive functions such as reasoning, learning, problem solving or creativity and Simmons and Chappell (1988) conclude that the behaviour of a machine which, if a human behaves in the same way, is considered as intelligent. Meanwhile, AI-based expert systems learned to behave faster or more precise than humans can ever be (Kreutzer & Sirrenberg, 2019). Therefore, to describe intelligent behaviour of machines, other authors use terms such as ‘imitate’, simulate, or mimic intelligent behaviour (Feldt et al., 2019; Nilsson, 2009). However, to dare a delimitation of ML and AI based on the reviewed definitions, it might be concluded that ML is defined to become operationalised and to deliver applicable results whereas AI is kind of unspecific in its applications and expected outcomes providing definitions such as Feldt et al. (2019) stating that “AI systems can learn by experiencing, universalize where direct experience is absent, and map from the inputs to the outputs”.

2.6.2 AI Classifications

Taking up the discussion from 2.6.1, Searle (1980) initiates a classification of AI into ‘strong AI’ and ‘weak AI’. Based on this classification, other scholars follow and classify AI into ‘Artificial Narrow Intelligence’, ‘Artificial General Intelligence’, or even ‘Artificial Superintelligence (ASI) (e.g. Dihal, 2020; Kelley & Atreides, 2020; Monett et al., 2020). All these arguments concerning the distinction between specialist expert systems and ‘strong AI’ revolve around the idea that a computer programme owns causal features which are capable to create consciousness or intentionality. The reasoning of Searle (1980) is that a computer programme can be called intelligent. However, what if McCarthy had not established the term ‘Artificial Intelligence’ to differentiate from other scholars (Nilsson, 2009, p. 78 et seq.) for his idea to create a programme which separates the knowledge repository from the interpreting part (the “advice taker” as formulated by McCarthy (1959)), but had called it ‘machine learning’ from the beginning of his studies? Then firstly and hypothetically the academic discussion about all these different types of AI would have not been necessary and their classification would have been obsolete. Obsolete since no scholar had the need to argue why or why not a machine respectively a computer programme should be (artificially) intelligent like humans. Secondly, the focus would be solely on the mechanical and technological solutions and their need of classification. Thirdly, the progress made of computer programmes in learning new capabilities or improving existing capabilities like speaking, detecting, acting, moving, or even feeling (Schmidhuber, 2017) would not be compared with human intelligence, but only with the capability of humans. Henceforth, machines or computer programmes which try to achieve a certain capability have nothing to do with ‘intelligence’ but with the functionality which makes this computer programme capable. Then the technology, with which the capability is constituted is moving in the centre of interest and not the philosophical reflections about the capability of causal features. Then, the capability of a computer programme to act with intentionality is only considered as a certain stage of progress of the technology of a computer programme, whether achievable or not. Joshi (2019) argues in a similar direction by stating that “the degree to which an AI system can replicate human capabilities is used as the criterion” to classify AI types.

However, the result of his classification in ‘reactive machines’, ‘limited memory machines’, ‘theory of mind’ and ‘self-aware’ aims to distinguish “AI-enabled machines based on their likeness to the human mind and their ability to ‘think’ or feel like humans”. In essence, this classification of Joshi (2019) makes no difference to the aforementioned classification between ANI, AGI, and ASI by other authors but only distinguishes the maturity of AI-enabled computer programmes related to human intelligence in ascending order.

Other authors apply more technologically oriented classification approaches. A collection of AI-related technologies is found at Anonym (2017a) which provide an overview of potentially relevant clusters such as NLP, speech recognition, virtual agent, ML, deep learning platforms, biometrics, or Robotic Process Automation (RPA). However, it resembles a disordered list of buzzwords and topics than a structured classification. Kreutzer and Sirrenberg (2019, p. 23) classify AI into applications NLP, NIP/Computer Vision, Robotics and Expert Systems. Assumed that human senses are considered as relevant capabilities of AI-enabled machines and programmes, then obviously the basic senses hearing and seeing are represented with this classification. Referring to the explanation of Kreutzer and Sirrenberg (2019, p. 23) already in 1970s to 1980s the capability of ‘expert systems’ has been extended to provide direct or indirect recommendations and problem solving comparable to the human capability of decision-making. Robotics is explained as the human capability to perform usually mechanical work or other tasks. It can be found that human senses such as temperature perception or sense of balance and a lot of other senses are covered through sensors and actuators in expert and as well as robotic systems. These four types represent humans’ capability to interact with the environment through passive (perception) and active (communication, movement) interaction. Kreutzer and Sirrenberg (2019, p. 23) correctly state that the boundaries between these applications are disappearing more and more and underpin their opinion with the example of autonomous driving. However, the classification primarily represents application fields with a certain maturity degree so that human capabilities such as feeling, tactile perception, olfactory perception, gustatory perception (taste) as well as pain sensation are not represented. This assumption is underpinned by the statements of Schmidhuber (2018) and Schmidhuber (2017) according to the current maturity degree of these AI-enabled capabilities. Chui et al. (2018), a McKinsey study, classifies AI into the problem types ‘classification’, ‘continuous estimation’, ‘clustering’, ‘all other optimisation’, ‘anomaly detection’, ‘ranking’, ‘recommendation’, and ‘data generation’ which are related to business settings and to which analytic techniques can be applied. These problem types express the ‘how to’ perspective of AI-enabled applications, how to categorise new inputs, how to estimate the next numeric value in a sequence, how to segment consumers etc. Additionally, the study classifies AI learning techniques such as transfer learning, reinforcement learning, or deep learning neural networks. The CeBIT interview of Wahlster (2016) shows a comparable view with the classification in ‘sensomotoric intelligence’, ‘emotional intelligence’, ‘cognitive intelligence’ and ‘social intelligence’. It appears that human-related capabilities can be assigned, that no overlapping is given, that maturity degree of a technology does not count and that there is no mismatch with problem or application types or with the learning methodology. It is also found that this classification covers the four problems, Wahlster (2016) mentions in the context of AI, uncertainty, vagueness, incompleteness and resource self-regulation.

2.6.3 AI Applications in the Supply Chain

The general definition says that an application field is an area to which a theory or a technical development is provided for actual use (2020a). However, this definition does not inform about the necessity and the reason why technical developments such as AI-enabled devices or agents should be used in a certain field and how application fields are determined. This is why the literature review shows that authors define, frame and distinct application fields for their own purposes and argue their intention to apply AI from different viewpoints (Aggarwal & Davè, 2018; F. Chan, 2005; F. W. H. Chan, 2004; Dash, McMurtrey, Rebman, & Kar, 2019; Hatiboglu, Schuler, Bildstein, & Hämmerle, 2019; Hecker et al., 2017; Kreutzer & Sirrenberg, 2019; Vyas, 2016). Hatiboglu et al. (2019) argue with the relevance of AI-enabled tools for certain application fields. They determine relevance through need-based optimisation or need-based performance improvement and underpin this relevance with use case examples. Thus, an application field is tailored to the need and the expected benefit from AI. Kreutzer and Sirrenberg (2019, p. 88 et seqq.) argue with the increasing complexity and cost pressure, and the need of agility in the SC. Morley (2017) explains how to solve these outlined challenges with the AI capability of data analysis to optimise costs, time and resources. Calatayud et al. (2019) argue that together with IoT, AI is the technology most often mentioned in practitioner research as enabler of the autonomous, predictive SC. However, IoT and AI cannot be viewed separately as Ustundag and Cevikcan (2018) underpin by providing application fields of AI such as adaptive robots, embedded systems based on cyber physical infrastructure, cloud systems, simulation and virtualisation through augmented or virtual reality and big data analytics which are combined to approximate self-decision making and autonomy as part of the IoT. Nevertheless, it seems that there is a common understanding that the SC itself is considered as an entire application field. These arguments underpin the general SC performance objectives discussed in 2.2 and make it comprehensible to consider the SC as an area encompassing fields to which AI shall be applied for performance purposes. However, no insights are given to which criteria AI application fields are determined and selected. Hatiboglu et al. (2019, p. 13) frame AI application fields such as ‘maintenance’, ‘logistics’, ‘quality management’ or ‘resource planning’ due to their scope of production environment. They explain that their selection is because already today AI applications exist in these fields and that their penetration is increasing in future. However, their selection criteria withheld possible application fields in which currently AI plays no role but in which AI could play a role in future. It is also found that Hatiboglu et al. (2019) distinguish between ‘AI application fields’ and ‘potential use of AI’ within application fields. They exemplarily outline that in the application field ‘logistics’, AI is used for picking & packing optimisation, vehicle planning, navigation of autonomous guided vehicles (AGV) or supports action planning and optimisation algorithms in warehouses. This distinction allows to determine a framework of more general application fields and flexibly assign to each of them selectively specific AI use cases. Other authors distinguish AI application fields from their functional perspective. Hecker et al. (2017, p. 8) differentiate physical and digital application fields of AI and distinguish these fields according to AI capabilities. AI is applied in physical autonomous robots and means of transports such as drones, or autonomous vehicles. Digitally, AI is used in autonomous agents such as RoboGames, algorithmic trade or social bots. Furthermore, cooperative skills of AI are applied in physical cobots which are, for an example controlled by gestures or support in driver assistance systems or serve as digital cognitive assistants such as mind-computer interfaces, personal virtual assistants, or cognitive expert consultants. Hecker et al. (2017, p. 8) illustrate application fields in which learning capabilities are important such as devices of smart working areas, preventive monitoring and anticipatory control or intelligent digital services such as fraud defence, risk management, or smart data discovery. Other authors such as Vyas (2016), Raissouni and Hamiche (2017), Al-Msloum (2020), Dash et al. (2019), Aggarwal and Davè (2018) add examples and use cases such as disruptive technologies, statistically supported SC improvement potentials, computer-based forecasting/demand planning, or AI-enabled curtailing of the Bullwhip effect to these functional application fields and underpin the relevance and contribution of AI in SC-related application fields. Finally, Kreutzer and Sirrenberg (2019, p. 88 et seqq.) propose a mixture of industry- and functional related application fields which results in the intersection of industry-specific SC. Nevertheless, all of these authors only illustrate excerpts of application fields. A holistic overview of application fields in the SC is not provided. This is expected from SC-related process models, first and foremost the SCOR model as discussed by Bolstorff and Rosenbaum (2003) with reference to Anonym (2020l) which provides an adequate process framework to which the aforementioned selection of application fields can be assigned. But a one-dimensional process model provides only limited completeness. Referring to Ehrenhoefer and Roeth (2010, p. 26 et seqq.), the “Pfohl’sche Logistics Cube” (Pfohl, 2016) provides a slightly different but complementary perspective on the structuring of a SC. On the one hand the distinction between decision level and operational level of information processing spans a broader net to collect AI relevant application fields. On the other hand, this cube shows relevant SC functions to which AI-enabled applications can be assigned. However, the Logistics Cube slightly ignores to dive deeper into production, procurement, and especially planning elements. But especially planning processes are a broad field of AI applications. These planning aspects are well-covered by the SC management task model of Hompel and Wolf (2013). Figure 2-2 illustrates process level 1 of the SCOR-model as the framework to which digital, physical, and functional application fields are assigned.

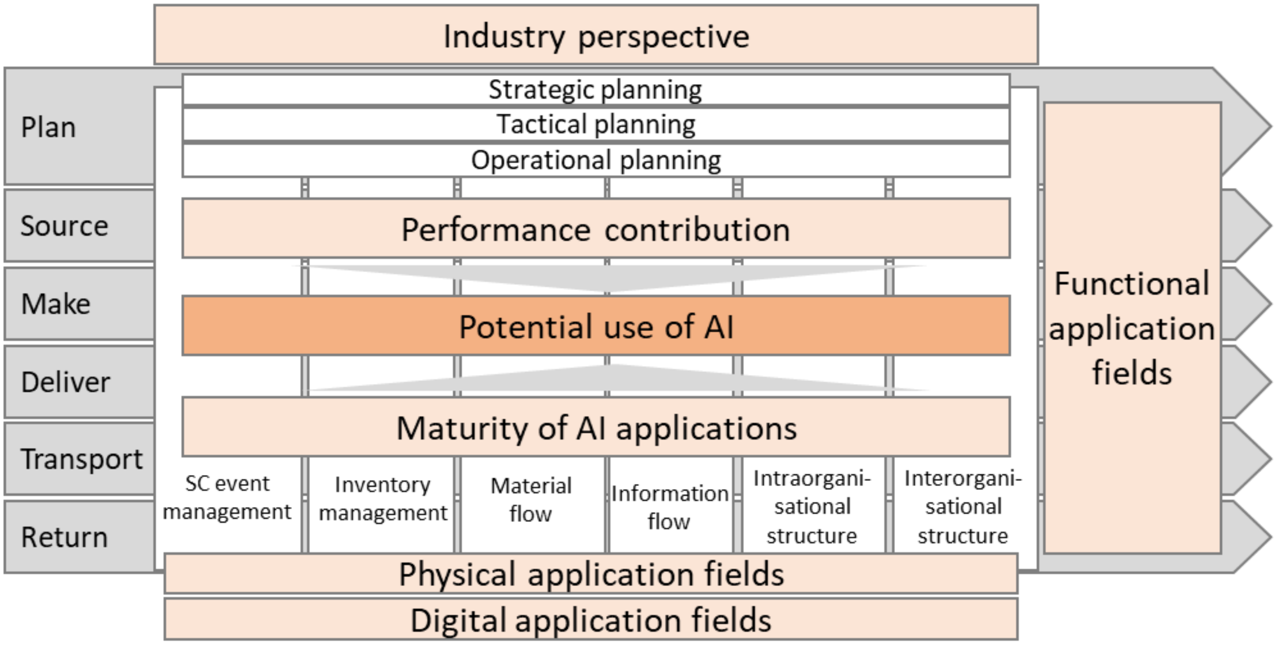


Figure 2-2: Different Viewpoints on AI Application Fields Based on Reviewed Literature

Strategic, tactical and operational planning refers to the application fields of the SC management task model of Hompel and Wolf (2013) which are specified in Table 2-3. It is found that Hompel and Wolf (2013) include warehouse and transport management in their model but omit to explicitly underpin transport planning and warehouse resource planning as referred to by Hatiboglu et al. (2019, p. 13) or Nakandala, Lau, and Zhang (2014). These two application fields are added for the sake of completeness and subsumed under ‘Logistics planning’

Table 2-3: AI Application Fields of the Business Process 'Planning' (Source: (Hompel & Wolf, 2013))

No.	AI Application Fields of the Business Process 'Planning'	Planning Horizon
Supply Chain Design		
1	Network- & system design	Strategic planning
Supply Chain Planning		
2	Sales planning	Strategic / tactical planning
3	Network planning	Strategic / tactical planning
4	Distribution planning	Tactical / operational planning
5	Procurement planning	Tactical / operational planning
6	Production planning	Tactical / operational planning
Collaborative planning		
7	Collaborative demand planning	Strategic, tactical, operational planning
8	Collaborative capacity planning	Tactical / operational planning
9	Collaborative inventory planning	Tactical / operational planning
Logistics planning		
10	Transport planning	Tactical / operational planning
11	Warehouse resource planning	Operational planning

Functional application fields as outlined in the "Pfohl'sche Logistics Cube" are itemised in Table 2-4. The dynamic of and inside AI application fields in the SC is indicated through the maturity degree of AI applications and the performance contribution of AI use cases. Both dimensions to which papers refer, impact the potential use of AI in the SC.

Table 2-4: Functional Application Fields in the SC as Outlined in the "Pfohl'sche Logistics Cube" (Source: (Pfohl, 2016))

No.	Functional Application Fields in the SC
1	Purchasing
2	Procurement
3	Production
4	Transhipment
5	Picking, packing & signing
6	Transport
7	Storing
8	Order management
9	Research & design

As seen in literature review of Section 2.2, AI can be applied to the material and information flow in intra- and interorganisational SC structures, with the aim to monitor events in the SC, and to adequately manage inventory. It is found that these activities happen in all SC processes. Therefore, these application fields pass all SCOR-model level 1 processes.

2.7 Value Creation in the Supply Chain

2.7.1 Value and Value Creation

Authors have disparate views on the process of VC and approach with the aid of different theoretical foundations. Rutherford (1977), generally defines it as the net contribution of each company to the total value of the production, which is accumulated to the VC of a national economy, or related to this research accumulated to VC of an entire SC. This viewpoint represents the more traditional research direction which looks on the quantifiable value such as the value-based management view, the economic value added (EVA) concept, or the shareholder VC concept to which the underlying assumption is that e.g. SC initiatives materialise their VC of inter-organisational cooperation by its discounted future cash flows based on balance sheet figures and profit & loss statement as outlined by Koller (1994), Hofmann and Wessely (2013), or Mastilo, Zakić, and Popović (2017). However, from a more general viewpoint, value also comprises components such as the importance, worth, or usefulness of a product, a service or the entire company which is not directly expressed in the balance sheet of a company (see general definitions also in "Cambridge Dictionary," 2019b; "Oxford Living Dictionary," 2019). Therefore, Mastilo et al. (2017) state that despite of tangible assets, the value of corporations is based on intangible assets such as brands, patents, quality, or highly skilled employees so that the resources themselves are valuable (C. Bowman & Ambrosini, 2000). However, this viewpoint is still company-centric so that influential stakeholders of a SC with divergent objectives such as suppliers or customers outside of the company are not appropriately respected. This is why Mastilo et al. (2017) and Lieberman et al. (2018) prefer the stakeholder VC concept in the full knowledge of its constraints according to risk of lobbyism and potential efficiency loss. They argue that shareholder value concepts ignore most of the economic value typically created and distributed by a firm. They conclude that the value of a product or a service can be expressed in the price and the use value by the customer. Therefore, Lieberman et al. (2018) define value as the sum of consumer and producer surplus in a specific interval of time. Lieberman et al. (2018) mean value which on consumer side is created but not covered through the price. This concept necessitates those assumptions are made on the reasons of consumers' willingness to pay. For that purpose, they provide the two main drivers innovation and replication through which willingness to pay is explained. Both drivers contribute to total economic value either through a new product or a new service or when a superior firm grows at the expense of its competitors. However, referring to Grönroos and Voima (2012) value is only materialised on consumer side that point in time, the consumer uses the product or service. They call this 'value-in-use'. Before 'value-in-use' happens, value is only hypothetically created. Nevertheless, the total economic value is only limited explained considering one period of time. For that reason, Lieberman et al. (2018) include in their concept, the dynamic VC which shows the delta between static VC in one period of time and the value created in another one. Lieberman et al. (2018) argue that it is necessary to consider this total economic value in order to fully understand the flow of economic value because firms that create new value may distribute it in different ways depending upon competition, legal rights, bargaining power etc. It is one aspect of the CF to be designed to understand if there is a plausible impact on shareholder value from the management of the firm to increase the price of firm's product and to earn more of consumers' surplus for their shareholders from the created value of the entire SC.

2.7.2 Conceptual Frameworks of Value Creation in the Supply Chain

The papers in Section 2.7 only limitedly discuss the mechanisms behind the process of VC. Therefore, other papers are consulted which are supposed to conceptually inform about the design of frameworks to create value in the SC. An overview of these papers is shown in Table 2-5. With the research aim to design a CF which describes the mechanisms of VC embedded in process flow, structure, and performance context, the proposed CF by other authors is compared to their potential contribution to this research intention. Some papers proposing CF for SC, end up with the argumentation of mechanisms to improve SC performance but omit to go the next step to include the impact on VC in the SC (Holweg & Helo, 2014). Other papers give the impression that the term 'value creation' is only used to make the paper more appealing and to spark interest for a pure conceptual topic (e.g. Ustundag & Cevikcan, 2018). The focus of other papers is either only on the technological and design aspects or on the performance impact of the SC. But the final step which links the performance result with the financial achievements on cash flow or revenue is missing (e.g. In, Bradley, Bichescu, & Autry, 2019).

The CF of Hammervoll (2009) describes the context of inter-organisational knowledge build through different situations of learning and developing of common products in the SC. The paper posits that competitive advantage and related value is created through the appropriate management of VC initiatives. The proposed CF provides a foundation to determine differences of VC logic using interdependence, objectives, and focus of coordination as attributes. The CF covers primarily information flow and performance aspects but leaves structure elements out. In contrast to Hammervoll (2009), Esper, Ellinger, Stank, Flint, and Moon (2010) propose to create value through intra-organisational knowledge management and provide a well-depicted structure of VC phases. On the one hand, intra-organisational approach is not specifically related to SC topics. On the other hand, the value which is created in one firm which brings together their supply market and demand market knowledge contributes to the value of the entire SC for the reason that this firm is one SC entity of others. In et al. (2019) propose a CF constituted of structure, processes, and strategy to link information flow with the mechanisms for information governance with the purpose to create value through improved SC performance with better information quality. In et al. (2019) suggest that value capitalises through quick response to changes in markets, regulatory frameworks and technological environments. However, the aspect of AI is not considered. Holweg and Helo (2014) provide with their value chain architecture five determinants, which enable strategic decision-making on structure and performance of SC networks but omit to include the flow aspect. Ustundag and Cevikcan (2018) propose a CF which relates foundational technology advances of IoT to design principles with the purpose to compose dynamic and integrated value-creation networks. VC aspects are only briefly outlined. Brinch (2019) discovers that VC through big data is linked to the adaption of elements in the field of IT, process, performance, human, strategic, and organisation practices. However, a direct connectivity between the benefits outlined and value created through financial or consumer/producer surplus effects is not provided. Elia, Polimeno, Solazzo, and Passiante (2020) propose a CF with five dimensions to outline the multiple value directions that big data paradigm can generate. Rehman, Chang, Batool, and Wah (2016) propose a framework to create value through big data reduction at the interface between two SC partners. Their VC initiative is an early data reduction approach to convert raw data streams into actionable knowledge patterns. The created value is profit maximisation and customer retention. Value is created on customer side as well as on supplier side through transparency of the created knowledge on both sides. However, big data only represents an extract of AI application fields. The subject and contribution to research of this thesis and the missing elements of the CF are summarised in Table 2-5. Finally, none of these CF comprehensively inform about VC in the SC through an entire consideration of AI-enabled applications.

Table 2-5: CF Thematising VC in SC and / or with AI

Authors and years	Subject and contribution to research of this Thesis	Settings			Missing thesis elements
(Brinch, 2019)	Conceptualisation and VC of big data. Informs about the mechanisms of the interplay between AI-enabled analytics and organisation practices.	SC	VC	AI	-
(Rehman et al., 2016)	Framework to create value through big data reduction at customer side. Informs about the mechanism to create value through knowledge sharing.	SC	VC	AI	F, S
(Hammervoll, 2009)	VC through relationships between SC partners. Informs about the management of VC initiatives to enable competitive advantages through mutual learning.	SC	VC		S
(Holweg & Helo, 2014)	Value chain architecture links the value viewpoint with the efficiency viewpoint. Provides insights to decision-making areas relevant for VC.	SC	VC		F
(Esper, Ellinger, et al., 2010)	CF of VC through knowledge management. Informs about the benefits to combine intra-organisational supply and demand activities.	SC	VC		-
(In et al., 2019)	CF which links information flow with information governance. Provides orientation for VC through governance mechanisms.	SC	VC		-
(Elia et al., 2020)	Multi-dimension framework for VC through big data. Provides a more critical view on VC mechanisms of AI-enabled analytics.		VC	AI	-
(Ustundag & Cevikcan, 2018)	CF relating IoT technology to design principles. Provides orientation to application fields of AI and the design of dynamic networks.	SC		AI	S

Legend: Process flow (F), Structure (S), Performance (P)

2.8 Impact Analyses and Systems Modelling

2.8.1 Impact Analyses

Arnold and Bohner (1993) define an impact analysis (IA) as “the activity of identifying what to modify to accomplish a change, or of identifying the potential consequences of a change.” The overall aim of this thesis is analysing and evaluating a substantial change in the SC through emerging technology AI. The CF serves to determine the SC descriptors which are a subject of modification. These SC descriptors compose a network of relationships of which the consequences of the impact of AI are evaluated. Other authors specify an IA as economic IA, financial IA (Weisbrod, Mulley, & Hensher, 2016), or regulatory IA (R. Reyes, Romano, & Sottilotta, 2015) and define 'Change' as one important dimension of IA. Weisbrod et al. (2016) explain that an economic IA shows changes in terms of jobs, compensation and business output and even regulatory IA are applied to provide changes between a current status and a future status (R. Reyes et al., 2015). In contrast, the financial IA is defined on the one hand as a methodology by which a differential in a margin or a ratio is converted to a monetary value (Burton, 2014) or on the other hand, as the calculation of the expected stream of expenditures and revenues associated with a certain initiative to assess its economic feasibility (2020h). The purposes of an IA are inherent to this thesis which conducts research of the impact of changes on SC performance and its capitalisation in financial dimension expressed in tangible values. It appears that an IA is the appropriate instrument to be applied in this thesis. The literature review shows that IA focusing on SC collect data empirically (Alves, Lima, Silva, Gomes, & González-Calderón, 2019) and that the analysis to measure the impact is conducted logically e.g. through classification, rating of factors and event pairs (Alves et al., 2019) or heuristically (Mononen, Leviäkangas, & Haapasalo, 2017) in quantitative terms e.g. with simulation models (Yee, 2005), or qualitatively (Shojachaikar, 2016) so that this study methodologically joins those mentioned above.

This thesis aims at a CF which combines macro-economic and micro-economic descriptors. IA in the field of SC are applied with macro-economic interest e.g. to investigate the correlation between socio-economic and socio-environmental issues and transports (Alves et al., 2019; Mononen et al., 2017), the impacts of cost and benefits on public transport investments (Weisbrod et al., 2016) or with micro-economic interest to investigate e.g. business impact of knowledge and information sharing (X. Li & Hu, 2012; Yee, 2005), or network re-design as well as disruption impact (Opasanon & Lertsanti, 2013; Tympakianaki, Koutsopoulos, Jenelius, & Cebecauer, 2018). IA in the field of AI is applied e.g. to investigate security challenges in Cloud and real-time environment (Junaid, Imran Ali, & Paul, 2012; Kiruthika Devi, Preetha, Selvaram, Shalinie, & Fourth International Conference on Recent Trends in Information Technology Chennai, 2014). In respect to VC, IA are conducted to explore ICT or environmental issues (Ceric, 2015a; Rodrigues Gurgel da Silva, Giuliano, Errico, Rong, & Barletta, 2019). These aforementioned investigation subjects evaluated by IA are strongly related to the overall aim of this thesis. However, literature review has not found IA combining these descriptors in one coherent CF to analyse systematically the impact of changes on the entire network.

2.8.2 Systems Modelling

The aim of this thesis is to analyse and evaluate a social network of agents in the SC, a method must be identified that allows to conceptually build the relationships between these agents. In general, modelling is essential to characterise and explore complex societal issues in systematic ways (Elsawah et al., 2020). Elsawah et al. (2020) as well as Mo, Bil, and Sinha (2015) emphasise the special feature of systems modelling compared to other business analytical approaches such as segmentation, customer life cycle analysis, or trends analysis in the interdisciplinary use of models to conceptualise and construct systems with the purpose to characterise and explore issues with inherent dynamic and network-based correlations. Elsawah et al. (2020) underpin, especially the potential and usefulness of systems modelling in the support of learning and decision-making processes to estimate and manage practical problems under uncertainty in complex systems. In Section 2.4 of this thesis, it is already stated that the CAS theory provides SC inherent attributes for modelling purposes. S. Levin, Xepapadeas, Crépin, and Norberg (2013) underpin that modelling is the most appropriate instrument which allows to explore CAS by arguing that neither causal empirical observations nor rational cognition allow to study CAS in an integrated and coherent way. They are of the opinion that both approaches risk to ignore crucial interactions and specific features of reality. This is the reason why both Elsawah et al. (2020) and S. Levin et al. (2013) therefore propose to apply primarily computer-based quantitative simulation approaches to investigate CAS. However, Pitt, Monks, Crowe, and Vasilakis (2016) point out that also qualitative methods in the field of systems modelling are useful, primarily with the reason to tackle unstructured problems, help to improve group understanding of the aims of a system, help to facilitate workshops with stakeholders, and to support the focus on key system issues. In contrast, computer simulation methods such as system dynamics, dynamic stochastic equilibrium models, or statistical microsimulation models often allow for fewer assumptions to be used to capture details of the respective system, support stakeholders in exploring system trade-offs, test what-if scenarios, or provide visualisations for clear understanding and dialogue among stakeholders (Elsawah et al., 2020; Pitt et al., 2016). Arbnor and Bjerke (2014) consider systems modelling to be one of the three basic methodological approaches for gaining business knowledge, besides the analytical approach and the agent-based modelling. In contrast, Elsawah et al. (2020) subordinate ABM to systems modelling as one of several computational systems modelling approaches. The combined application of systems modelling methods represented e.g. in social network analyses and ABM as proposed by Will, Groeneveld, Frank, and Müller (2020) is of special interest for this thesis. As seen in Section 2.4, subsystems consist of agents (e.g. SC entities) which interact so that the behaviour of the entire SC system and its processes are affected. Will et al. (2020) state that ABM is a process-based simulation approach that can capture and illustrate feedbacks between the behaviour of heterogeneous agents and their surroundings on a microlevel. They conclude that these simulated findings function on the macro-level as the interoperability of systems so that the entire system behaviour can be modelled and simulated so that conclusions can be made.

2.9 Summary: Discussion of the Originality and Importance of the Thesis

The review of SC definitions demonstrates that the finance flow of a SC has a special role to play; as a regulator of process and inventory costs as well as investments in tangible and intangible assets and as one lever of VC through the SC. The chronology of SC definitions illustrates that different performance improvement concepts have been prevailing through different decades and are supposed to be still relevant for future SC. Authors recognise that with the occurrence of AI-enabled technologies SC have been subjected to additional and profound change in the last decade. The body of literature agrees on a common viewpoint that a SC is enabled to include more and more AI-enabled autonomous and self-learning processes on strategic, tactical and as well as operational level. But reviewed literature misses to conceptually explore how emerging technology AI will adjust these prevailing SC concepts and what these adjustments mean for future VC in the SC.

Most of this literature derives its findings by looking back in the past or by exploring the presence. However, a significant growth of companies applying AI and therefore a significant economic impact in the upcoming decade is expected (Bughin, Seong, Manyika, Chui, & Joshi, 2018; Khodabandeh et al., 2019; Kirschniak, 2018; Pinkl, 2019). It might hold a certain likelihood that a related scenario might come true. Therefore, managers would be well advised to derive strategies for their own company or to show the entire SC how to tackle these challenges to stay competitive in future. However, it is not discussed how the increasing and intensifying application of AI in future either as contextual factor of the environment or as part of the SC system itself will affect the existing SC equilibrium. Furthermore, no CF is found which provides the foundation to explore the impact of AI on inter-organisational decision-making, SC planning, or autonomous devices and their impact on re-establishing of the SC equilibrium. The impact on the SC equilibrium through AI on other emerging technologies is not clarified through appropriate research. Furthermore, the body of literature reviewed gives only limited insights on how AI-enabled technologies have impacted or will impact conceptual interaction, coordination and collaboration or at least the structure of the SC system. It is also not comprehensively explored how inter-company cooperation will be changed due to autonomous processes culminating in autonomous driving or the self-thinking SC as suggested by authors with a courageous outlook to mid-term future. The literature review reveals the need to explain new or adapted connections and the necessity to explore changing mechanisms of action in the SC due to the progress of AI technology. It is important to identify and explore reasons and causes for expected forthcoming phenomena. With the purpose to provide foundation for action, recommendation and for further research, these findings should be combined into a coherent explanatory system, a theory. Therefore, this research is of importance and relevance from an academic perspective. From a business perspective, the literature review revealed that it is important and relevant to reassess and rethink the still valid SC concepts of the 1990s and 2000s, according to SC efficiency and responsiveness considering the challenges and the impact of new AI-enabled technologies and deduced concepts of autonomy and big data. This thesis provides instruments to be applied by managers to determine the prospectively created value of their intended SC initiatives respecting the likelihood of occurring SC scenarios. Therefore, from an academics and business viewpoint, the need to further research the impact of AI on VC in the SC embedded in a CF is identified.

Chapter 3 Research Design

3.1 Introduction

This chapter is to present the research design of this thesis which is divided into three parts: the research philosophy, the research strategy, and the research methods (Creswell, 2014; Paetzold, 2018). It is argued in Section 3.2 why the author of this thesis takes the position of a critical realist from ontological as well as epistemological viewpoint. Why abduction is more appropriate to the type of problem of this thesis than inductive or deductive reasoning as well as the underlying research methodology Grounded Theory is explained and argued in Section 3.3. Additionally, reasoning is provided for the choice of mixed methods, instead of a pure qualitative or quantitative research approach. With Section 3.4, it is explained why qualitative interviews and structured surveys as part of a Delphi Study have been applied. In Section 3.5, there is a CF and a CIB-analysis to develop a positive scenario of a SC system followed by the Section 3.6 about applied data presentation methods. Finally, in Sections 3.7 and 3.8, it is argued how this research design establishes rigour and validity considering ethical issues.

3.2 Critical Realism as Research Philosophy

The choice of the research design is affected on the one hand by the position of the researcher and his view on the nature of the world and on the other hand by the research question itself (Moses, 2007, p. 3; Saunders, Lewis, & Thornhill, 2012). Normally, the three ontological perspectives positivism, constructivism and critical realism which represent two poles and an in-between research philosophy are compared to each other so that the most appropriate one is selected to achieve the research objective (Armstrong, 2019; Boyd, 1992; Trochim, 2020). Thus, the research philosophy serves as the general framework to ensure a stringent epistemology with the underlying research strategy and methodology for structured, rigour and reliable knowledge building. Both critical realism and constructivism are in line with the relativist theory whereas positivism is related to methodological reductionism approach. Relativism is the idea that views are relative to differences in perception and consideration (Swoyer, 2015) and primarily represents qualitative research strategy. Halldórsson et al. (2015) confirms the position of the author of this thesis that SC management is in line with the relativist perspective of critical realism because SC are considered as CAS. Therefore, challenges for knowledge building occur, which are driven largely by their inherent network-like structure of direct and indirect relationships of SC entities. Furthermore, SC are very heterogeneous and operate in situations which differ from SC entity to SC entity and SC concept to SC concept. It is difficult to derive best practices required for positivist approach because a CAS is characterised by limitless openness (Holland, 2006). Additionally, the attribute of emergence and the accompanying potential of synergies make the behaviour in a CAS nonlinear and unpredictable with quantitative linear arithmetic. Therefore, it is problematic to establish causality and reduction to the smallest possible entities and their relations to each other with these conditions of reality (Bhaskar, 1975) as required by the positivist approach. The reality of the SC is coined by social interaction between decision units with undetermined preference models, individual interest and situational objectives. This research develops a CF which provides the basis for an exploratory investigation of a dependent network of multiple entities and descriptors. A relativist approach allows the researcher to identify, explore and seek to understand the structures and mechanisms of such a complex and dependent network (Abdul, 2015). In general, this kind of qualitative analysis requires a deep understanding and exploration which favours personal interactions and not the collection of numbered data from a large sample which is typical for the positivist objective of generalisation. However, this research explores SC performance and its quantification of created value. But, created value in a CAS, as elucidated in Section 2.7.1, is a reality which is constructed in a relationship between and by SC entities and additionally biased by analysts' and researchers' viewpoints. Another aspect which underpins the relativist viewpoint is that the theoretical concept of SC management as well as the concepts of AI are founded on complementary theories from multiple disciplines as discussed in Section 2.3 and Section 2.6.1.

Both philosophies critical realism and constructivism believe that the view on the world is based on perceptions of it and that perception and observation is fallible so that constructions must be imperfect (Trochim, 2020). However, Bhaskar (2010, p. 146) depicts that critical realists distinct between the real object and the object of knowledge so that the number of layers which bury the truth only need to be explored and removed to discover the real word phenomena (Moses, 2007, p. 13). Constructivists are not primarily interested in discovering a real world because access is not guaranteed by perception or human reason (Corbetta, 2003; Moses, 2007, p. 194). However, the CF of this thesis encompasses socio-technical subsystems which are supposed to be verifiable and predictable to a certain extent and therefore, it is a strong conviction of the researcher that on the one hand objectivity can be achieved through this research and on the other hand, the reflections of different experts and their exchange of opinions about expected behaviour of SC agents in the future with support of appropriately applied instruments and tools can very well lead to an approximation of the future SC reality.

3.3 Research Strategy

3.3.1 Abductive Reasoning

This thesis is intended to build new knowledge on future phenomena for which currently no rules and only a non-meaningful number of cases exist. Thus, a research strategy must be applied that allows for formulating and exploring propositions on phenomena. The epistemological approach ‘abduction’ was primarily taken up and again introduced by Charles S. Pierce to the academic debate in the 1890s. Purpose of abduction is to develop an explaining hypothesis. Referring to Reichertz (2013), compared to induction and deduction, it is the research approach which actually enhances findings and contributes to knowledge building. With this statement, Reichertz (2013) demarcates the neopositivist viewpoint that the claim of a scientific testimony is the context for grounds and reasons from the context of discovery. Referring to Pierce in the interpretation of Reichertz (2013), the underlying assumption is that this process alleviates doubts through finding new rules to establish new convictions. Discovery inherent is a categorical fallibilism which assumes knowledge as not static so that abduction is compatible to the stance of critical realism. New findings and new knowledge only arise if the circle between deduction and its empirical verification through induction is not consistent. Then, a new theory must be formulated with a new abductive conclusion. In the context of this thesis, existing rules of reasoning are provided by SC-related theories as described in Section 2.3. These theories inform the behaviour of SC entities and agents. Their behaviour causes events as described in Section 2.4. The theories are consulted to explain the behaviour based on known rules and to deduce a prediction of the behaviour in the future. However, AI-supported applications impact the behaviour of the SC entities and agents in such a manner that the explanation of the behaviour of a SC system and its components is not possible or limited with the existing rules of available theories. Therefore, new explanations must be found to predict how the behaviour of SC entities and agents affect events in the SC system. In other words, new hypotheses or even theories about the behaviour of a SC system must be developed. The traditional approach to develop new hypotheses or theories is inductive reasoning. However, the number of available AI applications to be studied is too low to find rules which can be generalised to provide a reliable hypothesis or theory to explain the future behaviour of the SC system. Thus, the current research situation is as follows: the observation is made so that a tremendous change will happen in the SC system. However, the rules to explain the impact of this change as well as the cases are almost unknown. Therefore, it needs an additional approach for reasoning from a known result of an observation of rules and cases so that future SC behaviour can be predicted. Abductive reasoning aims to find an explanation for a given observation in the light of some background knowledge (Schoenfisch, Meilicke, Stülpnagel, Ortmann, & Stuckenschmidt, 2018). In other words, abduction is required if the existing stock of knowledge does not lead to a respective explanation or rule (Reichertz, 2013). Richardson and Kramer (2016) underpin that the lack of practical and theoretical knowledge is an appropriate argument to apply abductive reasoning. Although Richardson and Kramer (2016, p. 500) confuse abductive reasoning with 'qualitative induction', ("*new idea [...] is added to two 'givens' (the rule and the result)*."), their general conclusion about abduction and Grounded Theory is viable. However, this thesis follows the interpretation of Reichertz (2013) who argues that abductive reasoning is founded on two unknowns, the 'rule' and the 'case' what comes closer to the nature of the research objective of this thesis. A comparison of the four research approaches is given in Figure 3-1.

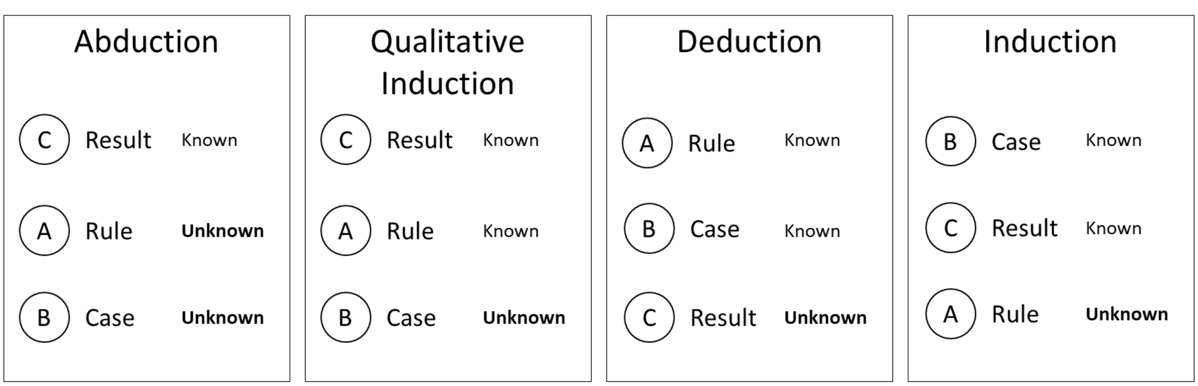


Figure 3-1: Comparison of Research Approaches: Abduction, Qualitative Induction, Deduction, Induction

The research interest which initiates the research objective of this thesis is formulated in three questions:

1) Which changes are SC systems confronted with due to increasing application of AI in the future?
2) How do these changes impact VC in future SC systems?
3) Which lessons can be drawn from the findings about VC in SC through AI-enabled applications?

The first question outlines that the result of an observation is perceived as a situation of change. This change appears significantly enough to explore the nature of the change. The second question shows that there is a need to explore cases with the purpose of finding an explanation for the observation. However, literature review in Section 2.7.2 already illustrated the lack of practical and theoretical knowledge according to the lack of availability of a sufficient number of appropriate cases. The third question aims to derive new rules from the data collection and associated theories consulted.

The above derivation shows that the theoretical foundation of how AI impacts VC in the SC cannot be elaborated without abductive reasoning. The alignment of the descriptors of the CF cannot be derived from theories informing about SC behaviours. However, these theories can be included and associated with collected data. The practical knowledge, how the equilibrium of the SC system is established is not available because the future situation how the descriptors shall be positioned so that the equilibrium of the SC system is established despite of the impact of AI is not available as a case. Therefore, abductive reasoning is needed with two unknowns, the rule and the case.

3.3.2 Grounded Theory as Underlying Research Methodology

Grounded theory represents a qualitative research strategy and claims that theory building should be based on empirically collected data (Glaser, 1967). The research approach of this thesis is based on empirically collected data. The hypotheses and theory building following the analysis of the CF is grounded in the views of and the information from the participating experts. Therefore, methods shall be applied which shed light on research participants' opinions and viewpoints (Creswell, 2014; Winter, 2013). Saunders et al. (2012) explain that also a case study as qualitative research strategy investigates a particular contemporary phenomenon within its real-life context based on empirical data. However,, case study is more related to inductive reasoning and primarily used to test and apply theories (Moses, 2007, p. 139 et seq.). The claim of this thesis to underpin abductive reasoning with a strict methodology is also not fulfilled with action research format. From future research views, action research is not supposed to directly predict future situations but is more focused on the analysis of the presence to build knowledge to explain the presence. A dialectical approach between data and theory (Creswell, 2014) is one of the strengths of Grounded Theory to establish an alternating interplay between induction and deduction (Winter, 2013) but neither ethnographic strategy nor archival strategy are supposed to provide this strict methodology. In contrast to these other qualitative research strategies, Grounded Theory is particularly helpful for research to predict and explain behaviour of agents in the SC, the emphasis being upon developing and building theory (Saunders et al., 2012). Pierce uses the term 'guess' in relation to abduction (Reichertz, 2013), but connects to 'guessing' the 'Heureka moment', the sudden inspiration or the abductive flash of genius of a researcher who has discovered the new explanation for his observation. To avoid that abduction is only 'guessing', a strict method is applied for data collecting and data analysis. This is also in the sense of Pierce, who figured out that prior to an abductive flash, hard academic work of investigation and exploration is necessary, so that cognitive activities form new individual knowledge which then initiates such a Heureka moment of ingenuity. Richardson and Kramer (2016) consider the abductive finding of useful explanations from observed facts as a process. Winter (2013) informs that Grounded Theory provides the systemic and flexible guidelines for this process. The approach of this research respects this interplay between a structured approach and the hoped-for Heureka moment. A detailed analysis phase, which serves to gather information and results, is followed by a deductive-inspirational section, which is intended to evoke the Heureka moment. Thus, the author of this thesis interprets both Winter (2013) and Richardson and Kramer (2016) in the sense that for collecting and analysing qualitative data to discover new rules, Grounded Theory provides a theoretical framework. It is allowed to apply a mixture of data collecting, data analysing and brainstorming methods. Reichertz (2013) points out that research logic of abduction with its purpose to develop theories equals research logic of Grounded Theory methodology. With the abductive approach, a rule is constructed with the help of a mental act which parallelly clarifies the case. However, the pure cognitive development of a hypothesis to be applied to a complex adaptive environment is difficult or even impossible (Z. Li, 2014). Therefore, it is intended to conduct the creation of propositions to build the theory with a strict methodological foundation.

3.3.3 Mixed Methods Approach

This research approach needs a method which allows for analysing qualitative and quantitative data due to the applied data collection and presentation approach of qualitative interviews, Delphi Study, and CIB-analysis. Mixed methods approach involves collecting and analysing both quantitative and qualitative data. The core assumption is that the combination of qualitative and quantitative approaches provides a more complete understanding of a research problem than one approach alone (Creswell, 2014; Saunders et al., 2012; Yin, 2011). The approach of this study ensures that not two studies with different conclusions are processed and compared to each other during one research approach, but the identity as a single study is retained and an integrated relationship between the qualitative and quantitative components is ideally reflected. It is ensured that both the quantitative and the qualitative data together are analysed and interpreted before arriving at a study's main conclusion (Yin, 2011). This study avoids the often-stated validity issue towards mixed methods, that conflicting results of qualitative and quantitative analysis delay a reliable conclusion by collecting both qualitative and quantitative data from the same individual people (Yin, 2011) and by applying a mixture of sequential and parallel analysis of these data (Creswell, 2014). It is of relevance to figure out why mixed methods are the preferred approach compared to singular qualitative or quantitative research. Saunders et al. (2012) inform that such a decision depends int. al. on the research question. Due to the research emphasis of this thesis, to develop a skeleton which enables a hypothesis to explain and to a certain degree predict the behaviour of a CAS, the pure application of quantitative methods is inappropriate as already depicted in Section 3.2. However, quantitative data preparation provides a structured foundation for further exploratory and explanatory data analysis so that the two forms of data are integrated in the design analysis through merging and connecting the data. Quantitative is predominantly used as a synonym for any data collection technique or data analysis procedure that generates or uses numerical data. in contrast, qualitative is used predominantly as a synonym for any data collection techniques or data analysis procedure that generates or use non-numerical data such as words, pictures and video clips (Saunders et al., 2012). The mix of qualitative and quantitative data collection is constituted in the questionnaires sent to and maintained by the participating experts in this study so that the claim to embed the two form of data is fulfilled (Creswell, 2014). Two different data sources are established. One smaller group are asked to provide qualitative input to pre-define the structure of the CF. Then another larger group of participants is asked to provide quantitative and qualitative data to design the CF framework. On the one hand this approach followed a sequential setup of data collection, on the other hand, a parallel collection of the two forms of data are processed. This approach allows to compare different perspectives drawn from quantitative and qualitative data. The author of this thesis exploratively analysed the collected data mix so that a qualitative follow-up with tools to be generally applied in Grounded Theory research resulted in a CF. This exploratory part is a valuable means of finding out 'what is happening; to seek new insights; to ask questions and to assess phenomena in a new light' (Saunders et al., 2012). It is particularly useful for the clarification of the understanding of the grounded problem and the precise nature of the problem. With a second questionnaire the consolidated group is asked to evaluate the mutual direct and direct relations between the descriptors of the CF. This quantitative data collection is accompanied by the request to qualitatively argue the quantitative evaluation, so that qualitative data help explain relationships between quantitative variables (Saunders et al., 2012). In a next sequence of analysis, the quantitative evaluation served as input for a mathematical simulation resulting in different models of future SC systems. A final qualitative exploration by the researcher with the aid of SC-related theories and the qualitative answers of the participants led to a hypothesis about a positive future SC scenario. This general research approach is summarised and illustrated in Figure 3-2.

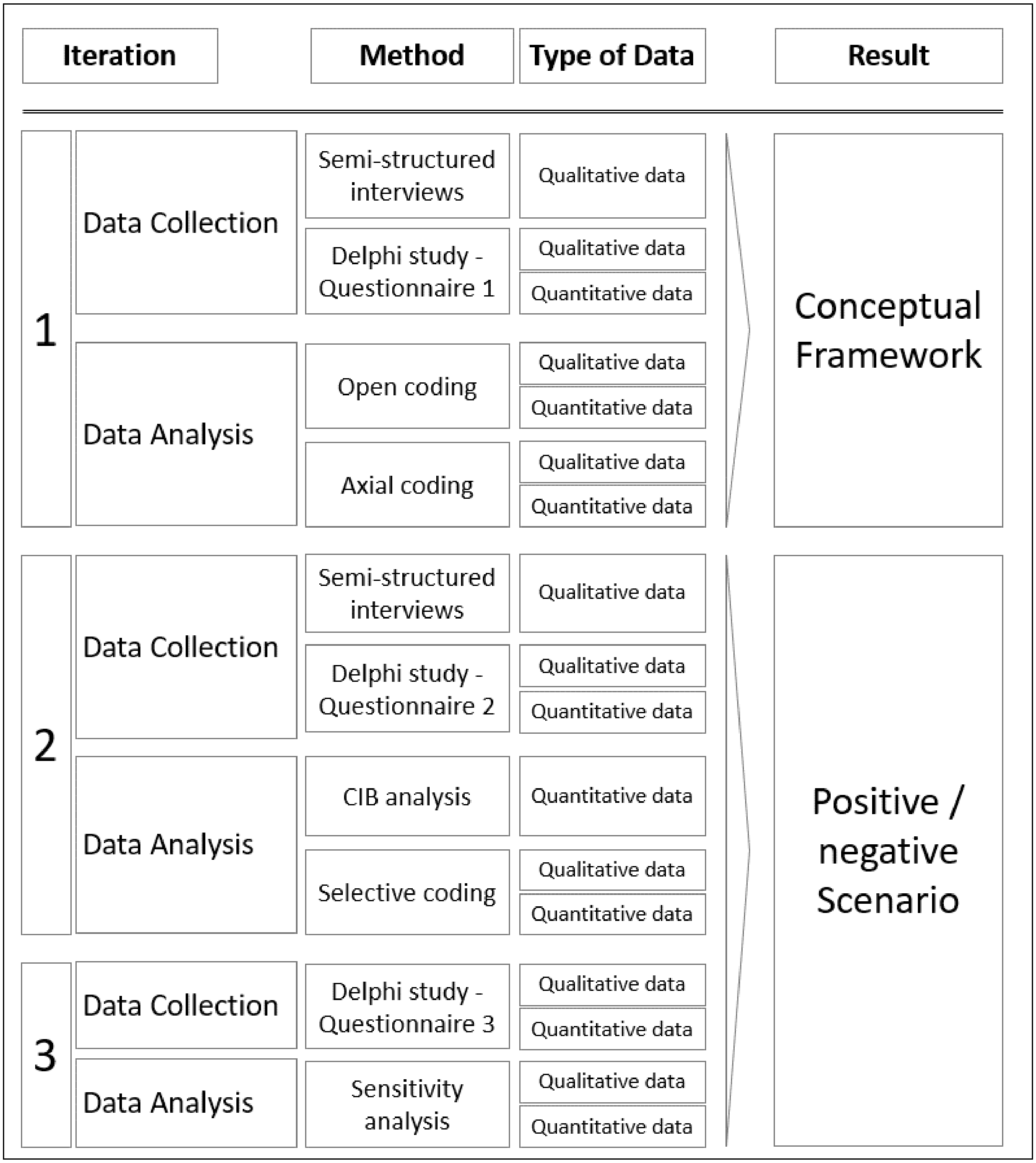


Figure 3-2: Mixed Methods Research Approach Applied for this Thesis.

This thesis follows the claim of continuous change between data collection followed by comparative analysis, and data synthesis as an iterative procedure (Legewie & Schervier-Legewie, 2004). After the collection and analysis of the first bunch of data in Delphi Study Poll

1, the next data collection happens so that the data is compared amongst each other. The researcher is enabled to permanently look for differences, similarities, and behaviour patterns with the target to build categories and thematic groups to elaborate correlations and relations between data segments (Creswell, 2014; Legewie & Schervier-Legewie, 2004). These permanent reflections lead to intermediate theories or hypotheses (Glaser, 1967, p. 9) which are rejected or aligned for a next circle of testing especially through the explanatory phase of scenario analysis and proposition building with existing literature. The moment of saturation occurs after the interpretation of the result of a positive scenario of the SC system. It is obvious that this kind of predominant qualitative mixed methods approach is strongly interlocked with the systematic steps of Grounded Theory. In the Grounded Theory the breakdown of data into units is called open coding, the process of recognising relationships between categories is referred to as axial coding, and the integration of categories to produce a theory is labelled selective coding (Creswell, 2014; Saunders et al., 2012). However, this applies to these steps, methods and tools such as CIB-analysis and scenario analysis which need numerical data for a structured explanation process. The author of this thesis wants to underpin expressly that this combination of the instruments from qualitative and quantitative research provides better opportunity to make a conclusion from the research findings. The exploration phase makes the nature of the problem tangible and transparent for the researcher. The numerical data providing exactly quantifiable results can be analysed towards their correlations.

This kind of data collection and data analysis needs a time-intensive activity of the participants with the questionnaire and a time-intensive analysis and synthesis phase by the researcher. Furthermore, the researcher needs to be and is familiar with both quantitative and qualitative forms of research, due to his more than 20 years of experience in the field of management consultancy. Nevertheless, the risk of researcher-biased analysis which influences the subjective results is inherent in such a relativist research approach.

Creswell (2014) claims for mixed methods to contain a theoretical framework within both quantitative and qualitative data. Furthermore, it is requested that researchers may both test theories and generate them. The mixed methods approach in this study allows both to create a CF which represents the first hypothesis about a SC system and then to test the viability of this CF by applying scenario analysis to create a positive scenario of a SC system as a second hypothesis of the SC system.

Generally, a mixed methods approach is supposed to minimise the limitations of each of the both approaches (Creswell, 2014). Inflexibility due to standardised research situation of a quantitative approach is overcome with parallel and sequential semi-structured qualitative interviews. Quantitative CIB-analysis' findings are not primarily established to identify the root causes of the behaviour of SC entities. Especially the combination of exploratory in-depth theory analysis and qualitative data provided by participants by answering both questionnaires limit this disadvantage of quantitative data collection. Furthermore, these open questions in the questionnaires allow for improvement suggestions in multiple directions. The often-posited claim for a highly qualified interviewer is fulfilled with the author of this thesis who executes all qualitative interviews by his own. The issue is that qualitative data do not allow a derivation of numerical measurement is overcome with the instrument of the CIB-analysis.

3.4 Methods for Data Collection

3.4.1 Overview Data Collection Methods

As itemised in Table 3-1, qualitative interviews and survey-based Delphi Study are applied for data collection. The qualitative interviews are grouped into one-on-one interviews and group interviews. The surveys applied in three Delphi Study Polls provide quantitative rating complemented by qualitative statements. The Delphi Study itself is only applied as data collection tool to gather experts' opinions about aspects of the research scope.

Table 3-1: Types of Inquiry

No	Type of inquiry
1	Qualitative interviews to investigate VC
2	Delphi Study Poll 1
3	Group interview to prepare Delphi Study Poll 2
4	Delphi Study Poll 2
5	Delphi Study Poll 3

First inquiry type serves to explore VC in the SC. Second inquiry type contributes to the preparation of the Delphi Study. Third, fourth, and fifth type of inquiry represent the three Polls of the Delphi Study.

3.4.2 Qualitative Interviews

Qualitative interviews are expected to have an exploratory character to seek new insights about each specific topic (Laya Prasad, 2010; Saunders et al., 2012). For that reason, qualitative interviews are selected with the aim to interact with the participants to receive in-depth understanding of the SC and its VC. These qualitative interviews are positioned in the first two of three iterations of the overall approach to investigate VC and to test results of Poll 1 and to inform Poll 2 survey. The interviewees of the one-on-one and group interviews have been selected according to their specific subject matter expertise in each focus topic. To investigate VC in the SC, the focus topic of each qualitative interview is loosely structured according to value terminology, creation of value, and allocation of created value. Qualitative interviews helped to examine and expand upon the responses of these acknowledged experts to give this research current insights into the correlation between SC performance as analysed in the CF and VC. Referring to Creswell (2014) and Saunders et al. (2012), there are various types of interviews, such as structured interviews, unstructured interviews, and semi-structured interviews. Generally, semi-structured interviews are commonly applied to collect specific and high-sophisticated expert knowledge in the course of a qualitative study. Especially for this study, the researcher took the opportunity to test experts' reactions with some uncommon statements and hypothesis about VC and future changes but sensitively paid attention that he did not overstep the mark to upset the interviewees. With structured interviews, the adaption on interviewees' reaction would have been impossible. With unstructured interviews, the interviewer would have possibly lost the underlying theme in a situation of relatively high stress. The resulting data types which have been tested in the group interview are illustrated Table 3-2.

Table 3-2: Resulting Data Type and Their Contribution to Delphi Study Poll 2

Data type	Contribution to Delphi Study Poll 2
Descriptors	Initial list of descriptors is aligned so that the research objective is better supported.
Descriptor variants	Descriptor variants have been defined and logically tested with a CIB-analysis run.
CIB-analysis rating	Rating is developed and used for logical test with the aforementioned CIB-analysis run.
Relationship between descriptors	The potential relations between the descriptors are drafted and qualitatively discussed to test the general applicability of the CF.
Rating of the descriptor event pairs	The established descriptor event pairs are rated as part of the pre-evaluation of Delphi Study Poll 2.

These results flew into the structure of the questionnaire developed for the Delphi Study. Poll 2. As follow up of this qualitative group session, the participants rated the descriptor event pairs according to the Likert scale in Table 4-11. This rating is provided to the participants of Delphi Study Poll 2 as part of the questionnaire.

3.4.3 Survey-based Three Poll Delphi Study

Referring to Jiang, Kleer, and Piller (2017), a Delphi Study is often applied to predict technical developments (technological forecasting) in the qualitative research. The main focus of this research is on the impact triggered by AI. As described in Section 2.6.3, AI is recognised as one of the key technologies of this era. A distinction to subjective estimate is combined with a comprehensible and reproducible structure and setup (Joseph A. Maxwell, 1996, p. 173 et seqq.), what allows for critical realist researchers to frame research questions also based on not directly observable entities (Josef A. Maxwell, 2012, p. 93). It could be questioned why a traditional survey should not be the better choice for data collection. The author of this thesis, follows the conclusion of Okoli and Pawlowski (2004, p. 19 et seq.) who compare traditional survey with Delphi method based on certain evaluation criteria. Primarily the criteria that a Delphi Study is supposed to smoothen and balance individual expert viewpoints to a common group opinion is a convincing argument for this thesis. Such a group opinion is supposed to be more reliable than non-aligned single expert views (Linstone & Turoff, 2002; Seuring & Müller, 2008a). This Delphi Study follows the typical setup of three Polls (Ogden, Petersen, Carter, & Monczeka, 2005; Seuring & Müller, 2008a). However, a Delphi Study is also subject of critics. Mueller (1998) criticises that not even 20 percent of the predicted innovations from Delphi studies in the 1960s have been realised till 2000. Looking back on the results of a Delphi Study conducted in 1998 (Cuhls, Blind, & Grupp, 1998), it can be stated that in the field of ICT and organisational evolution in economics the success rate is remarkable but a relatively high number of conjectures about the future have been inaccurate or even failed. Already known trends were often extrapolated with linear assumptions. Technologies with a relatively good degree of maturity were often expected later than they actually occurred. In contrast, technological visions were often forecasted with an earlier entry date than they occurred. Contemporary topics relevant for society at the point in time the Delphi Study was conducted are extrapolated with a much stronger effect than occurred with the result that some predictions from 1998 appear somehow outrageous in retrospect. However, despite these mixed perceptions, the Delphi Study of this thesis allowed the chosen experts to deal systematically with a complex problem (Wendee, 2011). Especially for the objective of this research, the expected time of occurrence is not subject of interest. Furthermore, this study shall serve as an anchor for an interested target group of academics or practitioners to develop their own ideas with respect to their individual work environment. Therefore, a Delphi Study is the chosen instrument for the structured data collection of this research. Data collection with the instrument of a ‘Delphi Study’ is conducted with formalised surveys using questionnaires based on a predetermined and standardised set of questions. All responses are recorded on a standardised schedule. Some questions are pre-coded answers (Saunders et al., 2012). As outlined in Figure 3-3, the Delphi Study is conducted in three Polls. Each of the Polls pursued a specific target. All three targets together compose the essence of this thesis. First Poll targets to identify the descriptors of the CF to be achieved. Second Poll establishes the relationship and the dependencies of the descriptors. Third Poll conducts a sensitivity analysis of the previous results. In essence, this setup represents the requirement to balance individual opinions through the participants themselves and to achieve a mostly agreed group opinion (Ogden et al., 2005; Okoli & Pawlowski, 2004; Seuring & Müller, 2008a).

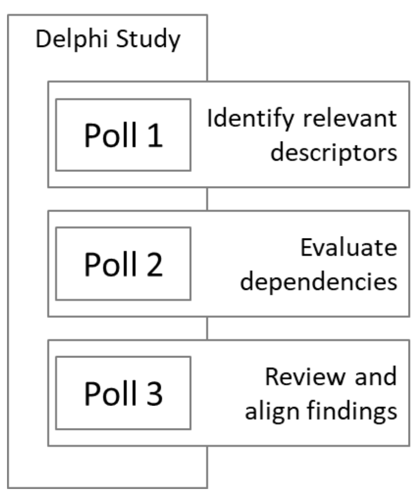


Figure 3-3: Purpose of Delphi Study Polls

3.4.4 Selection of Participants

The selection of experts follows the recommendation of Yin (2011) to include different viewpoints as well as potentially contradicting opinions in a qualitative research. A well-balanced mixture of academics and practitioners is intended with the selection of the participants. The Assumption is that academics contribute knowledge about SC theories and concepts regularly updated by new research findings with a focus on the long run with a time horizon of approximately 8 to 12 years. It is expected from practitioners that the operational business experience of companies' decision-makers and their interest at innovations already matured to be implemented in a tactical and strategic horizon of approximately 3 to 8 years. The experts' selection intended also to respect some cultural factors to receive a widespread picture of opinions and to set a counterbalance to the relatively strong Central Europe viewpoint. Key focus is set on the individual background of expertise of each participant so that a multi-dimensional picture of knowledge, interest, and expertise is brought into this study which enables to shed light on the research scope from all necessary perspectives in the SC and its impacting factors. According to the focus of the research, technological and as well as domain expert knowledge is required. Technological expertise should mainly concentrate on AI related technologies such as ML and ANN enhanced by general know-how about IoT supporting technologies such as sensor technology and common IT architecture expertise including Blockchain experts. Blockchain experts were especially searched for with the purpose to include an emerging technology which is in the beginning of its product life cycle in the time, survey started (Q1/2018). Experts with a pure SC domain background shall mainly bring in the insights on the business context, primarily their experiences and expertise on the context of SC effectiveness and process as well as organisational structure. First and foremost, technology expertise shall provide insights in and outlook on the innovations and technological developments to set up future scenarios based on the CF. For this study, technology is defined as a collection of tools which support the automation of material, information, and finance flow of the SC such as IoT-related technology, scanning or EDI-interfaces. An additional benefit for the research is expected by the contribution of experts combining AI and SC domain expertise, as kind of a comparison and junction group between both poles of separated domain and technological expert knowledge.

3.5 Methods for Data Analysis

3.5.1 Overview Data Analysis Methods

Conceptual framework (CF) and Cross-Impact Balance Analysis (CIB-analysis) are applied to explore the data collected with qualitative interviews and survey-based Delphi Study. In this research, the CF is prerequisite to perform the CIB-analysis because it determines and provides the descriptors and their variants which are rated in Delphi Study Poll 2 and reviewed in Delphi Study Poll 3. CIB-analysis then enables the scenario development based on the CF.

3.5.2 Conceptual Framework

In general, a framework is seen as a data-structure for representing a stereotyped situation with attached kinds of information (Minsky, 1974). A framework build on propositional logic or predicate logic allows explicit inference of derived statements from given statements (Bibel, Hölldobler, & Schaub, 1993). This kind of frameworks allow a stringent formalised approach and the generalisation of a statement. However, the underlying principle of explicitness or at least bivalence (Wuchterl, 1977) cannot be applied to explore the social system SC as a whole with its network-like descriptor structure and indeterministic in nature. Therefore, a framework is required which meets multivalent logic. Furthermore, a qualitative approach does not intend to generalise but explore and investigate situational cases to approach social reality of a SC. This kind of explanatory research usually focuses on ‘why’ or ‘what caused’ a phenomenon to occur. For such integrated research requirements, alternative methods such as the usage of a single idea or an organising principle to view the world (Berlin, 1953) are not applicable. This is why Jabareen (2009) proposes a ‘conceptual framework’ to be applied for such an interpretative research intention. With the attribute ‘conceptual’, it is expressed that the framework is little more than a temporary composition of distinct, heterogeneous components, based rather on soft interpretation of intentions than on ‘hard facts’ and is therefore incomplete and tentative (Joseph A. Maxwell, 2013).

A CF is defined as a network or a construct of interlinked concepts, assumptions, expectations, beliefs, and theories that together provide a comprehensive understanding of a phenomenon or phenomena (Jabareen, 2009; Joseph A. Maxwell, 2013; M. B. Miles & Huberman, 1994). Joseph A. Maxwell (2013) calls the CF a ‘tool’ to be applied for qualitative study which should be explained graphically or in narrative form the key factors, concepts of variables and the presumed relationships among them. However, CF can also be developed and constructed through a process of qualitative empirical analysis. This is why Tamene (2016) states that a CF serves essential role in inductive research design. Thus, the CF represents the result of the inductive part of the overall abductive research approach of this thesis. A CF is a tool which provides an overall picture of a context with several variations. It is used to make conceptual distinctions and to organise ideas (Berlin, 1953). Therefore, the CF is applied for data analysis in this research. Several types of CF are discussed in literature of which this thesis develops a CF to define a working hypothesis with the purpose to conduct exploratory research and to predict events expected in the future (Minsky, 1974; Shields & Rangarjan, 2013). Bibel et al. (1993) consider CF as formalisms to present knowledge. The CF to be designed in this thesis provides a fixed top level of a frame which represents components, respectively descriptors which are always true about the supposed situation (Minsky, 1974). But on the lower levels slots must be filled by specific instances or data to approach the expected exploratory and explanatory result. The top level structure of the CF to be designed is inspired by the proposed structure of Goepfert (2019) and Pfohl (2016) as illustrated in Figure 3-4. It is outlined that mutually impacting relations (1) to (10) between the SC environment, the SC system, and its grouping elements ‘SC performance indicators (I)’, ‘process and structure elements (II)’, and ‘contextual factor technology (III)’ exist. This top level structure is picked up in Section 5.3 with the purpose to apply specific determined descriptors and their variants on the lower levels of the CF so that a CF is created which can be deployed in different fields of the SC to explore various use cases.

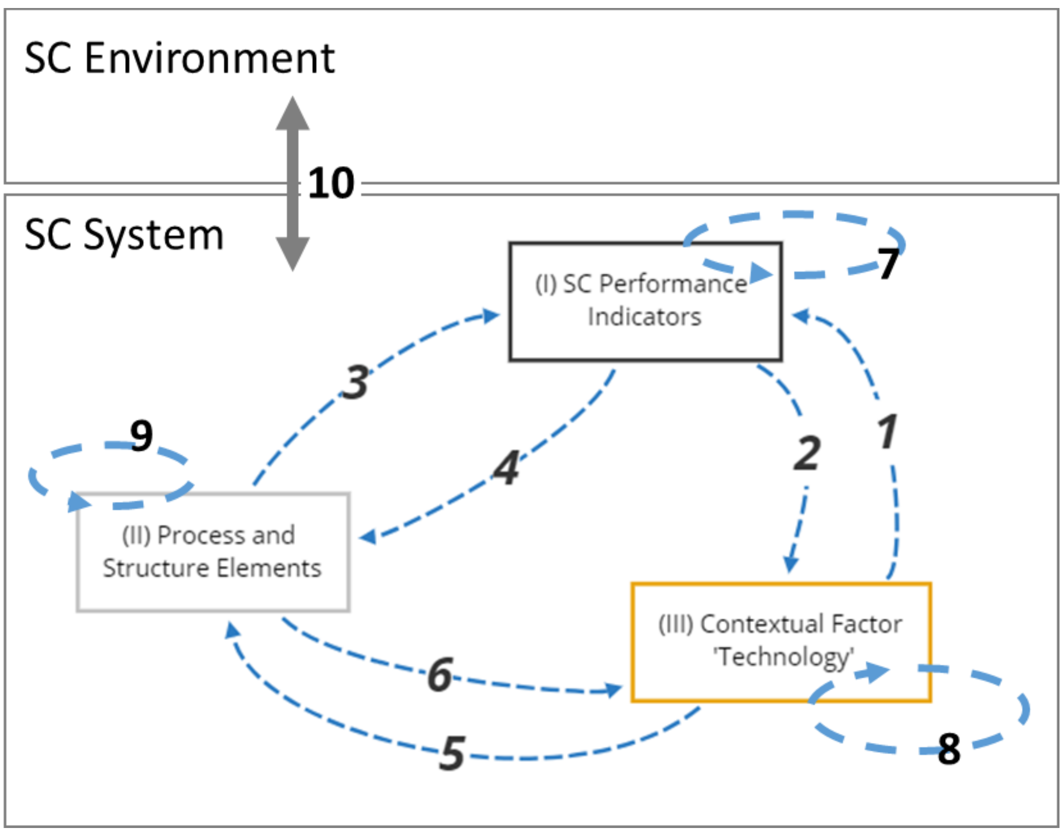


Figure 3-4: CF Illustrated Through Grouping Elements

As in Section 2.7.2 already concluded, none of the existing CF applied for SC are reasonable for the research objective of this thesis. One reason is that existing CF only allows to explore one certain extract of the entire mutual network of relationships. Another reason lies in the fact that mutual interdependencies between process and structure elements, and between process and structure elements and AI are not related to SC performance indicators, so far in research to the knowledge of the author of this thesis. This means, that only with the application of a newly designed CF it is possible to explore indirect as well as direct impact of all these descriptors within the SC with the purpose to apply this model then on the VC in the SC.

The CF in this research is needed to apply systems theory. As stated in Section 2.4, systems theory defines how systems are constructed of sub-systems. These sub-systems act and behave to each other. In some cases, the equilibrium of this system is impaired so that measures have to be applied to re-establish an equilibrium. Systems theory, in this case CAS theory provides the characteristics and attributes of the overall SC system. Other theories and concepts serve to predict how the sub-systems behave. These theories and concepts are linked to each other within the CF as the foundation for further investigation. Thus, the CF determines and visualises the descriptors and formalises the relation to each other so that the reaction of the CAS can be applied for different use cases. Therefore, the CF serves as a basis to develop future scenarios of the SC. For that reason, it is applied in the second Poll of the Delphi Study to establish the interdependencies between event pairs of the descriptor variants to be rated by the participating experts.

3.5.3 Cross-Impact Balance Analysis Applied for Scenario Development

Futurology, future(s) research or future study is the systematic and critical research of future developments in technical, economics, and social fields (Bishop, Hines, & Collins, 2007;

"Futurologie," 2001). In this thesis, the term ‘future research’ is used. Doing future research is always research under uncertainty with the awareness that only probabilities and the likelihood of their occurrences are discussed. However, future research aims to make the future and possible development stages more tangible and plannable with the support of methods, models and scenarios (Möhrle & Specht, 2018). For a better understanding of the discussion in this section, it has to be clarified for what reason the respective future research methods or techniques are applied. With the first Poll of the Delphi Study, the data to determine the descriptors for the CF of this study are collected. The CF forms the initial basis to collect the necessary data with Delphi Study Poll 2 to create a statement about the future development of SC systems. To achieve such a statement, firstly a technique is needed to analyse the collected data and secondly an instrument or a tool is needed to present the statement about the future. The proposed technique to explore the way forward to the statement about the future is the CIB-analysis. The Delphi Study can only consider a demarcated problem statement. The CIB-analysis is applied to overcome this shortcoming by analysing the mutual influences between potentially occurring events (Weimer-Jehle, 2006). The application of the CIB-analysis results in a statement about the future. However, the future itself is not unique but ambiguous. This is why multiple plausible futures are expected to happen (Bishop et al., 2007). Therefore, in this thesis a method is designed to present various statements of the future in different scenarios because scenarios contain the stories of these multiple futures in different constellations (Bishop et al., 2007). Nevertheless, it could be argued, that there are techniques which make it possible to predict only one future state, e.g., trend extrapolation. However, trend extrapolation is only of minor relevance due to the assumption of deterministic causality which is not in line with the critical realist stance and the CAS characteristics of the SC so that linear and positivist approaches are not further considered. But it could also be argued that mathematical approaches to identify trend reversals, trend shifts or trend changes can be applied (Möhrle & Specht, 2018). However, this interference in the trend causality results in events which lead to one or more scenarios which deviate from the extrapolated linear trend.

Data presentation through scenario development allows the combination of quantitative and qualitative data as well as opinions which underpins the mixed-method approach. The narrative and illustrative components of the scenarios allow for a comprehensible description of the way forward and the final result (2020i). With applying a scenario technique, this research approach follows the requirement that a statement about the future must fulfil the general scientific quality criteria of necessary relevance, logical consistency, and simplicity of verifiability (Möhrle & Specht, 2018). However, there is no best technique to develop scenarios about the future SC. The appropriate technique for this research must be selected, balancing advantages and disadvantages of each of the available techniques. Bishop et al. (2007) as well as van Notten (2006) describe a number of scenario techniques. Bishop et al. (2007) propose eight general categories of scenario techniques with two to three variations for each category. These approximately two dozen techniques are pre-selected by the author of this thesis so that at least one scenario technique represents each category. The pre-selection is based on the author's individual opinion of appropriate scenario techniques to be compared to each other to avoid redundancy. The author's individual evaluation of relevant scenario techniques is illustrated with Table 3-3. It is acknowledged that this ranking is based on a subjective evaluation by the individual viewpoint of the author. However, the requirements as well as the scenario techniques are given by peer-reviewed literature. The author's subjective contribution to map both parts through an evaluation which solely serves the author's own thesis is supposed to be acceptable.

For this thesis it is of high interest to analyse direct as well as indirect probabilities of a condition or an event with additional variants per each descriptor. Therefore, CIB-analysis is put into the centre. CIB-analysis is a subordinated analysis method of cross-impact analysis (Weimer-Jehle, 2006). Cross-impact analysis enables holistic understanding of interdependencies among the elements of a SC system (Ceric, 2015b) due to the method-inherent n+1 variants per each descriptor. The essentials of the CIB approach are a high methodological flexibility which is especially suitable for the use in expert discourses due to its transparent analytical logic. Due to its mathematical qualities, it is also particularly well suited for the analytical integration of calculable system parts (Weimer-Jehle, 2006) and fulfils the claim for contributing quantitative data to the mixed methods. Furthermore, CIB-analysis supports experts' intuitive scenario development and is to a high degree reproducible, contrary to other intuitive scenario methods. Also, it provides the possibility of integration of qualitative and quantitative knowledge of the system (Shojachaikar, 2016). The overall rating in Table 3-3 illustrates that this scenario technique best fulfils all requirements relevant for this study. Therefore, CIB-analysis is applied in this thesis to develop scenarios of the impact of AI on the SC system. However, CIB-analysis does not explore the scenario development but quantifies the individual opinion of the participants so that afterwards the quantified result can be explored and explained by the researcher as outlined in Section 3.3.3.

Table 3-3: Ranking of Evaluation of Requirements on Scenario Techniques

No	Requirements on scenario techniques for this thesis	Weighing	Genius forecasting		Trend extrapolation		SRI matrix		Probability trees		Horizon mission methodology		GBN matrix		Cross impact analysis		CIB analysis		Trend impact analysis	
1	Orientation according to future developments in the SC	2	1	2	2	4	2	4	3	6	2	4	3	6	2	4	2	4	3	6
2	Preparation of decisions in regards to technology evolution	3	1	3	3	9	2	6	3	9	2	6	3	9	2	6	3	9	3	9
3	Strategy development	2	1	2	2	4	3	6	2	4	1	2	3	6	2	4	2	4	3	6
4	Strategy verification	0	1	0	1	0	3	0	3	0	1	0	3	0	2	0	2	0	3	0
5	Early recognition of change opportunities	1	1	1	1	1	2	2	2	2	2	2	2	2	1	1	1	1	3	3
6	Find visionary scenarios independently from current trends	0	3	0	0	0	3	0	1	0	3	0	1	0	1	0	1	0	0	0
7	Quantified probability of occurence	1	0	0	3	3	1	1	3	3	1	1	1	1	3	3	2	2	3	3
8	Transparency on direct and indirect impact	3	1	3	1	3	0	0	2	6	1	3	1	3	2	6	3	9	3	9
9	Mass data-based evaluation	0	0	0	3	0	0	0	1	0	1	0	1	0	1	0	1	0	3	0
10	Expert-based evaluation (qualitative strategy)	3	3	9	1	3	3	9	3	9	3	9	3	9	3	9	3	9	1	3
11	Possibility to explore quantified results	3	0	0	3	9	1	3	1	3	1	3	1	3	3	9	3	9	3	9
12	Cover relatively high system complexity	3	2	6	0	0	2	6	1	3	2	6	1	3	3	9	3	9	3	9
13	Enable plausibility check of scenarios	2	1	2	1	2	1	2	2	4	1	2	2	4	3	6	3	6	3	6
14	Predict one expected future	0	3	0	3	0	0	0	2	0	3	0	2	0	1	0	1	0	1	0
15	Easily to apply	1	3	3	3	3	3	3	3	3	3	3	3	3	2	2	1	1	1	1
16	Provide what-if prediction	1	1	1	1	1	0	0	2	2	2	2	1	1	2	2	2	2	3	3
17	Strong methodological scaffolding	3	0	0	2	6	1	3	2	6	1	3	2	6	3	9	3	9	3	9
18	Consider multiple disciplines	3	1	3	1	3	2	6	2	6	3	9	3	9	3	9	3	9	3	9
19	Evalute more than one state per descriptor	3	1	3	1	3	1	3	1	3	1	3	1	3	2	6	3	9	3	9
20	Constitute the net impact of mutual impact	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	9	0	0
Total				**38**		**54**		**54**		**69**		**58**		**68**		**85**		**101**		**94**

The detailed evaluation with respect to the below mentioned explanation can be reviewed in Appendix A. . Rating of the scenario techniques according to the fulfilment of the requirements: 0: not at all fulfilling, 1: poor fulfilling, 2: acceptable fulfilling, 3: strong fulfilling. Weighting: 0: no relevance, 1: low relevance, 2: medium relevance, 3: high relevance. The result of the product of the weighting and the evaluation is outlined Table 3-3. The underlying weighting expresses the relevance of each requirement for this research respecting the ontological stance of a critical realist, the primarily qualitative epistemological approach and the characteristics of the investigation object, the SC as a CAS. The rating of the requirements is individually processed by the author of this thesis, for the individual purposes of this research although knowing that this evaluation is biased by personal interest and the author's individual viewpoint. The requirements are collected from several sources ((Bishop et al., 2007); (Gausemeier, Plass, & Wenzelmann, 2009); (Weimer-Jehle, 2006)) and slightly adapted for this thesis.

The scenario analysis is embedded in the broader research approach and provides the baseline of the future SC system. However, it is not the objective of this thesis to determine the most probable future SC scenario, but the future SC scenario which is probably the most positive one respecting the fact that AI will be a strong influencing factor in the future of the SC. This means that this thesis has a normative character with the claim to be applied by academics and practitioners to achieve this positive scenario, by developing the SC entities and agents which are represented by the descriptors of the CF towards the identified variants of the positive SC scenario. Thus, each application of the results of this thesis in a SC-specific environment represents a deductive approach of applying the CF with the purpose to test with case studies, the hypothesis of this research.

3.6 Methods for Data Presentation

Data presentation of this thesis is mainly based on methods for qualitative data presented by Laya Prasad (2010). Presentation of quantitative data refers mainly to Saunders et al. (2012). Onwuegbuzie and Dickinson (2008) provides a good foundation for data presentation in mixed methods approaches. Tabulation is applied to present the structure of the participants of the qualitative one-on-one and group interviews according to categories which have been defined in the beginning of the research to establish adequate broadness and depth of this study. This first survey of the Delphi Study contains questions to be answered with the aid of a Likert scale. The quantitative results are presented with bar charts. Furthermore, tabulation is used to present second level analysis of the original experts' Rating to outline probabilities and their consolidation into the table 'Process and Performance Indicator Intersection'. With the aid of NVivo 12, the result of a word frequency analysis is illustrated. Onwuegbuzie and Dickinson (2008) states that it is a challenge to develop and apply new methods of graphical exploration and display in order to translate effectively qualitative data into a visual format. Another challenge is to find graphical methods which can be used for both quantitative and qualitative data so that the integrated mixed-method approach as applied in this thesis can be presented. Especially for the data presentation of the collected data from Delphi Study Poll 2, the author of this study developed some new formats to integrate the illustration of quantitative and qualitative data in one figure. For that purpose, one template is developed which is individually adapted to explore the quantitative CIB-analysis event pairs and the qualitative experts' statements. Furthermore, available charts of the CIB-analysis tool 'Scenario Wizard' are applied to present the role of the descriptors with a system-grid chart, to present the overview of the selected descriptor variants, and to illustrate impact balances.

3.7 Establishing Rigour and Validity

Criteria in terms of validity (honesty and genuineness of the research data) as well as reliability (reproducibility and stability of the data) are defined through the research design so that the reader of this thesis will be convinced of the correct application and the correct type of methodology to achieve the research objective (Easterby-Smith, 2012). However, according to the interpretative research strategy, there is no objective knowledge building in the sense of realist approach expected (Creswell, 2014). Hence the conclusions of the qualitative interviews and even of the quantifiable rating of the structured questionnaires are based on the interpretations of the meanings of study participants by the researcher. Therefore, there is a risk that the researcher would interpret the findings incorrectly or that his background might influence his perspective. Biases might also rise from the interviewees. In every step of the research process, the researcher makes decisions, and the choices made by the researcher could influence the research results. Therefore, the researcher attempts to mitigate possible biases and to increase rigour and validity. A mixed-methods strategy is applied (Creswell, 2014; Saunders et al., 2012; Yin, 2011). Experts with different perspectives due to different academical and professional background are involved in the study by five iterations as described in Table 3-4.

Table 3-4: List of Study Participants

No.	P-ID	Categories	Expertise	Institutes	Role	Title	Country	Took part in inquiry
1	02	Academics	AI and SC Expert	University	Professor of Logistics and Information Systems	Prof. Dr.	DE	1, 2, 4
2	03	Academics	SC Expert	University	Professor for Transport Logistics	Prof. Dr.	DE	2
3	04	Academics	SC Expert	University	Professor for Business Economics & Logistics	Prof. Dr.	DE	2
4	05	Academics	General economist	University	Professor for Microeconomics	Prof. Dr.	DE	1
5	08	Academics	AI Expert	University	Professor in Applied Computing and Technology	Prof.	UK	2, 4
6	12	Practitioner	SC Expert	Production Industry	Director of EMEA Logistics		DE	2
7	13	Practitioner	SC Expert	Consultancy	Head of global Logistics - Partner		CH	2, 4
8	33	Practitioner	AI Expert	Consultancy	Head of Artificial Intelligence	Dr.	DE	1, 2, 4
9	39	Academics	General economist	University	Spokesperson for the Centre of	Dr.	DE	1

					interdisciplinary risk- & innovation research			
10	42	Practitioner	AI and SC Expert	Consultancy	Startup Founder		DE	2, 4
11	63	Academics	SC Expert	University	Professor for Logistics	Prof. Dr.	DE	2, 4
12	68	Academics	AI and SC Expert	University	Professor for Business Informatics	Prof. Dr.	DE	2, 4
13	69	Practitioner	Technology Expert	Production Industry	Computer Scientist		DE	2
14	70	Practitioner	SC Expert	Production Industry	Head of Operations	Dr.	SGP	2, 4
15	71	Practitioner	Procurement and SC Expert	Production Industry	Procurement Management		DE	2, 4
16	73	Academics	SC Expert	University	Supply Chain & Logistics Research Scientist	Dr.	SA	2
17	75	Academics	Technology and Logistics Expert	University	Assistant Professor of International Logistics and Transportation	Dr.	TR	2, 4
18	86	Practitioner	SC Expert	Production Industry	CEO		DE	2
19	87	Practitioner	SC Expert	Production Industry	Head of Transportation		US	2
20	88	Practitioner	Technology Expert	Logistics Service Industry	Director - IT Applications Design		US	2
21	89	Practitioner	SC Expert	Logistics Service Industry	Head of Business Strategy		CH	2, 4
22	92	Practitioner	AI Expert	Production Industry	Project Manager Supply Chain Strategy & Processes		DE	2, 4
23	93	Practitioner	Technology Expert	Consultancy	Senior Consultant		DE	2, 4
24	94	Practitioner	AI Expert	Production Industry	Data Scientist		DE	2
25	95	Practitioner	Blockchain Expert	Consultancy	Managing Consultant		DE	2, 4

26	96	Practitioner	SC Expert	Logistics Service Industry	KeyAccount Manager		DE	2, 4
27	97	Practitioner	AI Expert	Consultancy	Associate Partner		DE	2
28	98	Practitioner	SC Expert	Consultancy	Senior Consultant for SC management & procurement		DE	1, 2, 4
29	99	Practitioner	SC Expert	Consultancy	Senior Consultant		DE	1, 3
30	100	Practitioner	SC Expert	Consultancy	Management Consultant for SC & Information Technology		HU	3
31	101	Academics	SC Expert	University	Student		DE	3
32	102	Practitioner	AI and Blockchain Expert	Consultancy	Senior Consultant		CH	3
33	103	Practitioner	General economist	Consultancy	Principal		DE	3
34	104	Practitioner	SC Expert	Logistics Service Industry	Senior Expert Corporate Strategy	Dr.	DE	3
35	105	Practitioner	AI and SC Expert	Consultancy	Associate Partner	Dr.	DE	2, 3, 4
36	109	Practitioner	Operations Expert	Consultancy	Manager Business Development		US	4
37	110	Practitioner	Technology and Logistics Expert	Consultancy	Partner	Dr.	DE	2

1: Qualitative interviews to investigate VC aspects

2: Delphi Study Poll 1

3: Qualitative group interview to prepare Delphi Study Poll 2

4: Delphi Study Poll 2

5: Delphi Study Poll 3

The inherent approach of a Delphi Study ensured that single viewpoints and opinions are reviewed by the participants themselves to elaborate a group opinion. This broad mixture of expertise covers the different relevant dimensions as described in Section 3.4.4. All participants are acknowledged as experts in their field through publications and/or personally known networks and their individual career as responsible persons in their companies.

Moreover, different sources of evidence are used. In addition to the interviews and questionnaires, in the course of secondary research, literature providing theories and concepts are used to review the primary research results especially during the analysis phases. These activities increase the validity of the discovered themes and findings by allowing the researcher to compare the sources and substantiated the findings (Creswell, 2014; Saunders et al., 2012; Yin, 2011). Furthermore, as stated in Section 3.3.3, mixed methods serve all the same conclusion so that the often-stated validity issue of conflicting results is completely excluded.

The research design, including the research objective and the research approach and methods applied to conduct the research, is presented in the thesis. This process ensures that the procedure of the research is explicit to the reader (Yin, 2011). However, referring to Joseph A. Maxwell (1996, p. 87 et seqq.) the qualitative approach along description, interpretation, and theory building is faced with distinct threats to its validity and reliability. The context of this research is described in depth, and the boundaries of the research are clearly communicated. A detailed description of the context of this research is provided. Therefore, the reader is able to retrace the adequate method of data collection and data analysis and will be ensured that the deviated conclusions of the research can be taken for granted.

However, the author of this thesis is aware of the disadvantages of applying the CIB-analysis with academic and practitioner experts having only limited available time span to support data collection of this research. Therefore, a specific approach is conducted to keep the needed time for each expert appropriate but to ensure requested quality and reliability as described in Section 3.4.

Respondent-checking of the interpretations is applied (Creswell, 2014; Saunders et al., 2012; Yin, 2011). Especially the group interview to prepare Delphi Study Poll 2, is an important milestone to review and cross-check the researcher's analysis with six other experts.

Qualitative research is often criticised for lacking the potential for generalisation (Creswell, 2014; Saunders et al., 2012; Yin, 2011). However, the collection and exploration of individual opinions can be used to form a broader theory (Yin, 2011). This theory is then proposed for further investigation by other researchers in the sense of critical realism to iteratively discover new layers of truth to approximate reality. Therefore this research design follows Joseph A. Maxwell (1996) in terms of credibility for an external generalisability: "*There is no obvious reason not to believe that the results apply more generally*".

The Grounded Theory approach might be defective and deranged by inaccuracy or lack of completion of the data, by imposing own framework or meaning, rather than understanding the perspective of the qualitative interviews or Delphi Study participants and the meanings they attach to their words and actions, and by not collecting or not paying attention to discrepant data, or not considering alternative understandings of the phenomena the researcher is studying (Joseph A. Maxwell, 1996, p. 90). These threats are mitigated with recording and transcribing the qualitative interviews, whereas the Delphi Study is documented in written and structured questionaries' format. Theoretical sensitivity grow with the experience of the researcher of this thesis (Glaser, 1967). A relatively high theoretical sensitivity with this researcher is available due to academic and professional career as an expert in the SC domain who deals permanently with data collection and interpretation. Constructing hypotheses and theories is staff of life. For that reason, conviction can be given that ability to evaluate how far particular values might influence the conduct and conclusions of the study results. Possible bias and how it is dealt with is explained. The researcher of this thesis tries to understand and illustrate how participants statements will influence him, and how this affects the validity of the inferences researcher draw from interviews (Joseph A. Maxwell, 1996, p. 91; Moon, 2006, p. 45). Furthermore, validity and reliability are conceptualised as a constant component of this research design because "use strategies to rule out these threats" by permanently addressing particular validity threats and not only talking about validity in general, theoretical terms or by presenting abstract strategies such as bracketing, and member checks are applied. Rival hypotheses with conceptualised alternative explanations which would show a way that researcher might be wrong with temporary conclusions (Joseph A. Maxwell, 1996, p. 88) are composed especially with the resulting scenarios and their critical evaluation till the resulting positive scenario of the future SC composition. Especially from the ontological stance as a critical realist the researcher is interested in making evidence that the inference drawn represents as close as possible the mechanisms and structures of reality by assessing the applied methods itself in terms of purposes, for which they are used, the context of this use, the data, conclusions, and the understandings that are drawn in order to give conclusions credibility (Josef A. Maxwell, 2012, p. 130). Therefore, the explanatory connection between the fact and the claim is underpinned and not only informed that "*x causes y as a quantitative approach would require but address how it does so*", because "*evidence is claim-dependent and context-dependent*" (Josef A. Maxwell, 2012, p. 145 et seqq.) for the reason that causal mechanisms are subject to external conditions depending on the context. This is why it is not sufficient for critical realist view to stay in a closed system of scope but to permanently question the degrees of closure and the specific nature of quasi-closure to approximate the real mechanisms (Zachariadis, Scott, & Barrett, 2013, p. 863).

3.8 Ethical Considerations

Ethics is important in this research and guided the behaviour of the researcher during the entire research project. The research design follows the ethical principles stated by the University of Gloucestershire in “Research Ethics - The Principal Issues of Research Ethics: A Handbook of Principles and Procedures.”

One important principle applied during the research is that of informed consent. The study participants are fully informed of the research aims and objectives; the methods of data collection; how the data would be processed, stored and handled including handling of anonymity and privacy and how the findings are presented. The participants are informed and aware that they have the right to refuse participation, to decline to answer questions and to withdraw from the research without any negative consequences to them. The participants are also informed about the data gathering method. Because the participants are informed and it is their own choice to participate, the ethical requirement of free and informed consent is met by this research design.

3.9 Summary

This chapter demonstrated how the research design was organised to achieve the research objective whilst respecting rigour, validity, and ethics during the research approach. The research design of this thesis is conclusively illustrated in Figure 3-5.

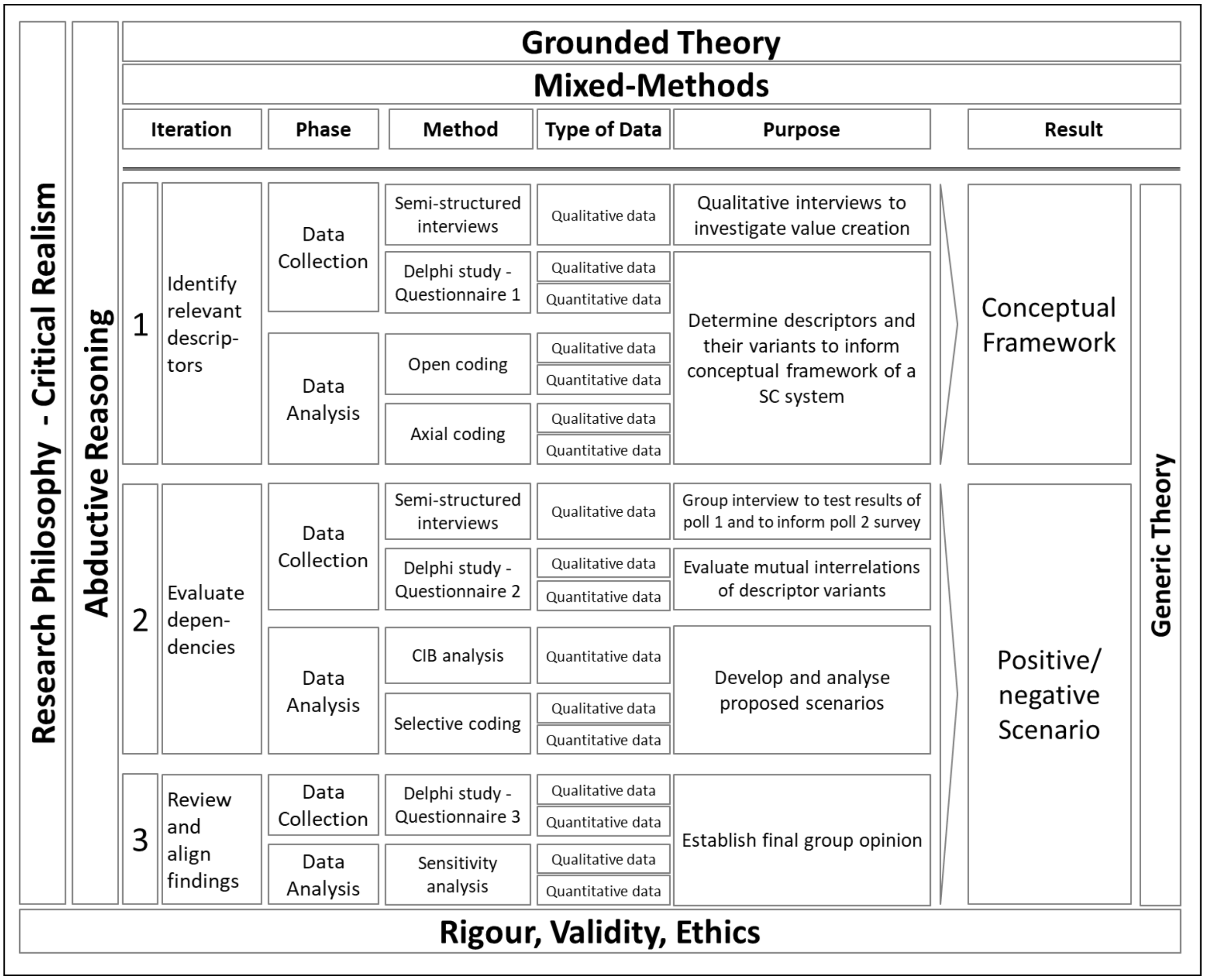


Figure 3-5: Applied Research Design

This research strategy is guided by abductive reasoning. The author of this thesis observed the phenomena that AI-enabled applications seem to significantly change the equilibrium of the SC system but has neither found an explanation nor sufficient cases to predict future SC composition. Therefore, epistemologically a new hypothesis must be found. Grounded theory provides appropriate proposition how to organise the way forward to develop such a hypothesis. The author is convinced that a complete understanding of a research problem should not fail due to dogmatically distinguish between qualitative or quantitative methods. Therefore, mixed methods for data collection and data analysis are applied in this study.

Chapter 4 Data Collection and Presentation

4.1 Introduction

In this Chapter 4 , the collected data are presented. Section 4.2 informs about data collection phases and purpose. In Section 4.3, an introduction is given about the selection and categories of participating experts. Sections 4.4 to Section 4.8 sequentially present the collected data from the five inquiry phases.

4.2 Data Collection

The design for data collection is presented in Section 3.4.1. The types of inquiry are presented in Table 3-1. Data are collected in five phases for the following purposes:

1) Three semi-structured interviews to investigate the overall aim of AI-enabled VC in the SC.
2) Delphi Study Poll 1 to collect data for establishing the CF.
3) Group interview to collect data for preparing Delphi Study Poll 2.
4) Delphi Study Poll 2 to collect data as input for the CIB-analysis.
5) Delphi Study Poll 3 to conduct a sensitivity check of CIB-analysis.

Data collection is designed sequentially. Qualitative data collected with the semi-structured interviews inform the second phase of data collection, the Delphi Study Poll 1. Qualitative data collected with the group interview after having conducted Poll 1 inform quantitative data collection of Delphi Study Poll 2. The final phase, Delphi Study Poll 3 allows for experts' mutual review of collected data from previous phases. Qualitative data collection follows exploratory strategy whereas quantitative strategy is used to examine collected data with CIB-analysis in a more generalisable fashion.

4.3 Selection of Participants

All experts are selected according to their background and expertise to best meet the requirements of the data collection and to ensure a rigorous approach of this qualitative study (Okoli & Pawlowski, 2004). 78 potential participants are contacted. Thereof, 33 contacts are without reply, and eight contacts deny participation. 37 participants confirm to participate in this study. Compared to other studies of this kind (qualitative approach, primarily applied tool Delphi Study), this number of participants is adequate to accomplish the rigorous approach and to ensure an appropriate validity of the research objective (Seuring & Müller, 2008a). Okoli and Pawlowski (2004, p. 19 et seq.) refer to the literature recommendation of ten to 18 experts on a Delphi panel. Participants working in a higher education institution in the public sector are considered academics in the sense of working in a scientific field whereas participants working in the private sector in business companies with years of experience are considered practitioners (2020k). The term 'practitioner' is chosen to express that these participants are expected to have a more practice-oriented viewpoint on the SC and AI whereas academics are expected to have a more research-oriented interest at the SC and AI. The responses to the invitation to partake in this study reveal a ratio of 30% participants with a research-oriented interest and 70% working with or within the SC as outlined in Table 3-4. Table 4-1 shows that within the practitioner group, an appropriate balance is achieved with 54% from consultancy, 15% from logistics service provider industry and 31% from production industries. This ratio provides two assumed viewpoints: A practice-oriented more conceptual view on the SC and a more operationally oriented view. A combination of both views delivers the requested qualification and knowledge set to inform about a future SC in regard to the scope of this research.

Table 4-1: Participants Assigned to Institutes

Category	Number of participants	Percentage of participants	Institute	Number of participants	Percentage within practitioner group
Practitioner	26	70%	Consultancy	14	56%
			Logistics Service Industry	4	15%
			Production Industry	8	31%
Academics	11	30%	University	11	
Total	**37**	**100**		**37**	**100%**

The focus on the European region is decided due to the assumption, that the necessity to evaluate the impact of AI technologies in an SC is of high relevance because of the relation between relatively high labour costs and required SC performance compared to other regions such as Asia and Africa. The high number of German participants is owed to the fact that the participation in the Delphi Study is voluntary and primarily based on the author's academic and business network. Nevertheless, especially all the German participants work in an international business environment with broad expertise in global SC networks.

Table 4-2: Number of Participants from Different Countries

Country of origin	Number of participants
Germany	26
Switzerland	3
United States	3
United Kingdom	1
Turkey	1
Singapore	1
Kingdom of Saudi Arabia	1
Hungary	1
Total	**37**

The participants are located in eight different countries, thereof four European countries enriched by experts from the US and Asia (Saudi Arabia and Singapore) as listed in Table 4-2.

Table 4-3: Number of Participants with Different Expertise Areas

Type of Expertise	Academics	Practitioners	Total
SC Expert	4	12	**16**
AI Expert	1	4	**5**
AI and SC Expert	2	2	**4**
Technology Expert	0	3	**3**
Economist	2	1	**3**
Technology and SC Expert	1	1	**2**
AI and Blockchain Expert	0	1	**1**
Operations Expert	1	1	**2**
Blockchain Expert	0	1	**1**
Total	**11**	**26**	**37**

16 participants are selected with the purpose of bringing in a valuable mix of AI and SC-related technological expertise. Pure SC domain and economics expertise are contributed by 22 participants. Table 4-3 also depicts that it is difficult to find more academics experts with a technology background, especially with Blockchain expertise. However, two Blockchain experts from the personal practitioners' network of the author of this thesis contribute with in-depth and leading-edge knowledge to this thesis so that the lack of academics' perspective is compensated. Three technology experts from the practitioners' field contribute sufficient expertise about state-of-the-art SC-related IoT and other technology so that the AI-related technology knowledge of 9 experts can be usefully combined. It is important for the diversity of the perspectives that two operations experts also participate in the study so that an SC-independent viewpoint on organisation and structure elements is given. Especially the contribution of the economists is highly appreciated for the insights on the SC environment.

Referring to Table 4-4, the data collection with this mixed-method approach is organised in five sequential inquiries so that all in all 84 inquiries are conducted as the input for data analysis and presentation. An anonymised list of participants is found in Table 3-4.

Table 4-4: Number of Participants per Type of Inquiry

No	Type of Inquiry	Number of Participants
1	Qualitative interviews to investigate VC in the SC	7
2	Delphi Study Poll 1	25
3	Group interview to prepare Delphi Study Poll 2	6
4	Delphi Study Poll 2	18
5	Delphi Study Poll 3	28
	Total	**84**

The number of the qualitative interviews in Row 1 and Row 3 is consciously limited to the specific problem statements intended to be answered with these interview types. Especially the 25 participants in Delphi Study Poll 1, ensure a strong validity of the design of the CF. For Delphi Study Poll 2, the rating of the event pairs is time-consuming so that only 18 participants of 25 contacted experts participate. Of these 18 responding experts 14 experts participate in Delphi Study Poll 1 so, a sufficient consistency is ensured. More important for the overall consistency and validity of the data collection is that 28 participants of Delphi Study Poll 3 respond and that 16 of these participants answer Poll 2 and 21 answer Poll 1.

4.4 Interviews for Investigating AI-enabled Value Creation in the Supply Chain

4.4.1 Purpose, Participants and Setup of Interviews

Three semi-structured one-on-one interviews are carried out with three different academics having specific expertise in the field of AI and SC management (see Table 4-5)[ii]. Each of the interviews has a specific purpose of building the investigation on VC and further defining the overall aim and research objectives. To achieve the research objectives, a full understanding of how the SC as a system can be used to create value for businesses is required. The expert interviews are conducted with a list of themes and questions. During interviews. the interviewer sometimes changed the order of questions according to the context of the responses and added additional questions to explore responses in detail. The semi-structured interviews with each participant took between one hour and one and a half hour. The author of this thesis conducted all interviews and recorded the answers with a computer during the interview sessions. An overview of the qualitative interviews is outlined in Table 4-5.

Table 4-5: Setup, Structure and Purpose of Qualitative Interviews to Explore SC Environment

P-ID*	Function	Role	Contribution to credibility and knowledge building	Purpose of the qualitative interview	Duration in h
02	AI and SC Expert	Professor of Logistics and Information Systems	Strong academic background in the field of SC Management, together with practical work in SC strategy.	Analyse VC in the SC. **Focus on terminology and distinction between tangible and intangible value.**	1.5
05	Economist and Researcher	Professor for 'Microeconomics'	Strong academic background of research in the field of AI. Member of the German Academy of technical sciences.	Analyse VC in the SC. **Focus on the creation of value related to SC performance.**	1
39	Researcher	Spokesperson for the Centre of interdisciplinary risk- & innovation research	Strong academic background in research methods and research design for macroeconomic studies.	Analyse VC in the SC. **Focus on the allocation of created value through AI.**	1

**P-ID: Personal Identification number of participants: To each interviewee for this research, a unique P-ID is assigned. The participants are anonymised. Clear names are available on request.*

On the one hand, the interviews are carried in such an environment in which the interviewees are encouraged to share their subjective ideas and experiences freely and open-mindedly. On the other hand, the interviewer is allowed to especially explain the required understanding of the focused topics and could further clarify unexpected understandings in direct communication with the expert. This kind of interaction between the interviewer and interviewees would neither be possible with a pure literature review to tackle the focus topics nor with a questionnaire sent out to Delphi Study participants. The researcher takes the chance to conduct face-to-face interviews because this relatively small number of interviewees are all located relatively close to the researcher. A face-to-face interaction makes it effective to give additional explanations and to clarify the interviewees' answers and the researcher can especially better monitor the group interview according to the dynamic of the participants. The semi-structured questionnaires were built similarly so that all qualitative interviews have the same starting conditions as illustrated in Table 4-6.

Table 4-6: Questionnaire Structure of Expert Interviews

No	General Introduction and Questions
1	Short introduction of the thesis context and research objective by the researcher.
2	Introduction on the term of value to prepare the same understanding of expert and interviewer.
3	Explanation of the term 'SC performance' applied in this study.
4	Do you agree with the definition of value used in this thesis?
5	How do you apply the distinction between intangible and tangible value in your academic work?
6	What is your opinion about the correlation between SC performance improved by AI applications and the impact of AI on VC?
7	How should AI-enabled value in the SC be measured?

As is typical for a semi-structured interview, supplementary questions are woven into the questioning process. Relevant supplementary questions which steer the discussion in a certain direction or raise through associating with a statement of the experts are listed in Table 4-7.

Table 4-7: Supplementary questions during qualitative interviews

No	Supplementary Question	Referring to Focus Topic
1	How to classify the term 'value driver'	Terminology
2	How to monetarise intangible value?	Focus on creation of value
3	How to integrate consumer surplus?	Focus on creation of value
4	Is competitive advantage possible without creating value?	Focus on creation of value
5	How to allocate value created by AI?	Focus on the allocation of created value

4.4.2 Analysis and Presentation from Expert Interviews

Interview results that contribute to further investigation of the relationship between SC performance, VC and AI are summarised below.

Distinction of value and VC related to SC performance

- The experts agree that SC performance is a value driver and that AI applications improve SC performance. The SC performance of delivering a product-on-time and in full combined with the delivered product is exemplarily mentioned to generate cash flow and is therefore tangible value for the selling SC entity and intangible value for consumers.

- One expert points out that real value is only created if revenues exceed expenses. This opinion refers to business case evaluation and related NPV. However, it is an opinion that is arguable and relatively unique in its rigour.
- The experts raise the point that the determination of weighting factors to link SC performance indicators of the CF to the financial performance figures such as sales, cost of goods sold (COGS), fixed assets, or total expenses might be challenging due to the complexity of the interrelations.
- The experts raise the point that VC in the SC should be considered from the perspective of the benefits of inter-company collaboration instead of evaluating isolated VC of each SC individual entity. However, this aspect makes it necessary to find an evaluation approach that allows to identify the value adding of different collaboration constellations.
- Supplementary, not only the additional value created is a matter of interest but also a fair distribution of the value amongst the SC entities.
- All three experts state that sustainable competitive advantage occurs through a higher profit margin over several booking periods compared to the competitors in the market. These higher profit margins create value in the form of cash flow. Cash without reinvestment in value creating drivers will reduce competitive advantage. Thus, the total amount of available cash needs to be applied to create value for relevant stakeholders and specially to meet the demand of consumers.
- The experts' state believe the CF informs about intangible value drivers such as forecast accuracy or autonomous SC planning. They argue that forecast accuracy should be

considered as a value driver because a value driver refers to those capabilities that add profitability and foster the growth of a company. Accurate demand forecast reduces e.g. the amount of inventory and contributes to revenue growth by e.g. avoiding out-of-stock situations.

- The experts recommend focussing and narrowing the exploration to particular value drivers which are directly related to AI applications for VC in SC. They point out that the results serve to concretise the fulfilment of the research objectives.

Allocation of value in the context of consumer and producer surplus

- One expert refers to the market price equilibrium and the resulting consumer and producer surplus and recommends including the remaining liquidity of the consumer surplus in the considerations of VC because this liquidity might trigger a purchase decision and therefore creates tangible value for other SC.
- Faced with this argumentation, another expert points out that producer surplus is more important for VC in the SC than consumer surplus. It is argued that producer surplus might be increased, and consumer surplus might be reduced by product segmentation and / or price differentiation with the purpose of increasing the existing maximum prices of the consumer or with the purpose to better meet existing maximum prices parallel to consistent equilibrium price. It is supposed that AI might contribute to this increasing producer surplus with the capability to learn demand patterns that are currently not known and therefore contribute to VC.
- The experts state that AI might contribute to increasing producer surplus with the capability to learn identifying patterns that are currently not known.

The following conclusions are drawn to pursue the research objectives:

- The CIB-analysis informs about the performance of the SC as a system. It is necessary to interpret the performance indicators of the SC system as value drivers for the non-financial performance of the SC. These value drivers should be mapped to the tangible assets of a value determining concept such as 'economic value added (EVA)'.
- Testing of the theory based on the resulting NPV of multiple case studies from different SC entities is not expedient because the explanatory power in regard to VC of the entire SC is limited. It is recommended to identify case studies that can only create value in case that all SC entities are involved. Cooperative Game Theory needs to be applied to analyse how the commonly created value should be allocated to the involved SC entities.
- AI-enabled forecasting or autonomous SC planning are indirect value drivers whereas SC performance is considered as direct value driver in regard to sales, COGS etc. Thus, a structure will be developed for testing purposes which links the relationships of the CF with relevant financial performance indicators.
- The experts' recommendation will be followed to narrow the exploration on value drivers directly responsible for the VC of AI.
- The experts' note on the high complexity of the relationship between SC performance and financial performance is respected in the construct for testing the theory. A model is exemplarily created which can be further expanded in subsequent research activities.
- The discussion of producer surplus and consumer surplus will not be pursued further but proposed for further research by applying the CF developed in this thesis. This is justified with the close connection to the assumption of rational decision-making of neoclassical theory. This thesis is more related to the analysing effects of AI application on VC considering the bounded rationality of NIE. In line with this decision, it is not examined

in this thesis how the available liquidity of the consumer surplus affects the VC of other SC. In Chapter 8 , the case study is focused on one single SC.

- It is also not relevant for this thesis how SC performance affects the SC environment in general and consumer VC in particular. The focus of VC is limited to the VC of the SC system itself. However, the impact of turbulent environments on VC within the SC is respected.
- The aspect of how AI contributes to VC by ensuring sustainable competitive advantages is reflected with support of extended RBV.

4.5 Poll 1 of the Delphi Study to Establish a Conceptual Framework

The SC system consists of multiple describing components. As illustrated in Table 4-8, the competence to provide perspicacious, valuable, and credible input for the determination of these descriptors is underpinned by each expert's role and function in his academic and business profession. An appropriate mix of AI-related and general technical expertise as well as thorough knowledge and experience in the field of SC management, is ensured.

Table 4-8: Delphi Study Poll 1: Expert Category and Expert Role

Expert Category / Expert Role	**AI and SC Expert**	**AI Experts**	**SC Experts**	**Technology and SC Experts**	**Technology Experts**	**Total**
Academics	2	1	4	1	0	8
Practitioners	2	4	8	1	2	17
Total	**4**	**5**	**12**	**2**	**2**	**25**

This first structured questionnaire contains ten identical questions for each participant (see Appendix B.). This first expert survey mainly aims to collect data to identify SC components and to agree on the objective of SC performance measurement.

<u>Question 1: What is your current job title?</u>

<u>Question 2: What industry do you work in?</u>

Since the research follows a qualitative approach, the experts are asked to share personal data so that the answers can be retraced and related to their experiences and former publications. This linkage between the opinions and their origins is necessary to classify and rate the analysis phase accordingly so that a better understanding of possible bias is given. The data is presented in Table 3-4, Column 'Role' and Column 'Institute', and are summarised in Table 4-1.

<u>Question 3: Do you agree with the SC definition?</u>

<u>Question 4: What changes would you make?</u>

<u>Question 5: Do you agree with the AI definition?</u>

<u>Question 6: What changes would you make?</u>

With the purpose of establishing the same understanding of the scope, a definition of SC is provided.

A supply chain is defined by the entire network of firms and activities involved in (1) designing a set of products or services and related processes, (2) acquiring and covering inputs into these products and services, (3) distributing and consuming these products or services, and (4) disposing of these products and services (Melnyk et al., 2009).

The experts are asked to what extent they agree with this definition and -if necessary- what changes they would make. The results are outlined in Figure 4-1.

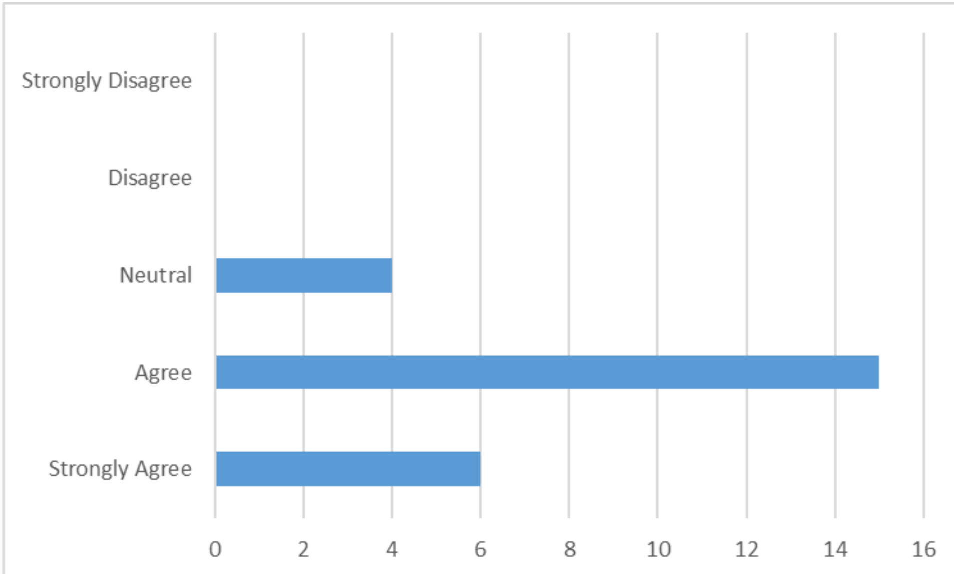


Figure 4-1: Confirmation of Supply Chain Definition

For the same purpose, a definition of AI is shared.

AI is the study and design of intelligent agents, where an intelligent agent is a system that perceives its environment and takes actions that maximize its chances of success in a particular task. Some key attributes of an "intelligent" machine include inference, reasoning, learning from experience, planning, pattern recognition and epistemology. It is developed in general for specific application domains such as expert systems. AI is the machines ability to keep improving its performance without humans having to explain exactly how to accomplish all the tasks it's given (Bogue, 2014; Brynjolfsson & McAfee, 2017). The results are outlined in Figure 4-2.

Likewise, the experts are asked to what extent they agree with this definition and -if necessary- what changes they would make. Two purposes are related to this starting point. One, towards the participants to establish a common understanding of the scope of the study, the other, towards the researcher to receive feedback from the experts about their interpretation of SC and AI so that learning happens for the CF design. In general, all experts agree with both definitions. Some give additional hints to narrow the scope by excluding the design of products and services and argue that it is more related to a value chain definition, others propose to expand the SC definition by a return process, by the involvement of risk management, the information flow and the dimension of cost and service trade-off, as well as explicitly including the customer as the trigger for all SC activities. Comparable hints mainly refer on the expected capability of AI technologies. Particularly, AI experts highlight that the limitation on “expert systems” might be too narrow regarding potential future development so that within our lifetime machines may surpass us in general intelligence, primarily because they might be able to transfer knowledge and patterns from one situation to another. In contrast, domain experts are more of the opinion that AI supports human activities in currently known fields such as simulation, robotics, and deep learning with limited capabilities. The definitions enhanced with the additional comments provide an acceptable and uniform picture representing a common theoretical construct on which further reflections for the CF elements can be established.

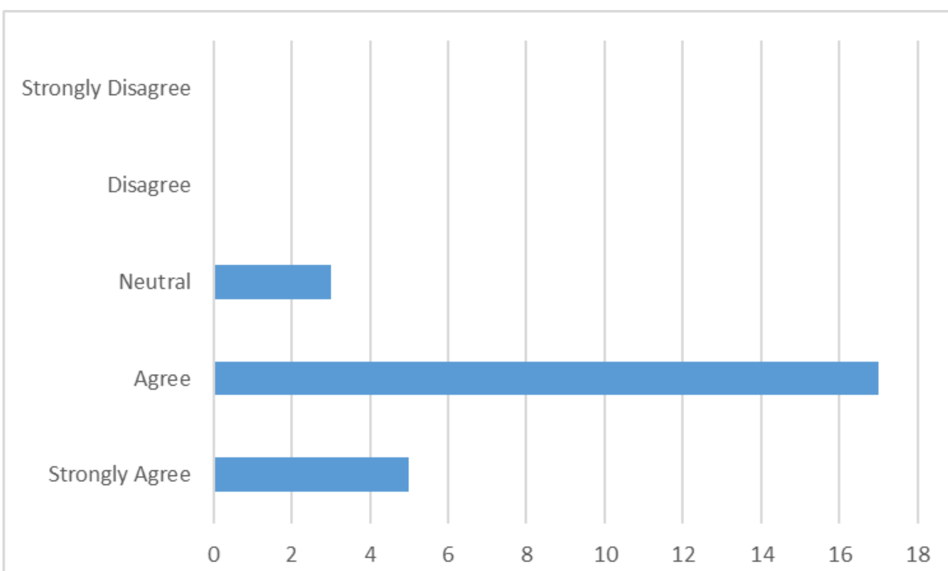


Figure 4-2: Confirmation of AI Definition

Question 7: Please rate the importance of AI for future SC.

This study systematically investigates the impact of AI applications on VC in SC. Therefore, with this question the experts are asked to rate to what extent AI technologies are supposed to take on that role to be an important technology in future SC.

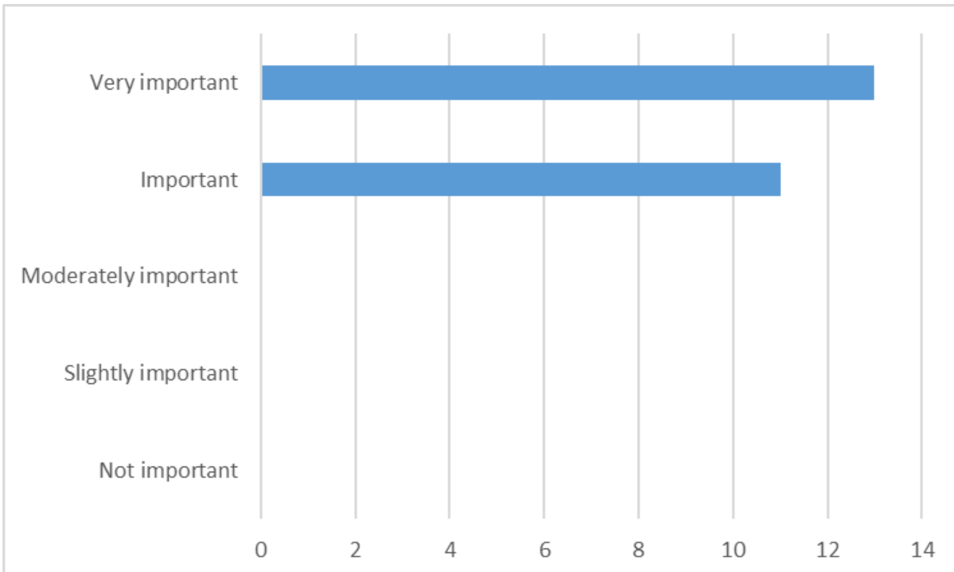


Figure 4-3: Importance of AI for Future SC

Figure 4-3 shows that not only AI experts but even SC domain experts assign AI technology high importance for future SC. With their answers, the experts indirectly confirm the relevance of this research and over that all experts think in a comparable direction in respect to the creation of future scenario development. The interest of this research is to analyse the impact of AI in the SC and not to argue if there is an impact at all. After having received participants confirmation that AI will play an important role in future SC, the survey scrutinises to what extent AI technologies are supposed to take on that role to improve SC performance.

Question 8: Please indicate how AI will improve SC.

The experts are invited to indicate the likelihood that AI can be used to improve the SC in terms of lower SC cost, higher service, lower activity time, higher flexibility and responsiveness or other factors to be mentioned additionally to the pre-selected ones (see Figure 4-4).

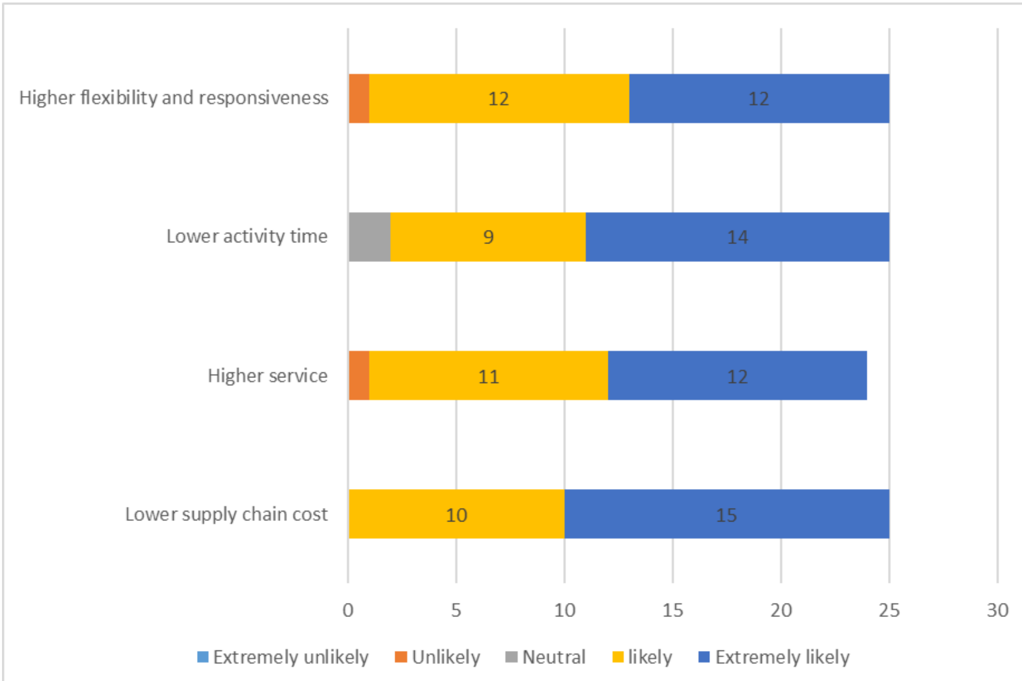


Figure 4-4: Indication of How AI will Improve SC Performance

The pre-selection is based on the literature review and represents commonly known and often described SC performance indicators (Beamon, 1999; Christopher, 2016; Cokins, 2009; Fan & Zhang, 2016). Experts' answers give a beneficial indication on generally expected elements to be respected in the CF as key drivers for an SC system. The result is presented in Table 4-9.

Table 4-9:Delphi Study Poll 1 – Additional Expert Statements

Additional statements by participants	Additional Performance Indicator	Contribute to one of the listed performance indicators	Others
Timeframe is unclear			Introducing time as an additional dimension to measure performance
Better utilization of capacities and resources		Affecting supply chain costs	
Better planning decisions		Affecting supply chain cost and activity time	
Every business case will be affected by data-driven decision making		Affecting supply chain costs, activity time, flexibility and responsiveness	
Reduced transaction cost through automation of repetitive processes		Affecting supply chain cost, activity time	
Quality increase and better safety processes which are very relevant in chemistry	Improved quality		
Manufacturing processes will increasingly use AI. Services industries like banks, hospitals, even call centers will increasingly use AI			Describing application areas
AI is expected to make customized and mass production possible at the same time			Describing application areas
Improved and more accurate forecasting and planning can be recognised as enabler for the mentioned performance indicators		Affecting supply chain costs, activity time, flexibility and responsiveness	
All mentioned performance indicators are strongly interdepending			Additional aspect on correlations between performance indicators
In addition, lower error rates in operations as well as planning by automised plausibility and anomaly checks		Affecting quality, supply chain costs	

Some of the experts reason their rating with the expectation that AI will contribute to better utilisation of capacities and resources by better decisions planning due to improved and more accurate forecasting. It is also expected that AI will reduce TC through automation of repetitive processes, wherefore more AI technologies will be applied along the SC. The qualitative statements in Table 4-9 are grouped according to three categories: ‘Additional performance indicator’, ‘Contribute to one of the listed performance indicators’, and ‘Others’. It is stated that although it is very likely for all listed SC performance indicators to be improved by AI, the timeframe is unclear. However, the removal of a determined reflection is a conscious decision when such a change might happen for two reasons: firstly from the methodological viewpoint, to keep complexity low with rating the probability of impact on performance indicators; secondly, as described in Section 3.4.3, experience with former Delphi studies showed that although experts correctly predict the occurrence of an event, they often fail according to the point in time of this occurrence. From the analysis of experts’ qualitative statements, it is derived that ‘improving quality’ could be considered as an additional performance indicator. However, this research considers quality as a prerequisite of the potential correlations of the SC system and not as an investigation object. Though it is believed that data quality is a prerequisite for satisfactory demand planning, data quality issue will not be particularly considered so that this research does not evaluate to what degree data quality meets requirements of demand planning, or what degree of data quality is necessary that demand planning supported by AI delivers adequate results. The interest of this research lies in the correlation between AI and demand planning improvements. In case of minor quality of processes or services, non-value-adding transactions have to be executed to adjust the transformation process. These quality costs are expressed in increasing TC as part of the SC cost. Additional activities to eradicate quality discrepancy are mirrored in the performance indicator activity time. Minor quality of data in demand planning affects the performance indicator responsiveness. The delivery quality of an SC as an additional performance indicator is not useful for this research because quality is covered by already respected performance indicators. All other qualitative expert statements underpin the reasoning why the listed performance indicators are rated with such a high likeliness.

As illustrated in Figure 4-4, the experts' opinions follow the common trend described in Section 2.6.3 that AI is expected to significantly improve SC performance in all of the outlined performance indicators. It could be assumed that these experts are informed by available literature so that their opinion only copies the trend statements. However, the additional value of their perspective is that these experts built up self-experienced knowledge by their academics and operations' daily work and that that their rating is a mixture of literature affected opinion and own observations in combination with experience in the least.

Question 9: Consider the key SC processes. Please indicate the probability for the future use of AI.

The experts are asked to indicate the probability for the future use of AI considering the key SC processes "plan-source-make-deliver" according to the Supply-Chain Operations Reference (SCOR) model (Bolstorff & Rosenbaum, 2003). The given structure frames the scope of the survey and directs experts' reflections to the intended SC system extract. The data presented in Figure 4-5 show that future use of AI is very probable not only in SC planning processes but also in all other SCOR processes, AI is expected to play an important role in future SC.

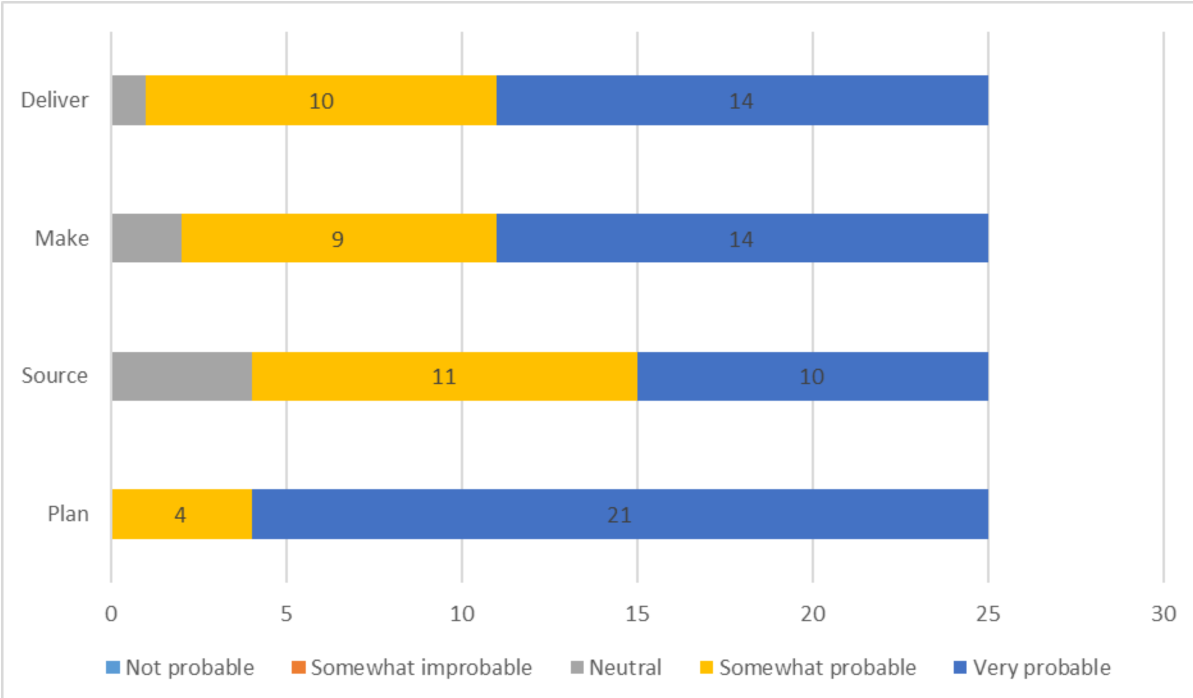


Figure 4-5: Rating of Future Use of AI in SC Processes

<u>Question 10: What do you consider to be the most important applications of AI in SC?</u>

The experts are asked to name and briefly describe up to five most important use cases or applications (UC/APP) of AI in future SC (For a list of all UC/APP see Appendix C.). These UC/APP are meaningful for the subsequent assignment of VC for the justification of theory building. The experts are asked for UC/APP and not directly for SC descriptors or SC components constituting the CF because the Delphi Study Poll 1 should be of low complexity, and the main intention is to keep the effort to answer the questionnaire at a minimum to balance expected outcome with acceptable input by experts. This question type facilitates experts' reflections because the term 'application' or 'use case' is ubiquitously present and neither an additional explanation to read and understand is needed nor a comprehensive set of rules about system theory elements needs to be provided. The stated UC/APP are linked with all other criteria elements so that no disadvantage occurs from this approach. The experts named and described 72 UC/APP of AI technologies they consider to be most important in SC such as

"Smart robots", "Joint collaboration planning", "learning of typical, repetitive, but more complex behaviours", "support of every decision where more than 3 factors are considered" or "forecasting of demand and sales using ML algorithms".

4.6 Qualitative Group Interview to Prepare Data Collection of Delphi Study Poll 2

The group interview is executed before the Delphi Study Poll 2 and based on the results of Delphi Study Poll 1. The participants are selected based on their complementary skill sets and the local availability so that a face-to-face session can be held. The six participant types are outlined in Table 4-10. Experiences with the development of strategic and operational SC concepts are paired with technological expertise and up-to-date research methods knowledge. An economist is asked to bring in the socio-environmental perspective on the scope to be examined. For this six-hour group interview, practitioners with consultancy backgrounds are selected because this professional group contributes mostly with a conceptual and methodological background to develop most results in a limited timeframe.

Table 4-10: Setup, Structure and Purpose of Qualitative Group Interview to Prepare Delphi Study Poll 2

P-ID	Function	Role	Contribution to credibility and Knowledge building	Purpose of the qualitative group interview
100	SC Expert	Management Consultant	Strong background in conceptual thinking and SC strategy.	Test determined descriptors of the developed CF against applicability of CIB-analysis.
101	SC Expert	MSc Student	Insights in academical research methods in the course of conducting AI-related master thesis of anticipatory shipping in the SC.	
102	AI and Blockchain Expert	Senior Consultant	Strong background in SC-related emerging technology.	
103	Economist	Principle	Strong background in SC strategy and SC-related economics factors.	
104	SC Expert	Senior Expert Corporate Strategy	Strong background in industry-specific SC strategies and operational thinking	
105	AI and SC Expert	Associate Partner	Strong backgroundof SC-related technology and conceptual thinking.	

This qualitative group interview aims to examine the descriptors which have been identified based on the data analysis of Delphi Study Poll 1. The approach has the character of an all-day workshop. A pre-determined list of descriptors is discussed and tested against applicability in a CIB-analysis. The type of data that result from this approach is listed in Table 3-2. The workshop is organised and led by the author of this thesis. The involvement of the researcher raises the question of how far a researcher should participate in the data collection process (Saunders et al., 2012, p. 293 et seqq.). The researcher in the role of both the host and moderator is clearly argued in qualitative interview situations. However, in this group interview the author of this thesis also takes the role of an expert who contributes with his expertise in the knowledge-building process of the group. Nevertheless, since the group interview primarily serves to test and evaluate the explored data by the researcher, this involvement is considered as a continuing process of analysis and collection of new data which serves the iterative approach of the Grounded Theory methodology. The results of the group interview are presented in the structure of the Delphi Study Poll 2 survey.

4.7 Poll 2 of the Delphi Study to Rate Cross-Impact Balances of the Supply Chain System

The descriptors identified in Delphi Study Poll 1 for the CF inform the data collection of Delphi Study Poll 2. With Poll 2, data are collected as input for the CIB-analysis and the subsequent scenario development. The primary expert task is to rate the descriptor event pairs. The questionnaire is standardised but not identical so that participants received different questions (see Appendix E.). This specific but not unusual approach (Yin, 2011) is owed to the fact that the pre-evaluation with the qualitative group interview as described in Section 4.5 outlines that an entire rating of all descriptor variant relations would take too much time for the participating experts. As an appropriate compromise, the questionnaire contains two different types of standardised response requests: Part 1 provides the sixteen interrelations of descriptor event pairs. The experts are asked to actively rate each provided pair of relation with the elucidated Likert Scale in Table 4-11. Additionally, the experts are asked to argue their reasoning so that the rating is comprehensible for a subsequent exploration in the analysis phase.

Table 4-11: Likert Scale to Rate Descriptor Variant Event Pairs

Rating	Descriptors' variant event pairs
-3	Strongly restricting influence
-2	Restricting influence (moderate)
-1	Weakly restricting influence
0	No influence
1	Weakly promoting influence
2	Promoting influence (moderate)
3	Strongly promoting influence

It is decided for pure quantitative numbering instead of qualitative characteristics for one main reason: the interpretation of the rating is supplemented through the qualitative statements. Additionally, during Poll 2 of the Delphi Study, some ratings are clarified by direct calls with selected experts (experts 02, 13, 42, 89, 96, 100, 102, 105) with the purpose of improving interpretation of both the rating and the qualitative statements. The interpretation of the Likert scale groups is generalised in Table 4-12 for further application in Chapter 6 . Especially with the moderate rating, the experts express a kind of 'instinct rating' whenever they try to strike a balance between weak or strong so that moderate rating can be interpreted as a kind of uncertainty in their opinion. Thus, rating -2 or +2 only provides the general direction of restriction or promotion but no strict conviction by the experts. However, only 13% of all event pairs are rated with moderate (-2 / +2) so that generally a strict conviction of experts' opinion can be supposed for further analysis. Nevertheless, a -2 or +2 rating reveals an important impact on the system. Rating with 'weak' (-1 / +1) can be interpreted on the one hand as already well-established mechanisms of event pairs which entail only low changes and on the other hand as the assumption that the active descriptor is incapable for specific reasons to exert more impact on the passive descriptor. In contrast, a ‘strong’ rating (-3 / +3) indicates, on the one hand, a relatively low-established mechanism of event pairs which entails strong changes in future scenarios, and on the other hand an active descriptor which is powerful enough to exert a significant impact on the passive descriptor. The distinction of the root cause is in most cases transparent through the qualitative statements.

Table 4-12: Interpretation of Likert Scale Groups

Likert Scale Groups	Interpretation
Weak	Already well-established mechanisms of event pairs entail only weak changes (1). Active descriptor incapable to exert significant impact on passive descriptor (2)
Moderate	Instinct rating. The expert is uncertain about the impact of the event pair so that this rating provides the general direction of ‘restriction’ or ‘promotion’ (1). However, the impact on the passive descriptor variant is important for the system (2).
Strong	Low-established mechanisms of event pairs entail strong changes (1). Powerful active descriptor exerting significant impact on passive descriptor (2).

Part 2 of the questionnaire consists of questions for the respondents to align the previously rated descriptor event pairs in Poll 1 and to provide their reasons. The pre-defined ratings are the result of the pre-evaluation inquiry described in Section 4.5. The author of this thesis knows this compromise between effort and reliable research results is criticisable and vulnerable. However, the author takes two measures that help to defend this compromise: First, all descriptor event pairs of part 2 are at least twice actively rated by part 1 of the questionnaire. Second, from methodological stance, it is deductive reasoning within the Grounded Theory approach. The inductively created and provided hypotheses of mutual interrelations from the pre-evaluation inquiry are tested by the experts of this Delphi Study Poll.

The structured preparation of the quantifiable data that are collected is processed with the CIB-analysis tool ‘ScenarioWizard 4.3’ (Weimer-Jehle, 2018). The collected qualitative data is prepared with the aid of MSExcel and NVivo 11 / NVivo 12 for further analysis. In this Delphi Study Poll 2, only 18 experts participate. However, referring to the mix of expertise in Table 4-13, this Poll is comparable to Poll 1.

Table 4-13: Delphi Study Poll 2: Expert Category and Expert Role

Expert Category / Expert Role	**Academics**	**Practitioners**	**Total**
AI and SC Expert	2	2	**4**
AI Expert	1	2	**3**
Blockchain Expert	0	1	**1**
Operations Expert	0	1	**1**
SC Expert	0	7	**7**
Technology and SC Expert	1	0	**1**
Technology Expert	0	1	**1**
Total	**4**	**14**	**18**

Furthermore, all mutual interrelations are additionally rated by the six experts during the pre-evaluation phase so that in conclusion 24 experts rate the descriptor network. As outlined in

Table **4-14**, each descriptor variant event pair is at least rated by four different experts and to a maximum of twelve different experts. The numbers in each field represent the number of experts who evaluated that event pair. The green-coloured gradations illustrate these numbers.

Table 4-14: Head Map of Event Pairs Evaluated by the Number of Experts

#	Descriptor	SC responsiveness	SC efficiency	Transaction costs in the SC	Interorganisational decision delegation	Type of interorganisational specialisation	Type of coordination	Dimensions of process design	Network material flow	Use AI in forecasting	Use of autonomous SC planning techniques	Use of autonomous driving	Use of emerging technnology blockchain	Use of AI to attack SC system architectures
1	SC responsiveness		4	4	4	4	4	4	4	4	4	4	3	4
2	SC efficiency	5		5	5	5	5	5	5	5	5	5	4	5
3	Transaction costs in the SC	4	4		4	4	4	4	4	4	4	4	4	4
4	Interorganisational decision delegation	4	4	4		4	4	4	4	4	4	4	3	4
5	Type of interorganisational specialisation	4	4	4	4		4	4	4	4	4	4	3	4
6	Type of coordination	4	4	4	4	4		4	4	4	4	4	3	4
7	Dimensions of process design	5	5	5	5	5	5		5	5	5	5	4	5
8	Network material flow	4	4	4	4	4	4	4		4	4	4	4	4
9	Use AI in forecasting	5	11	11	5	5	5	5	5		5	5	5	5
10	Use of autonomous SC planning techniques	6	12	12	6	6	6	6	6	6		6	6	6
11	Use of autonomous driving	5	11	11	5	5	5	5	5	5	5		5	5
12	Use of emerging technnology blockchain	4	10	10	4	4	4	4	4	4	4	4		4
13	Use of AI to attack SC system architectures	4	4	4	4	4	4	4	4	4	4	4	4	

The result of the collected data is presented in Appendix F. . It shows the impact balance matrix of all variants of the thirteen descriptors. Due to the large size of the impact balance matrix, Table 4-15 exemplarily shows an excerpt of the entire table presented in Appendix F. Each figure represents the average expert of all experts.

Table 4-15: Exemplary Excerpt of Impact Balance Matrix Event Pair Rating

Descriptor variant		**Responsiveness**		**Efficiency**		**…**
		High	**Low**	**High**	**Low**	
SC responsiveness	Relatively high			-1	1	…
	Relatively low			2	-2	…
SC efficiency	Relatively high	0	-1			
	Relatively low	1	0			
…	…					

The detailed analysis and presentation of the experts' ratings are presented in Section 6.2. This shift is because the analysis of the experts' ratings is strongly interlinked with the author's analysis so that a consistent storyline facilitates the reader's understanding.

4.8 Poll 3 of the Delphi Study to Conduct Sensitivity Check of CIB Analysis

With Poll 3 of the Delphi Study, the participants are asked to review their common results from Delphi Study Poll 2 with the purpose of questioning their own former individual ratings due to the rating by other participants. Therefore, a selection of event pairs is shared with the aid of the survey tool 'mentimeter' (www.mentimeter.com / www.menti.com; Code: 32 07 60 1; original charts see Figure 4-6).

Figure 4-6: Delphi Study Pol 3 – Mentimeter Event Pair Reports

The criteria for this selection are determined by the author of this study and include event pairs which rating raises issues either because the author's expectation is completely different to the ratings of the experts, the qualitative statements cannot explain the rating or the individual ratings have a strong scattering so that a sensitivity check is useful. The Event pair ratings to be reviewed are listed in Table 4-16.

Table 4-16: Event Pair Ratings to Be Reviewed

No	Event pair	Initial rating Poll 2
1	Commonly spread and fully integrated use of AI in forecasting weakly promotes relatively high SC efficiency.	+1
2	Commonly spread and fully integrated use of AI in forecasting promotes decreasing of TC in the SC.	+2
3	Speculation restricts decreasing of TC in the SC.	-2

4	Commonly spread and fully integrated use of AI in forecasting strongly promotes speculation.	+3
5	Commonly spread and fully integrated use of AI in forecasting weakly promotes postponement.	+1
6	More autonomy in interorganisational decision delegation weakly restricts commonly spread and fully integrated use of AI in forecasting.	-1
7	More autonomy in interorganisational decision delegation has no influence on commonly spread use of autonomous SC planning techniques.	0

The strong need to have the rating of these event pairs confirmed arises through the resulting outcome of the scenario analysis which is strongly based on the correctness of these event pairs. Additionally, the participants of Delphi Study Poll 3 are asked to agree or disagree on three resulting statements from Delphi Study Poll 2 as listed in Table 4-17.

Table 4-17: Three Statements to Agree or Disagree With

No	Resulting Statements from Delphi Study Poll 2
1	Commonly spread and fully integrated use of AI in forecasting lead to stronger preference of speculation in hybrid scenarios.
2	A pure demand-driven SC for unpredictable products is not able to bring the SC performance to its optimum.
3	Fully implemented use of AI in forecasting only provides a competitive advantage if combined with commonly spread use of autonomous SC planning.

These three statements represent the key results from the scenario analysis which follow on the Delphi Study Poll 2 in regard to the application of AI in the SC. Statement one asks for a differentiated consideration of the decoupling point paradigm in a ‘leagile SC concept. Statement two supports statement one by emphasising the need for speculation. Statement three restricts statement one and statement two with the prerequisite to have commonly spread use of autonomous SC planning in place to leverage competitive advantages. The combination of all three statements questions commonly accepted SC concepts and stances. Therefore, a review of these consolidated results by the participants is requested to have the statements confirmed or adjusted.

The selection of the 28 participating experts as outlined in Table 4-18 ensures the reliability of the result of this sensitivity analysis through an appropriate mix of technological and SC expertise.

Table 4-18: Delphi Study Poll 3: Participants' Expert Categories and Expert Roles

Expert Category / Expert Role	**Academics**	**Practitioners**	**Total**
AI and SC Expert	2	2	**4**
AI Expert	0	3	**3**
Blockchain Expert	0	2	**2**
Operations Expert	1	2	**3**
SC Expert	3	9	**12**
Technology and SC Expert	1	1	**2**
Technology Expert	0	2	**2**
Total	**7**	**21**	**28**

Specifically, the credibility of this Poll 3 and of the entire study in general is underpinned by the fact that 18 experts consistently participate in all three Delphi Study Polls. Additionally, 9 experts participate in two of the three Polls so that 27 experts of the Poll 3 survey have thorough insights in the development steps and the relationships of the investigation objects until the final results are achieved. One expert only participates in this final Poll so that the assumption of a bias can be neglected. The results of the event pair rating review are outlined in Table 4-19.

Table 4-19: Result of the Event Pair Rating Review

No	Event Pair	Poll 3 results	Delta to Poll 2 Results	Analysis
1	Commonly spread and fully integrated use of AI in forecasting weakly promotes relatively high SC efficiency.	+1.4	+0.4	Former rating confirmed
2	Commonly spread and fully integrated use of AI in forecasting promotes decreasing of TC in the supply chain.	+1.6	-0.4	Former rating confirmed
3	Speculation restricts decreasing of TC in the supply chain.	-1.5	+0.5	Former rating in general confirmed
4	Commonly spread and fully integrated use of AI in forecasting strongly promotes speculation.	+2	-1	Former rating weakened; however positive impact confirmed
5	Commonly spread and fully integrated use of AI in forecasting weakly promotes postponement.	+1	0	Former rating fully confirmed
6	More autonomy in interorganisational decision delegation weakly restricts commonly spread and fully integrated use of AI in forecasting.	-0.7	+0.3	Former rating confirmed
7	More autonomy in interorganisational decision delegation has no influence on commonly spread use of autonomous SC planning techniques.	0	0	Former rating fully confirmed

In general, the experts confirm the former rating of the event pairs. Only the former rating of event pair 4 is weakened from promoted to weakly promoted. However, the positive impact is confirmed. The experts' rating of the second part of Poll 3 is outlined in Table 4-20.

Table 4-20: Result of the Statement Evaluation

No	Resulting Statements from Delphi Study Poll 2	Average Poll 3 Rating	Evaluation of Experts' Ratings
1	Commonly spread and fully integrated use of AI in forecasting lead to stronger preference of speculation in hybrid scenarios.	0.6 - agreement	General agreement received
2	A pure demand-driven SC for unpredictable products is not able to bring the SC performance to its optimum.	0.9 - agreement	Full agreement received
3	Fully implemented use of AI in forecasting only provides a competitive advantage if combined with commonly spread use of autonomous SC planning.	0.4 - agreement	Agreement received with relatively strong distribution of ratings

On a scale from -1 (disagree) to +1 (agree), all three statements, in general, are agreed. Statement 2 receives full agreement with a very low distribution of experts' ratings. Only one expert disagrees and two are undecided. 24 experts fully agree. Statement 1 also receives agreement in general. However, four experts disagree and 3 are undecided. Statement 3 is heterogeneously evaluated by the experts. Six out of 27 experts disagree with this statement, three experts are undecided and rate with 0. In contrast, 18 experts fully agree to this statement. One expert is technically not able to rate this part of the Poll.

4.9 Summary

The presentation of collected data in this Chapter 4 has revealed that the composition of experts' experiences and their academic and professional background allows an appropriate and reliable mix of qualitative and quantitative data. The sequence of semi-structured qualitative one-on-one and group interviews combined with structured Delphi Study surveys has been confirmed to contribute appropriate dimensions of the research design. Collected data have been presented and will serve as foundation of the iterative data analysis and theory building in the following Chapters 5 to 7.

Chapter 5 Design and Development of Conceptual Framework

5.1 Introduction

This chapter serves to design and develop the CF. With Section 5.2, the SC descriptors are established based on the collected and presented data of SC and AI experts during the Delphi Study Poll 1. In Section 5.3, variants are defined for each descriptor to be applied in CIB-analysis. Section 5.4 summarises the results of the Grounded Theory approach and presents the CF as the basis for scenario development.

5.2 Establishment of Supply Chain Descriptors

5.2.1 Analysis of AI Relevance in the SC

Based on the data presented in Figure 4-4 and Figure 4-5, an analysis in regard to the experts' expectations towards the potential of AI to improve SC performance and the probability for the future use of AI in key SC processes is conducted. As illustrated in Figure 5-1, data for this analysis is collected with Question 8 and Question 9 from Delphi Study Poll 1. Question 10 from Poll 1 provides collected UC/APP listed in Appendix C. to strengthen the analysis. A five-step approach results in the Process and Performance Indicator Matrix (PPIM).

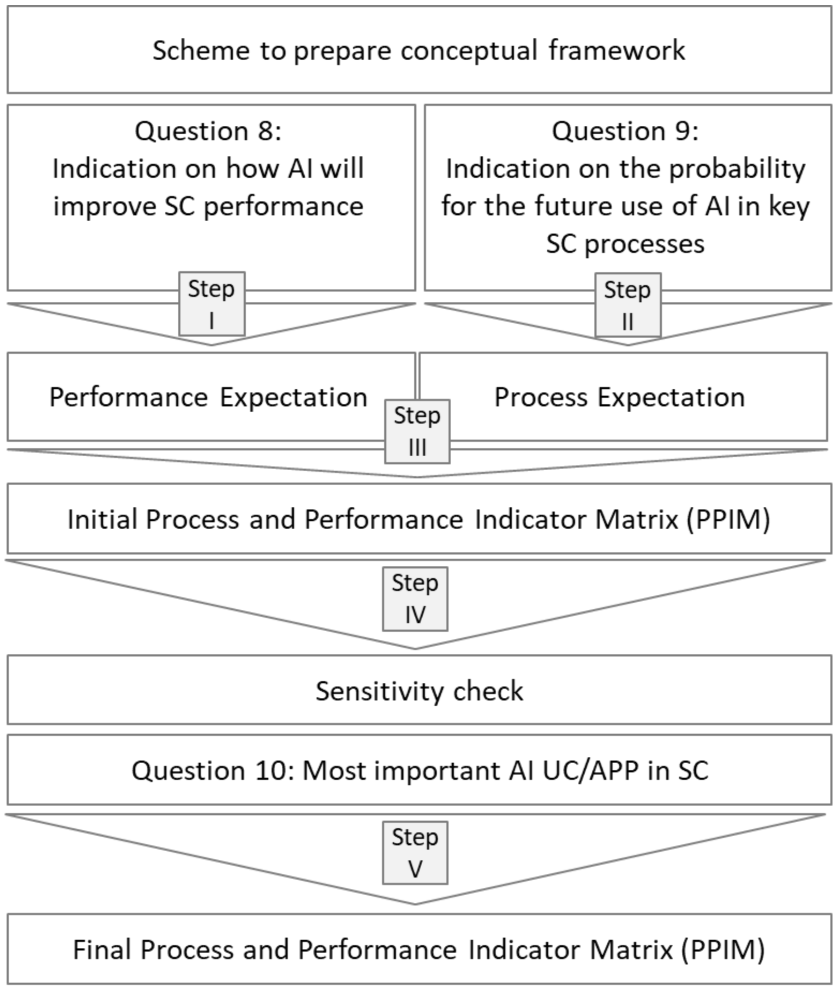


Figure 5-1: Five Step Approach to a Process and Performance Indicator Matrix

Step I to III from the scheme of Figure 5-1 is transferred to the matrix shown in Figure 5-2. This matrix allows to quantify the qualitative experts' answers from Delphi Study Poll 1.

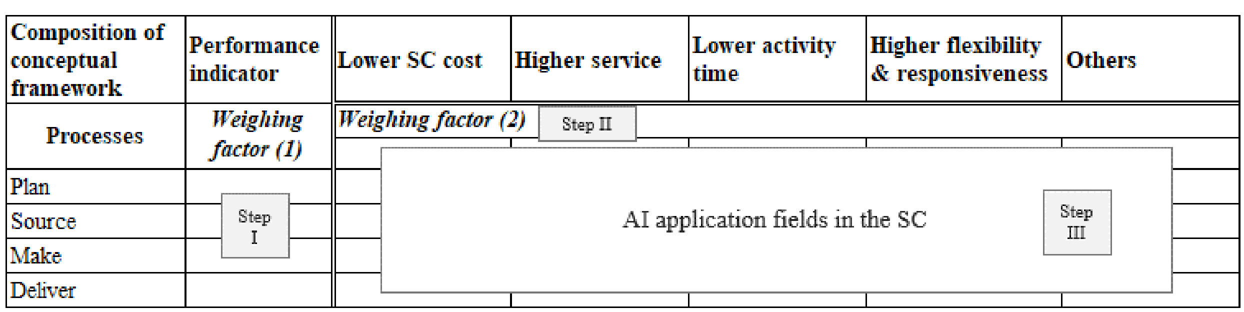


Figure 5-2: Structural Composition of CF: Performance-Indicator-Process-Matrix (PPIM)

Table 5-1 shows that the experts' ratings are quantified with a weighting scale with the same space between each value. This weighting scale is needed to quantify the results of the Likert-scale-based experts' answers. Quantification is needed for the purpose that both ratings from Question 8 and Question 9 can be compared to each other and applied in one matrix. The value of the weighting factors is consciously chosen to distinguish this rating from the Likert Scale of the CIB-analysis (see Table 4-11).

Table 5-1: Weighting Factor Representing Rating Scale of Questionnaire of Poll 1

Please indicate how artificial intelligence will improve supply chain performance	**Consider the key supply chain processes. Please indicate the probability for the future use of artificial intelligence**	**Weighting scale**
Extremely unlikely	Not probable	-20
Unlikely	Somewhat improbable	-10
Neutral	Neutral	0
Likely	Somewhat probable	10
Extremely likely	Very probable	20

Step I: Evaluate performance expectations:

Table 5-2. shows that the experts' rating is multiplied by the weighting factor scale and summed up. The result determines the expectation of each scale characteristic representing an SC performance indicator. All four SC performance indicators are expected to be improved by AI with reducing SC cost in the leading position.

Table 5-2: Expectation of How AI Will Improve SC Performance

SC performance	**Extremely unlikely**	**Unlikely**	**Neutral**	**Likely**	**Extremely likely**	**Weighting factor (1)**
Weighting scale	-20	-10	0	10	20	
Lower SC cost	0	0	0	10	15	**16.0**
Higher service	0	1	0	11	12	**14.2**
Lower activity time	0	0	2	9	14	**14.8**
Higher flexibility and responsiveness	0	1	0	12	12	**14.0**

Step II: Evaluate process expectations:

The same method as in Table 5-2 is applied in Table 5-3 to quantify the expectation towards future use of AI in SC processes. The experts have the highest expectation towards the process ‘planning’, followed by ‘make’ and ‘deliver’ processes. AI applications in the ‘source’ process are expected but with a relatively lower relevance, even so, the expert for sourcing expects applied AI technology in sourcing to be very probable. One expert hesitates with applied AI for all four SC processes. Two others indicate a lower probability of applied AI in planning although they expect a very high probability for the other three processes. All in all, the expert opinions represent a uniform picture of the future use of AI in SC processes.

Table 5-3: Probability of Future Use of AI in SC Processes

SCOR Model	**Not probable**	**Somewhat improbable**	**Neutral**	**Somewhat probable**	**Very probable**	**Weighting factor (2)**
Weighting scale	-20	-10	0	10	20	
Plan	0	0	0	4	21	**18.4**
Source	0	0	4	11	10	**12.4**
Make	0	0	2	9	14	**14.8**
Deliver	0	0	1	10	14	**15.2**

Step III: Develop Initial Process and Performance Indicator Matrix:

To learn in which SC process which performance indicator conveys the highest expectations of AI, weighting factor (1) and weighting factor (2) are multiplied by each other and summed up as depicted in Table 5-4. The intersection between weighting factor (1) and weighting factor (2) represents AI application field in the SC.

Table 5-4: Probability Evaluation of AI Impact at the Intersection Between Process and Performance

SCOR Model	Performance indicator	Lower SC cost	Higher service	Lower activity time	Higher flexibility & responsiveness
		Weighting factor (1)			
Process	*Weighting factor (2)*	**16.0**	**14.2**	**14.8**	**14.0**
Plan	**18.4**	294	261	272	258
Source	**12.4**	198	176	184	174
Make	**14.8**	237	210	219	207
Deliver	**15.2**	243	215	225	213

The experts expect that applied AI technologies will most probably contribute to SC planning processes to reduce SC costs (294 points). Relatively high impact on cost reduction is also seen in delivery processes (243 points). A relatively low contribution is expected in sourcing processes to lower activity time (184 points) or increase flexibility and responsiveness (174 points). Nevertheless, the probability that AI improves flexibility and responsiveness in delivery processes (213 points) is relatively high than lowering costs in source processes (198 points).

<u>Step IV: Conduct Sensitivity Analysis:</u>

A sensitivity check is applied to divide and allocate the uncertainty of the initial PPIM to a second source. Collected UC/APP in Delphi Study Poll 1 are assigned to the performance indicators and SC processes as shown in Appendix C. and summarised in Table 5-5. The number of UC/APP assigned to the SC processes and performance indicators is divided by 10 (column 'Weighting factor (3)) to reduce the size of the calculation result in Step V.

Table 5-5: Number of UC/APP Assigned to Performance Indicators and SC Processes

SC Processes and performance indicators	Number of UC/APPS assigned	Weighting factor (3)
Plan	37	3.7
Source	19	1.9
Make	31	3.1
Deliver	39	3.9
Lower SC cost	69	6.9
Higher service	18	1.8
Lower activity time	43	4.3
Higher flexibility and responsiveness	30	3.0

The calculation logic of the initial PPIM is applied on the Weighting Factor (3) of the UC/APP. The UC/APP represent AI applications in the SC with the purpose of improving SC performance. Thus, this approach is appropriate for a sensitivity check. The result is shown in Table 5-6.

Table 5-6: Sensitivity Check of PPIM with UC/APP

SCOR Model	**Performance indicator**	**Lower SC cost**	**Higher service**	**Lower activity time**	**Higher flexibility & responsiveness**
Process	***Weighting factor (3)***	**6,9**	**1,8**	**4,3**	**3**
Plan	**3,7**	25,53	6,66	15,91	11,1
Source	**1,9**	13,11	3,42	8,17	5,7
Make	**3,1**	21,39	5,58	13,33	9,3
Deliver	**3,9**	26,91	7,02	16,77	11,7

Table 5-7 compares the ranking of the initial PPIM with the ranking of the sensitivity check. The application fields ‘higher services through planning’ shows the main deviation from the initial PPIM. The importance of AI in the application field ‘lower SC cost from sourcing process’ is meaningfully lower in the sensitivity check than in the initial PPIM. Due to the rough approximation of the results for all other application fields, the results have no significance.

Table 5-7: Comparison of Initial PPIM Ranking with Sensitivity Check Ranking

Performance Indicator	Lower SC cost		Higher service		Lower activity time		Higher flexibility & responsiveness	
Process	**iPPIM**	**SensC**	**iPPIM**	**SensC**	**iPPIM**	**SensC**	**iPPIM**	**SensC**
Plan	1	2	3	13	2	5	4	9
Source	13	7	15	16	14	11	16	15
Make	6	3	11	14	8	6	12	10
Deliver	5	1	9	12	7	4	10	8

iPPIM = initial PPIM; SensC = Sensitivity Check

Step V: Develop Final Process and Performance Matrix:

With the purpose to integrate the results of the initial PPIM with the sensitivity check, the weighting factor results from Table 5-6 are multiplied with the weighting factor results from Table 5-4. The results are shown in Table 5-8. Additionally, the ranking of the initial PPIM with the final PPIM is listed to emphasise the impact of the UC/APP on the importance of AI in the application fields.

Table 5-8: Final Process and Performance Indicator Matrix

Performance Indicator	Lower SC cost			Higher service			Lower activity cost			Higher flexibility & responsiveness			Total
Process	**PPIM**	**R_f**	**R_i**	**PPIM**	**R_f**	**R_i**	**PPIM**	**R_f**	**R_i**	**PPIM**	**R_f**	**R_i**	
Plan	7,516	1	1	1,736	11	3	4,333	4	2	2,859	6	4	**16,444**
Source	2,601	8	13	601	16	15	1,499	13	14	990	15	16	**5,691**
Make	5,065	3	6	1,170	14	11	2,920	7	8	1,927	10	12	**11,082**
Deliver	6,545	2	5	1,512	12	9	3,773	5	7	2,490	9	10	**14,318**
Total	**21,727**			**5,018**			**12,524**			**8,266**			

R_f = final Ranking; R_i = initial Ranking

Two changes are worth highlighting in the sequence of importance of the final PPIM compared to initial PPIM in Table 5-7; The impact of the UC/APP is mainly reflected in the importance of AI to lower costs in sourcing and in the significant higher importance of AI to enable higher services with SC planning processes. The importance of the SC planning process is underpinned by the analysis as well as the experts' belief that AI will improve SC performance in the field of SC cost reduction.

5.2.2 Analysis for Identifying Categories Through Open Coding

After having used UC/APP as an analysis element to argue the relevance of AI according to SC performance, the UC/APP are analysed with the method of open coding as described in Section 3.3.3. The UC/APP as itemised in Appendix C. are analysed to identify underlying concepts and categories which will serve as foundation to determine SC descriptors. With support of NVivo 12, a word frequency analysis is conducted to elaborate the most frequent nominations of terms as shown in Figure 5-3. The frequency of words in all experts' answers is counted and ranked.

Figure 5-3: Word Frequency Analysis: Applications of AI in SC

However, the cleansing of these first results reveals that the term '**supply'** is frequently used in the term 'supply chain'. Due to the context of this research, this term is frequently repeated but without the necessity to derive a relevant code for the CF. The term '**planning**' refers in all the expert nominations to the requested context (e.g. "demand planning", "continuous planning parameter optimization", "better planning", "formalize existing procedure and planning approaches") as well as the term '**forecasting**' (e.g. "forecasting of demand and sales using ML", "better forecasting of required demand", "decision support for forecasting A items", "forecasting of near future as machine defects") and the term '**autonomous**' (e.g.

“autonomous trucks”, “autonomous production”, “autonomous networks”, “autonomous supply”, “autonomous driving”). The term ‘**demand**’ always occurs in combination with “forecasting”, “predict” or “planning” and is always directly related to the raised question. The term ‘**decision**’ is consistently linked to an AI-related context such as “scenario simulation”, “support of operative logistics decisions”, “increase productivity in planning […] on urgent or high-impact decisions”, or that “AI could complement human decisions in operations”.

The term ‘**learning**’ occurs in most of the mentioned UC/APP referring to “ML”, “computer learning” or “deep learning”. These word combinations indicate that acquiring skills and improving functional abilities through learning are inherent in AI applications. The experts expect SC performance improvements through AI learning abilities (“…use learnings for future planning…”, “Learning of … more complex behaviours…”) but as part of the AI so that ‘learning’ is considered as an indirect element of UC/APP. The term ‘**customer**’ is in direct connection with mentioned UC/APP (e.g. “ML helps to combine big data such as customer recommendations”, “customer or product segmentation using ML”, “Using (ML) algorithms to predict customer behaviour”). Finally, the term ‘**data**’ only serves as the object to be used in proposed UC/APP and as the reason for applying AI instead of traditional instruments (e.g. “ML helps to combine big data”, “systems evaluating bigger amount of data”, “it starts always at stages with high uncertainty and many data”, “predictive analytics and data modelling”). As a first finding, most of the experts see UC/APP of AI in SC in the field of customer demand forecasting and planning as well as in autonomous activities.

Double content can be exemplarily illustrated by UC/APP 03 “forecasting of demand and sales”, UC/APP 17 “Demand prediction”, UC/APP 55 “Demand Planning/Forecasting”, and UC/APP 69 “Demand forecast”. It became apparent, that UC/APP could be assigned to one or quite a few categories, e.g., UC/APP 53 “SC visibility: With the IoT, high visibility of materials, work in progress (WIP) and finished products and precise forecasting in supply chain” is assigned to category monitoring and forecasting. The expert statement touches the aspect of real-time transparency on movements as well as the speculation aspect to predict possible events in the near future. This way of coding concludes in the categories itemised in Table 5-9.

Table 5-9: List of Determined Categories Based on Experts’ UC/APP with Number of Nominations

No	Categories	Number of Nominations
C1	Forecasting	21
C2	Collaboration	11
C3	Movement	8
C4	Monitoring	8
C5	Scheduling	7
C6	Communication	7
C7	Consumer Centricity	4
C8	Supply Network Design	3
C9	General Statements	3

The categories are determined in five steps. In a first step, the meaning of each UC/APP is clarified, and orthography is corrected. In a second step, all UC/APP are categorised into terms that come up as an intellectual process of content analysis of the UC/APP. The result is a list of approximately fifteen terms. In a third step, the number of nominations per term is determined and a descending sequence is drawn up. 48 UC/APP were assigned to seven main terms. During the fourth step – a review and re-assignment of 24 UC/APP assigned to other terms, these seven main terms are finally distilled as seven categories to cluster 66 of all 72 UC/APP. One additional category “Supply network design” is determined for three UC/APP with the corresponding content. Only three UC/APP “Service and self-service industries such as hospitals and banks”, “Supervised and semi-supervised training simulators or training support simulators”, and “Military training, police forces and related applications can use AI to reduce the loss of lives in danger” are assigned to an additional category “General statements”. In a fifth step, the assigned UC/APP per category is reviewed content-related and summarised to key statements per category without losing the diversity of content or falsifying the meaning (see Appendix D.). These categories are the starting point to determine the descriptors for the CF.

5.2.3 Development of SC Descriptors from Identified Categories

The detected relevance of AI for SC performance in Section 5.2.1 and the categories C1 - C8 identified through open coding of the UC/APP in Section 5.2.2 serve as foundation to develop appropriate SC descriptors for the CF. The following discussion results in describing elements to constitute the CF to be designed:

- Use of AI in forecasting,
- Use of autonomous SC planning techniques,
- Interorganisational exchange such as type of coordination, specialisation, and delegation SC efficiency,
- SC responsiveness,
- Autonomous driving,
- Emerging technology Blockchain,
- Dimensions of process design,
- Transaction costs,
- Intelligent attacks to global SC system architecture.

The experts who participated in the Delphi Study Poll 1, consider forecasting (C1) and planning of supply and demand with support of ML as one of the most important action fields in future SC. Supply and demand planners are still important to supervise the SC and interfere in case of alerts primarily for cost-intensive decisions but AI should overtake low-impact decisions to release employees from repetitive routine processes. These repetitive processes are depicted by the experts in the field of forecasting necessary maintenance of devices and equipment to avoid downtimes and interruptions of material flows. Permanent learning of SC systems about customer behaviour and customer requirements is seen as important input for more automated SC planning. However, the need of system capabilities to identify interdependencies between different internal data (historic sales data of products, master data, campaigns and promotions, pricing etc.) and external factors (point-of-sales/customer data, social media data, weather, etc.) are recognised as prerequisite for autonomous system activities. One expert summarises this learning to the question “which product offers most value to the customer and which price will be paid.” This statement strongly refers to the underlying theory of consumer and producer surplus as described in Section 2.7.1. Another expert requests the combination of big data and time series as prerequisite for independent system activities. Thus, the CF is requested to identify autonomously cross-SC surplus based on the pattern recognition of permanent access to big data.

The experts consider ML as key supporting technology for any kind of forecasting to process predictive analytics in the SC. Therefore, **the use of AI in forecasting** should be a strong part of the CF. The experts also consider the integration of SC planning with forecasting as important application. Repetitive planning processes of the SC should be executed autonomously based on constant and bi-directional data transfer between physical material and information flow. Therefore, the **use of autonomous SC planning techniques** should be part of the CF.

Collaboration (C2) through information and resource sharing is seen by the participating experts as a key enabler for a more efficient SC. Collaboration is expected for all types of machines to human interfaces and exemplarily mentioned between humans and smart robots. Support in human interaction in the SC can be provided e.g., in order taking processes or customer service calls. Experts see AI to assist by complementing human decisions in operations to ensure reliable delivery dates along the SC to ensure available inventory for production and to reliably predict delivery dates to proactively notify SC planners in case of SC disruptions. AI should be able to learn typical, repetitive, but more complex behaviours such as e.g., problem solving in case of delays and in case of issues during supply chain execution. This capability enables technologies to automatically detect faults in operations by analysing diverse inputs e.g., video, audio and sensor data like weight or temperature in combination with (inaccurate) master data e.g., to uncover packing errors (e.g., wrong product in package) or shipping errors (e.g. wrong pallet in container). Another aspect highlighted by the experts is that AI might be able to formalise existing procedure in operational logistics planning and scheduling using ML and deep learning. The experts strongly link this approach to Blockchain technology. However, well-improved collaboration in the SC needs to assess structural and organisational aspects so that the application of future business technologies will be effective and efficient. Therefore, the CF should comprise aspects of **interorganisational** exchange such as different **types of coordination** and **specialisation** and **delegation**. The result of changes in a SC organisation should be measured to understand how SC performance is affected. Therefore, the performance indicator **efficiency of a SC** should be part of a CF. **Blockchain** as **emerging technology** is explicitly mentioned. The author of this thesis recognises that at the time of conducting the survey, there is a lot of hype about Blockchain (Hayrutdinov, Saeed, & Rajapov, 2020; Queiroz, Telles, & Bonilla, 2019; Scherelis & Bothge, 2019; Treiblmaier, 2018). Blockchain technology is currently considered as a future key technology to make data sharing and information exchange in SC execution more reliable. Therefore, the CF should also contain **Blockchain** as necessary element.

The category ‘movement’ (C3) is referred to by experts with examples of autonomous shipping in automotive industry. First trucks in the logistics industry are also started to be equipped with drones for autonomous last mile delivery. Experts refer to first tests of cargo vessels sometimes running sections of long voyages on autopilot, making fully autonomous vessels e.g., for large scale or long-haul transportation and item-based delivery as a logical next step. Some of the experts refer to already performed test runs with extremely high cutting costs (e.g., up to 44% of a ship’s running costs are in the crew). In addition to cutting costs autonomous vessels will have the possibility to reduce need for human interaction and human errors. All these innovations are supposed by the experts to result in autonomous driving with autonomous trucks. Internal logistics is expected to be equipped by autonomous production and business technology supporting operative logistics decisions to manage inhouse logistics and material flow. Autonomous movements might end up in autonomous networks with AI to be better in sampling, cleansing, processing and storing data that have the biggest value for SC. Therefore, **autonomous driving** in various forms is supposed to be an important application of AI in future supply chains. Therefore, it should also be part of the CF. With these expected tremendous changes in movement, significant infrastructural changes are expected which might affect the **physical material flow**. Therefore, the logistics **network structure** should be a component of the CF.

From the aspect of monitoring (C4) the SC, the experts assume that external and internal processes will be more and more combined and considered from end-to-end perspective. Such a continuous monitoring of inbound and outbound shipments as assumed, to taking into account multiple parameters from SC partners and other external parameters like vessel schedules, weather data etc. Monitoring of manufacturing processes in high-tech industries such as computers, tele-communication devices, cell phones and automotive production industries is expected to lead to quality and output optimisation. AI can help to identify more complex patterns and interdependencies in order to earlier warn about arising issues e.g. detection of unusual behaviour patterns, maintenance of machines or detection of fraud in finance bookings, ordering etc. This can lead to autonomously decided uninterrupted provision of supplies with minimum costs from numerous optional suppliers by taking unforeseen events into consideration and respond immediately. Personal avatars can be deployed in IT to organise, control, prioritise the SC or even the life of a material, container, or vehicle. The participating experts suppose that AI ensures (near) real-time transparency on decentralised activities and processes of the overall end-to-end SC. Real time visibility accomplishes quick response on exceptions and misleading decisions. Permanent awareness and control of activities and decisions enable companies to adequately balance responsibility and accountability of processes and decisions between SC partners and organisations the most efficient way. Therefore, **interorganisational decision delegation** should be part of the CF.

From the viewpoint of scheduling (C5), experts state that in comparison to humans, AI is able to handle a much higher number of influencing factors on decisions made during strategic, tactical and operational SC planning activities. This AI capability allows to design optimal SC in terms of material, information and funds flow. This optimisation primarily concerns time scheduling during transportation, warehousing and route planning, but also specific ad-hoc routing of shipments with the requirement to choose carrier and/or routing for each shipment in real-time depending on cost and time of each delivery option. It should also be possible to integrate planning of transports with production planning and goods supply for production. The experts consider AI to tremendously improve decision-making in all action fields along the SC.

This capability is expected to lead to significantly improved scheduling of delivery dates in much shorter timeframe. This assumption could lead to completely different design of SC strategies and processes according to responsiveness and efficiency. Therefore, **process design dimensions** and its impact on **SC responsiveness** and **SC efficiency** should be assessed in the CF.

The category 'communication' (C6) is referred to by autonomous networks requiring intelligent interfaces to capture order entry information and digitise it with the target to support operative logistics decisions and finally living up to expectations of B2B EDI between companies. Intelligent interfaces can be supported with speech recognition systems applied in call centres. AI is considered to be applied in the field of data exchange and automated process management between SC partners and organisations. However, in all these expert statements the expectation of reducing TC in the SC shines through. This expectation is underpinned by the often-made statements referring to reducing costs of information flow in case of disruption or to reduce interferences to find joint solutions. Additionally, and explicitly referred to reducing TC, experts mention the influence of AI on supplier pricing. All these aspects of communication have to be coordinated. Therefore, the CF should allow assessments on different **types of SC coordination**.

Experts' opinion is that consumer centricity (C7) is a field of high uncertainty despite of the availability of many data. However, ML can support an improved view on customers by providing relation of all information about customers and inferences on decisions e.g. regarding marketing, profiling and shaping. This could result in customer or product segmentation with the target to establish a link to SC management planning systems for more precise targeting of customer or product groups. Improved segmentation due to better customer profiling with support of AI could result in changes of SC strategies and processes. Fields of high uncertainty are always related to potentially high TC. One expert explicitly refers to the influence of **TC** on customer pricing. TC in the field of customer centricity is supposed to be positively impacted by improvements in forecasting customers' buying behaviour. Therefore, **dimensions of process design,** which could support either **responsive** or **efficient SC** should be taken into consideration for the CF.

Referring to experts' opinions Strategic supply network design (C8) might be supported in future by systems evaluating bigger amount of data e.g. to find alternative supply sources or to design and plan an overall network. However, strategic design of SC mainly focuses on SC segmentation due to volatility and uncertainty of demand and supply in order to determine best fitting operational structure to achieve SC delivery reliability. Strategic design of SC comprises mostly of the already discussed structural and technological components as well as performance indicators of a SC system. Nevertheless, an additional aspect arises with the fact that such a global and closely linked IT network permanently deploys a big amount of data from multiple resources. The more such big data are deployed in an autonomous IT system architecture, the more this network is imperilled by external threats with the support of intelligent technologies. Therefore, one additional component of the CF should deal with the impact of **intelligent attacks to global SC system architecture**.

The category 'general statements' (C9) comprises of experts' statements referring to specific industries such as service and self-service industries (e.g. hospitals and banks) or specific application fields such as military training or police forces. Experts explain that the application of AI in these fields facilitates service provision or reduces the loss of lives in dangerous situations. However, these fields of AI application are not determined as relevant for this thesis due to the fact that on the one hand the focus lies on cargo SC and related services and on the other hand, police and military area is too specific to be included in the general SC system view. Therefore, these expert statements will not be considered for further analysis.

Table 5-10 lists the describing elements of a SC system which results from the analysis of the determined categories in Section 5.2.2.

Table 5-10: Describing Elements of A SC System Related to Categories

Category		Describing Elements of a SC System
C1	Forecasting	Use of AI in forecasting
		Use of autonomous SC planning techniques
C2	Collaboration	Interorganisational exchange such as type of coordination, specialisation, and delegation
		Efficiency in the SC
		Emerging technology Blockchain
C3	Movement	Autonomous driving
		Physical material flow in network structure
C4	Monitoring	Interorganisational decision delegation
C5	Scheduling	Dimensions of process design
		SC responsiveness
		SC efficiency
C6	Communication	Type of coordination
		Transaction costs
C7	Consumer centricity	Dimensions of process design
		Responsive SC
		Efficient SC
		Transaction costs
C8	Network design	Intelligent attacks to global SC system architecture

With the PPIM of Table 5-8, the relevance and importance of these SC describing elements is validated. This quantitative analysis identified the relatively highest probability of AI impact on SC performance in the planning and delivery process. AI technologies are expected to mostly contribute to lower SC cost and activity time. Therefore, the identified describing elements of the SC system should support these action areas. TC are identified as an important cost category in the SC. Therefore, TC is defined as a SC descriptor. So far, use of AI in forecasting, and use of autonomous SC planning techniques fit directly to the planning and delivery process. Additionally, SC efficiency affects cost and activity time driven performance indicator. Interorganisational exchange such as coordination, and delegation of decision as well as dimensions of process design serve as components to analyse system behaviour according to all determined SC performance indicators along all SC processes. Likewise, physical material flow in network structure and autonomous driving can be further analysed according to their contribution to system performance towards efficiency or responsiveness. The potential descriptor SC responsiveness directly refers to the action area of higher flexibility & responsiveness. It is also worthwhile to analyse system performance along all determined SC processes according to the impact of emerging technology, Blockchain and intelligent attacks to global SC system architecture on the outlined SC performance indicators. The identified descriptors are summarised in Table 5-11.

Table 5-11: Constituting Descriptors for CF

No	CF Constituting Descriptors	Grouping Element	
01	SC responsiveness	I	SC Performance Indicators
02	SC efficiency		
03	TC in the SC		
04	Interorganisational decision delegation	II	Process and Structure Elements
05	Type of interorganisational specialisation		
06	Type of coordination		
07	Dimensions of process design		
08	Network material flow		
09	Use of AI in forecasting	III	Contextual Factor “Technology”
10	Use of autonomous SC planning techniques		
11	Use of autonomous driving		
12	Use of emerging technology Blockchain		
13	Use of AI to attack SC system architecture		

The identified SC descriptors are grouped into process and structure elements, contextual factor Technology, and SC performance indicators inspired by the proposed structure of Goepfert (2019) and Pfohl (2016). However, to apply these descriptors in a CF to develop future scenarios with the aid of a CIB-analysis, appropriate variants for each descriptor must be found. The relationship of these variants to each other are then subject of further evaluation. Therefore, Section 5.3 conducts a more detailed descriptor analysis with the objective to specify the descriptors through their variants. Referring to Pfohl (2016) the triad of SC shaping options consists of ‘central’ versus ‘decentral’, ‘postponement’ versus ‘speculation’, and ‘bundle’ versus ‘separate’. These contrasting pairs are applied to determine the variants of the established SC descriptors. However, this determination of variants makes it necessary analyse and describe the SC descriptors.

5.3 Specification of Descriptors Through Decisive Variants

5.3.1 Descriptors Related to Supply Chain Performance Indicators

Three descriptors are grouped as SC performance indicators: SC responsiveness, SC efficiency, and TC in the SC. The following discussion results in two variants for each of these descriptors:

- SC responsiveness: Relatively high/relatively low.
- SC efficiency: Relatively high/relatively low.
- TC in the SC: Relatively increasing/relatively decreasing.

Referring to Fisher (1997), SC responsiveness (01) is expressed through the capability to adequately react to unpredictably changing and therefore uncertain and volatile customer demand. The theorem of Christopher (1998) from the 1990s that short order-to-delivery cycles are a key competitive advantage of a SC is nowadays still accepted. For that reason, lead time is seen as a strong service level element to meet customer’s claim of reactiveness. Depending on the type of operations, adequate lead time service level also makes it necessary to include the agility of manufacturing systems to enable rapid change through reduced setup times so that responsiveness increases. In contrast, the availability of appropriate inventory is considered as one main lever to reduce lead time (Christopher, 1998). However, hedging responsiveness with higher inventory increases SC costs. This is where Christopher (1998) claims for other agility increasing measures substituting inventory. One measure to be analysed with this CF is AI-enabled predictive analytics to lower working capital tied in inventory as part of SC costs and to lower activity time as part of make and delivery process. Depending on the success of these measures, SC responsiveness is either 'relatively low' or 'relatively high' what determines the variants.

In contrast to SC responsiveness, SC efficiency (02) focuses on well-predictable products what facilitates market mediation through relatively low inventory because a nearly perfect match between supply and demand can be achieved (Fisher, 1997). Performance objective is to fulfil customer demand with minimal effort (Fisher, 1997; Mendes, Leal, & Thomé, 2016). Installing continuous cost reducing and performance increasing programmes and lean approaches in the material flow is predominant choice of measures. Relatively high efficiency depends on high average utilisation rate in manufacturing, transport and warehouse achieved with appropriate management effort. It is subject of analysis with the CF to describe how AI-enabled applications can be used to reduce physical costs and to contribute to lean information flow and lean coordination of SC partners. Therefore, SC efficiency can either be 'relatively high' or 'relatively low'.

TC in the SC (03) encompasses all activities dealing with the information of and the communication with suppliers and customers and arise from interactions with other companies in the SC (Seuring, 2002). Ex-ante search and contracting costs and ex-post TC as the relationship continuous are incurred as monitoring each party's behaviours and then taking the actions necessary to confirm whether the SC partners perform their obligations (Um & Kim, 2018). The cost of doing transactions could be too high under certain conditions. In those cases, the economic transaction within a firm or hierarchy governance structure might be superior to it as market-based governance structure (Grover & Malhotra, 2003). For that reason, the descriptor contributes to investigate whether direct or indirect impact of other descriptors affected by AI might lead to a shift in make-or-buy decisions in the long run (Hobbs, 1996; Williamson, 2008). Thus, the variants of TC in the SC are characterised as ‘relatively increasing’ or ‘relatively decreasing’.

5.3.2 Descriptors Related to Process and Structure Elements

Five descriptors are grouped as process and structure elements as illustrated in Table 5-11. These descriptors primarily constitute the organisational dimensions of decision-making and partner coordination as well as the design of the material flow. The following discussion results in two variants for each of these descriptors:

- Inter-organisational decision delegation: More autonomy/less autonomy.
- Type of inter-organisational specialisation: Process orientation/functional orientation.
- Type of coordination: Centralised by one focal company/Equally decentralised by SC partners.
- Dimension of process design: Postponement/Speculation.
- Network material flow: Centralised network (hub-and-spoke)/decentralised network (grid system).

The descriptor interorganisational decision delegation (04) orientates at the RBV broadened by SC-related complementary theories as described in Section 2.3. In general, delegation is the assignment of any responsibility or authority to another person to carry out specific activities (compare "Cambridge Dictionary," 2019a; "Delegation," 2019). Delegation expresses the allocation of leadership competence from a principal to an agent (Jensen & Meckling, 1976). Interorganisational delegation represents the allocation of leadership capabilities between companies of different value-adding stages of different SC partners. Therefore, decision delegation is the measure for a certain degree of decision autonomy within the supply chain. However, the question arises which degree of decision delegation among SC partners is most beneficial and effective. Referring to Seuring (2002), it is assumed that intermediate forms of coordination which are positioned between hierarchical companies with a clear governing structure and those of unlimited markets are superior within SC management to both extremes of the spectrum. Nevertheless, it is subject of investigation with the CF to what extent AI enables autonomous decision-making on different value-adding stages and how far the SC performance indicators are affected by this interorganisational change in decision delegation. Therefore, the descriptor variants are more autonomy and less autonomy.

Type of interorganisational specialisation (05) primarily refers to structuring of labour division and specialisation along the SC beyond company boundaries with focus on joint use of IT to optimally share data between SC partners. Christopher (2000) states that full potential of shared information can only be achieved by process integration. Process integration means collaborative working between buyers and suppliers, joint product development, common systems and shared information. Along with process integration comes joint strategy determination, buyer-supplier teams, transparency of information and even open-book accounting. However, interorganisational process integration is still based on existing, often traditional organisational company structures either functional or process oriented within each company organisation. The principle of connectivity says that internal relations are more intensive than external relations (Goepfert, 2006, p. 72). Therefore, it is of interest from an organisational perspective to understand how the division and specialisation of labour ("Oxford Living Dictionary," 2019) should be organised along the SC and beyond company boundaries to achieve best future SC performance. This descriptor is used to assess whether it is conceivable that relations between organisation units of different organisations at their interface grow more strongly together than at their internal interfaces, with the result that this external relation is more intensive than with internal relations. For that purpose, this descriptor serves to investigate how functional- or process-orientation impacts the future SC system. Therefore, the variants are characterised by process orientation and functional orientation.

The need of coordination in a SC (06) arises from the fact that people work together in organisations which collaborate to achieve a common goal in a process of joint decision making (D. J. Wood, Gray Barbara, 1991). Typical targets of interorganisational coordination processes are effective communication enabled by adequate information exchange associated with partnering approaches, channel coordination, operational efficiency and performance monitoring (Arshinder, Kanda, & Deshmukh, 2008). Coordination instruments are exemplarily outlined by Goepfert (2006, p. 75) as personal instruction, plans, programs or self-tuning (self-optimisation). Especially self-tuning as a coordination instrument represents a decentral coordination type (see definition of self-tuning in "Wirtschaftslexikon24.com," 2018) whereby swarm-intelligence is the strictest form of a decentralised self-organized system (Beni, 2005). However, collaboration in a SC must be coordinated because of the general dilemma of a system with divided responsibilities: The isolated development of partial solutions for a common objective claims an integrated alignment of all partial activities (Frese, Graumann, & Theuvsen, 2012). Coordination can be based on different governance approaches such as formal control by contractual governance or relational governance. For that reason, this descriptor aims to contribute the adequate and successful coordination of SC partners for the purpose of improving performance of individual companies and the SC as a whole (Mentzer et al., 2001) by taking into account correlations with AI technologies. Therefore, the variants of coordination types are defined as centralised by one focal company or equally decentralised by SC partners.

Process design (07) enables sequence of interdependent and linked procedures which, at every stage, consume at least one resource (employee time, energy, machines, money) to convert inputs (data, material, parts, etc.) into outputs. These outputs then serve as inputs for the next stage until a known goal or end result is reached ("Business Dictonary," 2019a). A SC consists of a network of directly and indirectly related processes. All these processes serve the target to meet customer demand. Products are pushed through the supply and production process and kept in stock to satisfy upcoming demand. In contrast, pull-driven production responds directly to existing customer demand (Seuring, 2002). The challenge of the process design in the SC is to seek to develop an optimal decoupling point to combine push-and pull-strategies within one SC whereas upstream lean and efficient strategies are prevalent and downstream agile strategies are the preferred strategy of choice (Christopher, 2000). Postponement and speculation are the processual aspects of this challenge. With postponement, decisions of product differentiation are shifted as far as possible into the future; either by creating product variants (production-oriented) or by delivering into regional markets (geographical). Is a speculation strategy selected, decisions are made on an early stage based on prediction and forecasting (Pagh & C., 1998). The CF serves as instrument to assess how this descriptor might be impacted by AI technologies and how it might impact or will be impacted by other SC elements. Therefore, the variants of the dimensions of process design are determined by ‘postponement’ or ‘speculation’.

Network material flow (08) refers to nodes of sources and destination locations connected through edges (Kim, Yu-Su, & Linderman, 2015). The configuration of a physical material flow between source and destination locations can be defined as, a grid system (direct relation between each location) or a hub-and-spoke system (physical material flow runs through a central hub) also interpretable as singulation and bundling of material flow (Goepfert, 2006, p. 73f). The design of physical material flow is a factor impacting SC performance. AI might lead to changes in the design of the physical material flow. Improved prediction of customer demand could allow companies to more often deploy anticipatory shipping (Gast, 2018), so that the selection of transport modes and/or network structures could change towards longer transport time. Bundling on the one hand or more singulation due to e.g. drone deployment on the other hand could be part of future scenarios. The variants of network material flow are characterised as centralised (hub-and-spoke) or decentralised network (grid system).

5.3.3 Descriptors Related to Technology

The third grouping is inspired by environment analysis ("PESTLE analysis," 2020; Theobald, 2016). Impact factor Technology refers to technological developments which might affect workflows, transactions as well as ICT and therefore should be considered for strategic decisions of firms. Descriptors assigned to this group primarily deal with AI-enabled applications in forecasting, SC planning, their impact on autonomous driving and how AI can manage Blockchains more efficiently. However, one descriptor also deals with AI to be illegally used to harm, damage, or destroy a computer network. The following discussion results in two variants for each of these descriptors:

- Use AI in forecasting: Commonly spread and fully integrated/isolated with individual data bases.
- Use of autonomous SC planning techniques: Commonly spread/not widespread.
- Use of autonomous driving: Fully implemented/partially implemented.
- Use of emerging technology blockchain: Globally organised /regionally organised.
- Use of AI to attack SC system architectures: Globally organised/regionally organised.

Forecast inaccuracy due to volatility and uncertainty is still considered as a continuous problem for most organisations (Christopher, 1998; Sjöqvist, 2019). Use AI in forecasting (09) is expected to enable planning tools to better cope with the uncertainty of the future, relying on data from the past and present and analysis of trends ("Business Dictonary," 2019b). With the occurrence of improved predictive analytics supported by AI technologies, the possibility to better analyse the underlying big data of the above-mentioned demand volatility reasons is assumed. However, the SC performance is expected to depend on the fact how many partners of one SC apply integrated forecasting methods and instruments. Therefore, the variants of use of AI in forecasting can be characterised as 'commonly spread and fully integrated' or isolated with individual data bases.

Planning in organisations is supposed to increase efficiency, reduce risks and utilises the available time and resources (Montana & Charnov, 2008). In general, the three planning horizons long-term, mid-term and short-term are to be distinguished. Autonomous SC planning (10) is seen as the process of conceptually anticipating and simulating the activities required to achieve a desired goal whereby the process of anticipating and simulating is executed by AI technologies. Autonomy is given, if the processing software is empowered to act independently of intervention by human beings (van Hove, 2019). Autonomous SC planning can be applied in four key planning cycles: plan SC, plan sourcing, plan making and plan delivering. Referring to Section 2.6.3, main planning subjects that matter are demand, supply, production, transport, resources, capacity, availability, and inventory (Bolstorff & Rosenbaum, 2003). It is supposed that autonomous SC planning needs permanent exchange and synchronisation of internal and external (near) real-time processed data of customer behaviour as well as the simulation of controlling of the entire SC networks in real-time for multi-stage processes (Nishi, Konishi, & Hasebe, 2005; Roßmann, 2018). However, the SC planning success is expected to depend on how many partners of one SC apply integrated planning methods and instruments. Therefore, the variants of use of autonomous SC planning techniques are characterised as ‘commonly spread’ or ‘not widespread’.

Autonomous driving (11) as defined with this descriptor refers to interorganisational shipments, mainly for public transports with typical transport modes such as road, air, rail, water. Thereby, transports with drones could be respected for scenarios wherever beneficial. A self-driving vehicle, also known as a robot car, autonomous car, or driverless car (Thrun, 2010), is a vehicle, that is capable of sensing its environment, extracting real-life driving scenarios from an extensive amount of data (Schmidhuber, 2015), and moving with little or no human input (Gehring & Stein, 1999). AI in the form of machine vision enables autonomous cars to combine a variety of sensors to perceive their surroundings, such as radar, lidar, sonar, GPS, odometry and inertial measurement units and supports in the form of e.g,, deep learning neural networks (Huval et al., 2015) advanced control systems to interpret these sensory information to identify appropriate navigation paths, as well as obstacles and relevant signage (Lassa, 2013). Autonomous means self-governing whereby autonomous control implies satisfactory performance under significant uncertainties in the environment and the ability to compensate for system failures without external intervention (Antsaklis, Passino, & S.J., 1991). Most of the vehicle concepts utilize a communication connection to the Cloud or other vehicles (S. P. Wood, Chang, Healy, & Wood, 2012). Amongst others, investigation object aims to get informed on how autonomous driving might impact structure and process elements of the SC. One key factor is how far autonomous driving might affect future SC is the future global implementation degree. Therefore, the variants of use of autonomous driving are determined as fully implemented or partially implemented.

By using several concept from cryptography, including digital signatures to hash functions, a Blockchain (12) is a method of storing a list of entries which cannot be changed easily after they are created (Narayanan, Bonneau, Felten, Miller, & Goldfeder, 2016). Given the same input, these methods must return the same output (hash value/message digest). Operating Blockchain data require a large amount of computer processing power. This is how AI comes into play to manage Blockchains more efficiently ("How will AI use Blockchain?," 2018; Jamison & Tariq, 2018). It is supposed that AI and Blockchain mutually impact each other (Montes & Goertzel, 2019). This descriptor aims to understand what role Blockchain might play in future scenarios of a SC network. AI improves Blockchain by finding the appropriate fit to verify e.g. Brute Force transactions and might make decentralized AI calculations more secure (Goertzel, 2007). However, the future scenario will depend on the variants of use of emerging technology Blockchain characterised as a 'global process driver for the whole SC' or 'only used as data memory'.

Cyberattacks (13) are the illegal attempt of hackers to harm, damage or destroy a computer network or system or the information on it, using the internet ("Cambridge Dictionary," 2019a; "Oxford Living Dictionaries," 2019). Less attention has historically been paid to the ways in which AI can be used maliciously, but also in this field, AI capabilities become more powerful and widespread (Brundage, 2018). According to Brundage (2018) and Milojicic and Shoop (2017), it is expected that major cyberattacks will involve AI systems to a certain extent, so that AI can become a significant threat used by attackers. The growing importance of autonomous systems with AI as the backbone (Beuth & Böhm, 2018; Johnson, 2017) underpins this expectation and makes SC architectures increasingly vulnerable to cyberattacks. Identity theft, denial-of-service attacks, password cracking or distributed attacks, which involve triggering a remote program on several computers or devices to overwhelm servers (Straub, 2017) are expected to get more powerful when AI-enabled. Additionally, AI systems can help gather, organise and process large databases to connect identifying information, making this type of spear phishing attack easier and faster to carry out. AI systems could even be used to pull information together from multiple sources to identify people who would be particularly vulnerable to attack (Straub, 2017). The cost of attacks may be lowered by the scalable use of AI systems to complete tasks that would ordinarily require human labour, intelligence and expertise. New attacks may arise through the use of AI systems to complete tasks that would be otherwise impractical for humans (Brundage, 2018). It is assumed that this descriptor represents a negative AI impact on the SC system. The resulting impact is expected to depend on the extent of geographical spreading of this kind of organised crime. Therefore, the variants of use of AI to attack SC system architecture are characterised as ‘regionally organised’ or ‘globally organised’.

5.3.4 Descriptors and Their Variants

The findings of Section 5.3 are summarised in

Table **5-12**. These CF constituting descriptor variants will serve as input for the CIB-analysis and the scenario development.

Table 5-12: Descriptors and Their Variants - Brief Description and Mainly Referred Literature

SE	#	Descriptor	Brief Definition	Variants	Mainly referred literature
I	01	SC responsiveness	Responsiveness of a SC expresses the capability to adequately react on unpredictable demand. Thereby, it claims to react in appropriate time with the requested service level.	Relatively high / relatively low	(Fisher, 1997); (Christopher, 1998)
I	02	SC efficiency	An efficient SC in the sense of this research is characterised by the fulfilment of the principle of minimum. The efficiency focus is on costs and profitability on operational level.	Relatively high / relatively low	(Fisher, 1997)
I	03	Transaction cost in the supply chain	Costs, which occur by usage of the market in the context of transactions of disposal rights.	Relatively increasing / relatively decreasing	(Seuring, 2002), (Grover & Malhotra, 2003); (Williamson, 2008)
II	04	Inter-organisational decision delegation	Allocation of leadership competence from a principal to an agent between organisations on different value adding stages of different SC partners.	More autonomy / less autonomy	(Jensen & Meckling, 1976)
II	05	Type of inter-organisational specialisation	Structuring of labour division and specialisation along the SC beyond company boundaries.	Process orientation / functional orientation	(Christopher, 2000); (Goepfert, 2006)
II	06	Type of coordination	Process of managing dependencies between activities so that actors achieve goals by using adequate resources.	Centralised by one focal company / Equally decentralised by SC partners	(D. J. Wood, Gray Barbara, 1991); (Frese et al., 2012)
II	07	Dimension of process design	Sequence of interdependent and linked procedures which consume one or more resources to convert inputs into outputs following either push or pull principles.	Postponement / Speculation	(Christopher, 2000); (Seuring, 2002)

II	08	Network material flow	Networks are a configuration of nodes and edges which determines the design of physical material flows.	Centralised network (hub-and-spoke) / decentralised network (grid system)	(Goepfert, 2006); (Kim et al., 2015)
III	09	Use AI in forecasting	Forecasting represents a planning tool to cope with uncertainty and volatility of the future. Primary target is forecast accuracy.	Commonly spread and fully integrated / isolated with individual data bases	(Christopher, 1998)
III	10	Use of autonomous SC planning techniques	Process of conceptually anticipating and simulating the activities required to achieve a desired goal. The process is executed by AI technologies	Commonly spread / not widespread	(Montana & Charnov, 2008); (Roßmann, 2018)
III	11	Use of autonomous driving	Self-governing driving under significant uncertainties in the environment refers to interorganisational shipments.	Fully implemented / partially implemented	(Thrun, 2010); (Huval et al., 2015),
III	12	Use of emerging technology blockchain	Method of storing and exchanging data between SC entities which cannot be changed easily using concepts from cryptography.	Global process driver for whole SC / only used as data memory	(Narayanan et al., 2016); (Montes & Goertzel, 2019),
III	13	Use of AI to attack SC system architectures	Cyberattacks are the illegal attempt of hackers to harm, damage or destroy a computer network or system or the information on it, using the internet.	Globally organised / regionally organised	(Straub, 2017); (Brundage, 2018)

5.4 Proposition of Conceptual Framework

5.4.1 Constituting a Network of Direct and Indirect Relations from SC Descriptors

As discussed in 3.3.1, the underlying assumption of the abductive approach that neither a rule nor a case can be observed, makes it necessary that the researcher develops hypotheses with the help of a mental act of cognitive endeavour supported by a strict methodological foundation (Section 3.3.2). Therefore, based on the findings of the qualitative interviews and of Delphi Study Poll 1, the relations between the elements of the CF are analysed.

This Delphi Study Poll confirms the relevance of AI in the future SC. The experts are of the opinion that AI will impact the interplay of descriptors in the SC. Furthermore, they expect a significant SC performance improvement through AI-enabled applications. However, the experts only refer to a direct correlation between AI and SC performance. They do not take the network of direct and indirect relationships into account for this assumption. Therefore, a network of SC system constituting descriptors is established and presented as CF for further analysis.

The mutually impacting relations (1) to (9) within the SC system, and its grouping elements SC performance indicators (Category I), process and structure elements (Category II), and contextual factor technology (Category III) as illustrated in Figure 3-4 in Section 3.5.2. are detailed in Figure 5-4 which zooms into the SC system and shows the assigned SC descriptors of each grouping element. Furthermore, both figures underpin that the descriptors within each grouping element also influences each other.

- It is assumed that AI will improve SC performance (Relation 1). However, as expounded in Section 2.2, the claim to continuously improve SC performance also affects increasing applications of AI, at least in the field of planning, forecasting and physical movements (Relation 2).
- It is expected that increasing applications of AI lead to adjustments of process and structure elements (Relation 5).
- It is argued that AI might lead to adjusted principal-agent relationships within the SC. The expected changes in decision-making allocation might lead to changes in the interorganisational labour division (Relation 9) and different allocation of activities. However, changes in interorganisational structure might in turn open doors to reinforced AI applications.

- The experts expect an increasing number of AI-enabled applications in future SC, so that the descriptors of this group are expected to mutually encourage each other (Relation 8). They see most impact by AI on the SC planning process with the result to improve forecast accuracy.
- Adaptations in descriptors constituting process and structure elements are assumed to impact SC performance descriptors (Relation 3). Same assumptions vice-versa, so that the claim to improve SC performance lets SC decision-makers establish changes in process and infrastructure elements. Adaptations of these descriptors are anticipated as mutually encouraging each other (Relation 9).
- Changes of SC responsiveness or SC efficiency are assumed to impact TC in the SC and again vice versa (Relation 7).
- It is anticipated that the adaptation of process and structure elements opens doors for additional AI-enabled applications (Relation 6). The experts who participated in the qualitative interviews propose to establish SC resilience, towards the impact of these factors so that the SC system itself might impact these macroeconomic factors. The experts, expect a positive impact on the SC system through the technological factor digitalisation and implicitly confirm that AI and Blockchain are useful to be explored according to their impact on other descriptors of the SC system.

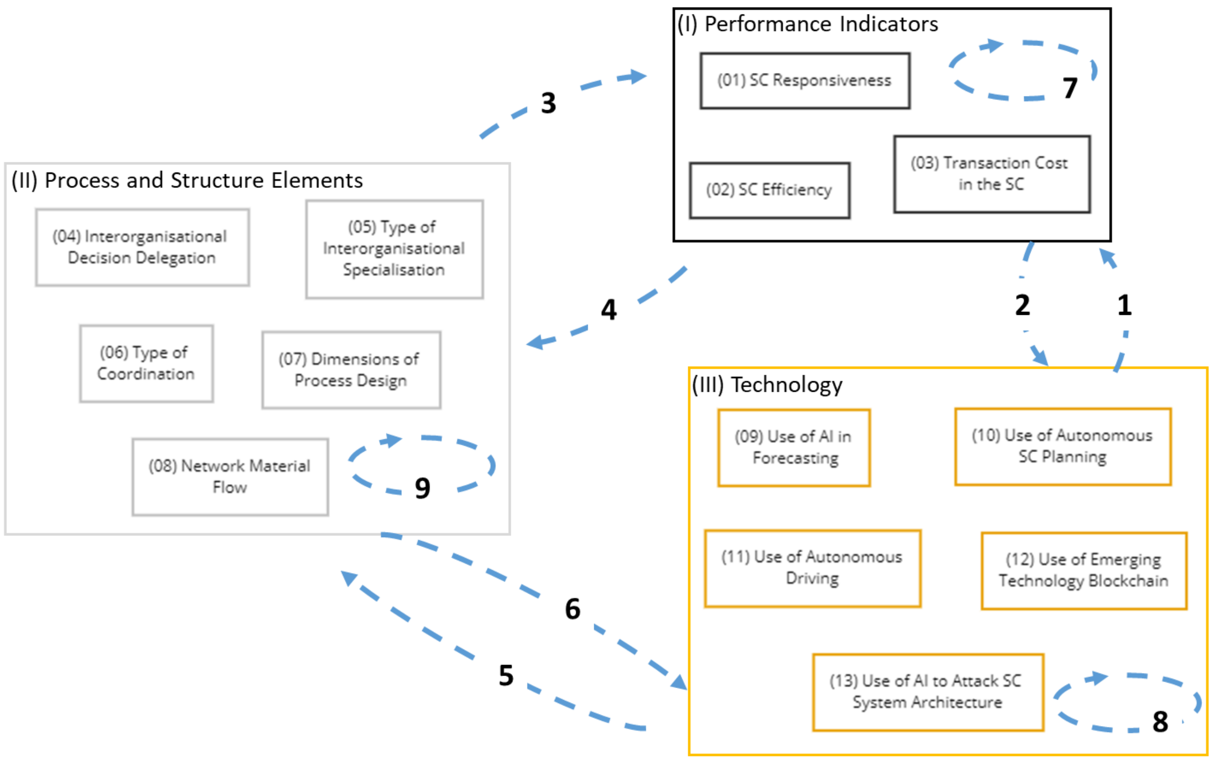


Figure 5-4: Zoom on SC System with Its Descriptors as Constituting Elements of the CF

However, it is expected that each descriptor adopts various statuses through the interplay with other descriptors of the SC system which can be either relatively positive or relatively negative. These statuses are represented in the CF through variants. These descriptor variants are illustrated in Figure 5-5.

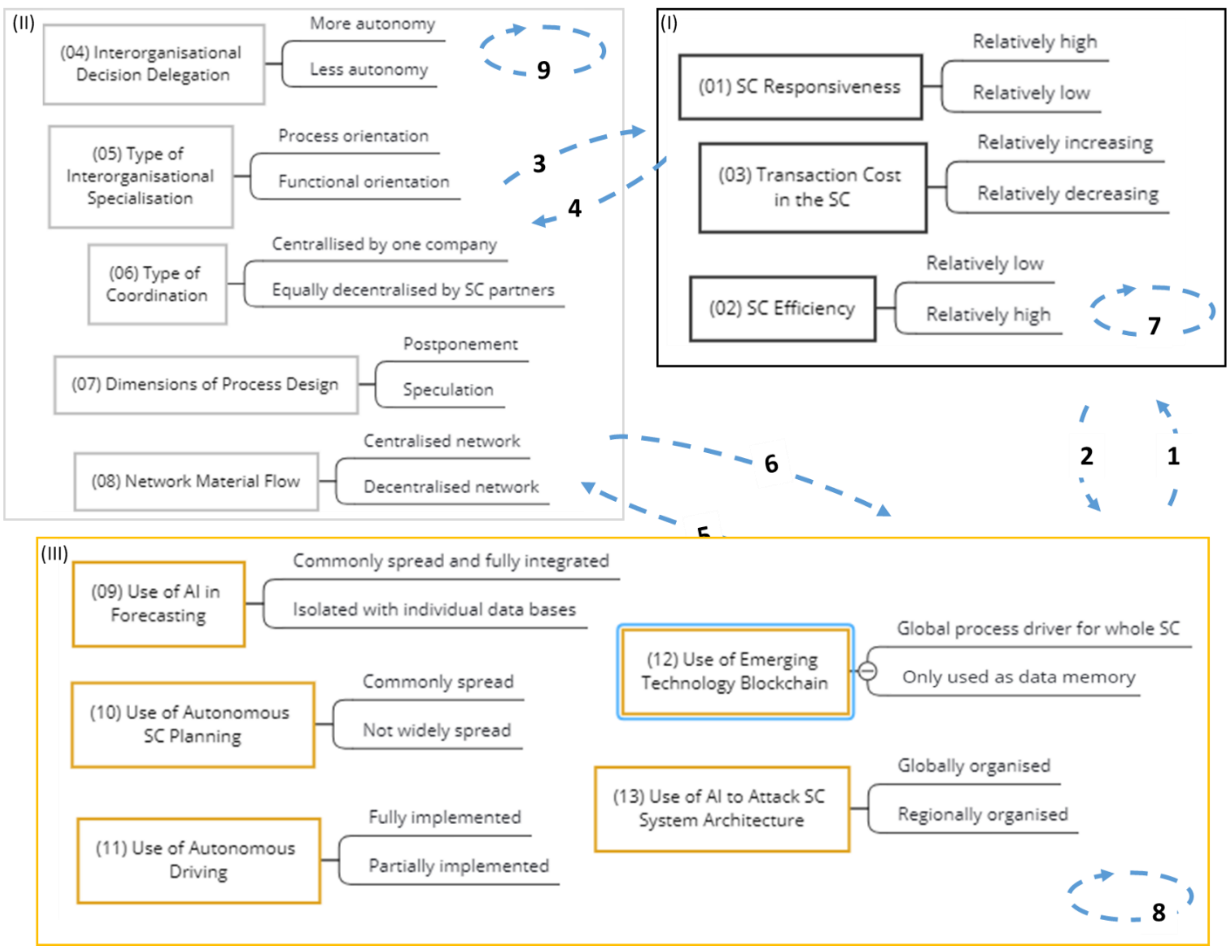


Figure 5-5: Descriptor Variants in the CF

5.4.2 Application of the Conceptual Framework

The variants determine the relationships between the descriptors in the CF. These identified relationships between the SC descriptors of the CF, serve as basis for data collection with Delphi Study Poll 2 and as scaffold for the CIB-analysis in Chapter 6 . Based on the CF, the CIB-analysis allows for developing future SC scenarios to explore phenomena related to VC through AI. It is the task of this scenario development to find out which constellation of the descriptor variants entail positive or negative impact on SC performance. As pointed out in Section 2.7.2, literature reveals that existing CF are not capable to provide an entire system of

SC components to explore these phenomena. Thus, this CF serves as skeleton for theory building in Chapter 7 .

5.5 Summary

In this Chapter 5 , the CF has been designed. The PPIM has been developed proposing AI application fields for further use for theory building. With the method of open coding, the SC descriptors have been determined. Descriptor variants have been defined and assigned. Relationships between SC descriptors have been identified that constitute the mutual impact in the CF.

Chapter 6 Evaluation and Findings of AI Application to the Future Supply Chain

6.1 Introduction

In this chapter, the CF is applied with the purpose to provide the foundation for developing a theory. In Section 6.2, the CIB-analysis provides a first high-level system-grid of descriptors' importance in the SC system and two scenarios are proposed for further evaluation. In Section 6.3, the findings from the qualitative interviews are evaluated with the target to link aspects of VC with the different performances of the two scenarios. In Section 6.4 and Section 6.5, the two scenarios are explored to detect findings for future SC.

6.2 Application of the Conceptual Framework for Cross-Impact Balance Analysis

The expert rating of the Delphi Study Poll 2 results in a basic system-grid outlined in Figure 6-1.

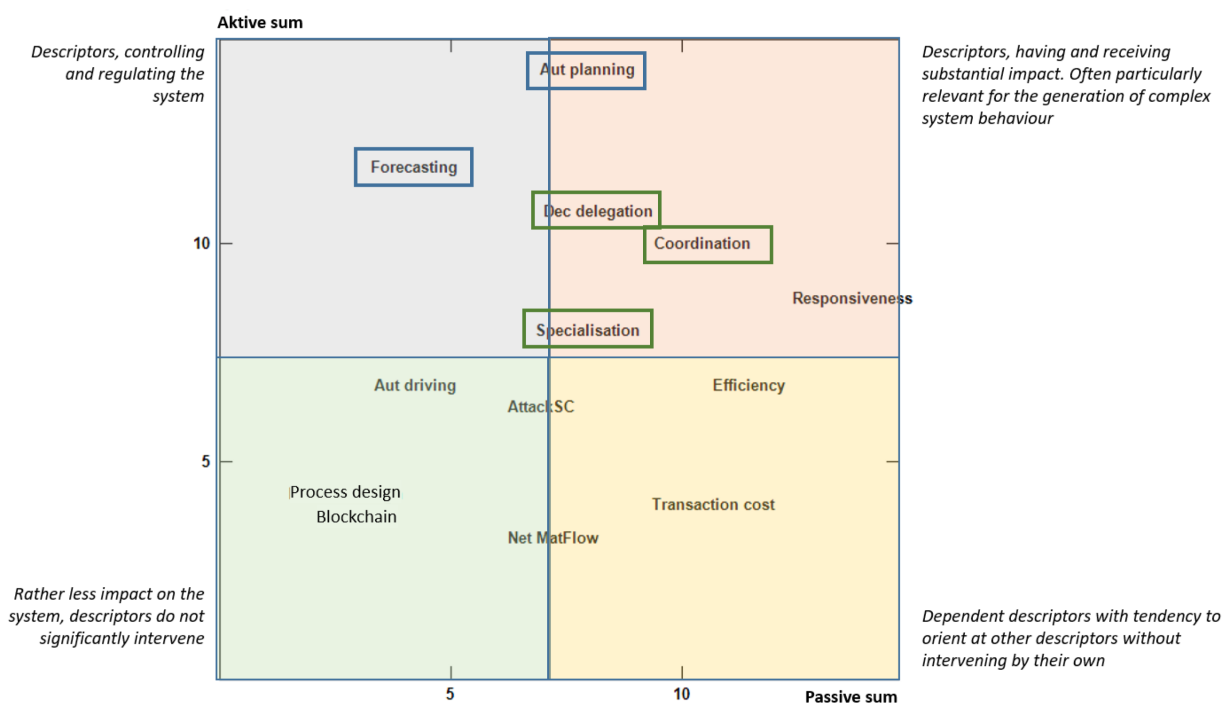
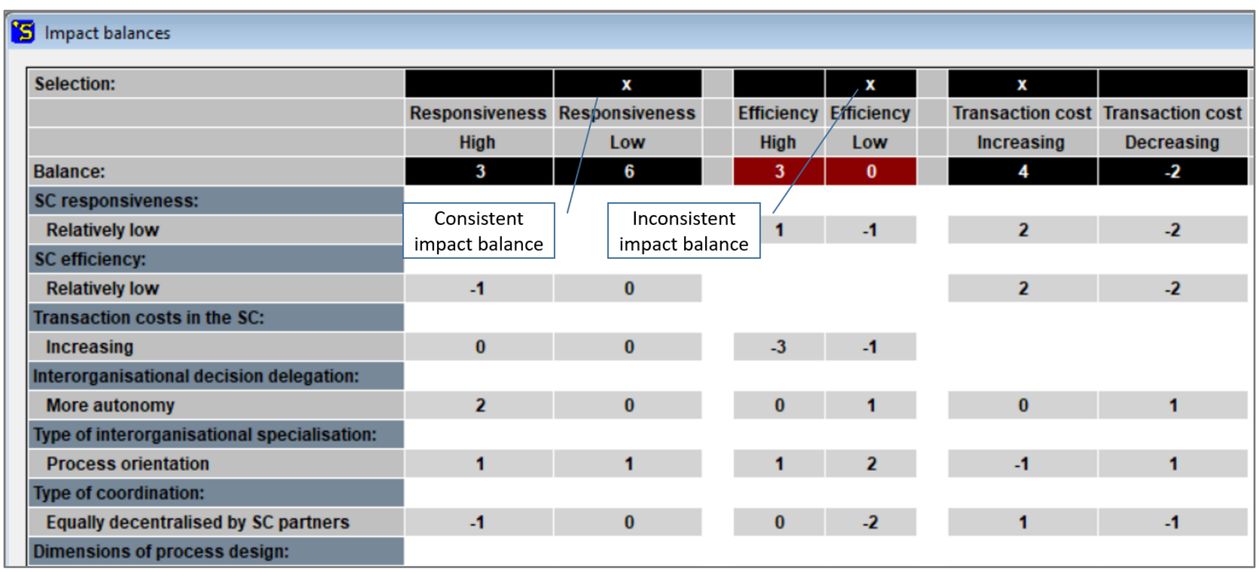


Figure 6-1:ScenarioWizard – System-Grid

The system grid is a tool to assess the role of the descriptors in the analysed system. The sum of all impacts exerted by a descriptor ("active sum") and the sum of all impacts exerted onto a descriptor ("passive sum") is calculated (Weimer-Jehle, 2018). The system-grid shows that five strong descriptors primarily determine the SC system: Forecasting, autonomous SC planning, type of coordination, interorganisational specialisation, and decision delegation. The following discussions are mainly focused on these descriptors. The impact of all other descriptors is respected whenever necessary. The expert rating of the Delphi Study Poll 2 results in four consistent scenarios. An impact balance of a scenario is consistent if the impact sum of the selected variant is not surpassed by the impact sum of another variant of the same descriptor (Weimer-Jehle, 2018). Additionally, consistency of a scenario is given, if a Nash equilibrium is achieved so that an exchange of the selected variant would not lead to a further increase in the impact sum (Weimer-Jehle, 2020). The ScenarioWizard form in Figure 6-2 illustrates a cross-impact matrix with consistent and inconsistent impact balance. In the row "Selection" the selected variant for each descriptor is marked by "x". The inconsistent impact balance is printed on red background in the row "Balance". This is the case for descriptor "SC efficiency" whereas the descriptor "SC responsiveness is consistent.



Selection:		x		x	x	
	Responsiveness	Responsiveness	Efficiency	Efficiency	Transaction cost	Transaction cost
	High	Low	High	Low	Increasing	Decreasing
Balance:	3	6	3	0	4	-2
SC responsiveness:						
Relatively low			1	-1	2	-2
SC efficiency:						
Relatively low	-1	0			2	-2
Transaction costs in the SC:						
Increasing	0	0	-3	-1		
Interorganisational decision delegation:						
More autonomy	2	0	0	1	0	1
Type of interorganisational specialisation:						
Process orientation	1	1	1	2	-1	1
Type of coordination:						
Equally decentralised by SC partners	-1	0	0	-2	1	-1
Dimensions of process design:						

Figure 6-2: Example of Consistent and Inconsistent Calculation of the Impact Balances of a Scenario

The chart from the ScenarioWizard as illustrated in Figure 6-3 outlines the four consistent scenarios with the identified variants per each descriptor. The chart illustrates how each descriptor variant as one row is assigned to each of the scenario No. 1 to No. 4 in the columns. The same descriptor variant can be assigned to one or more scenario columns. In case of more than one assignment, the fields are merged to one field (e.g., SC responsiveness: relatively high is merged across scenario No. 1 and scenario No. 2).

<table>
<tr><th>Scenario No. 1</th><th>Scenario No. 2</th><th>Scenario No. 3</th><th>Scenario No. 4</th></tr>
<tr><td colspan="2">SC responsiveness:
Relatively high</td><td colspan="2">SC responsiveness:
Relatively low</td></tr>
<tr><td>SC efficiency:
Relatively high</td><td colspan="3">SC efficiency:
Relatively low</td></tr>
<tr><td colspan="2">Transaction costs in the SC:
Decreasing</td><td colspan="2">Transaction costs in the SC:
Increasing</td></tr>
<tr><td colspan="4">Interorganisational decision delegation:
More autonomy</td></tr>
<tr><td colspan="4">Type of interorganisational specialisation:
Process orientation</td></tr>
<tr><td colspan="2">Type of coordination:
Equally decentralised by SC partners</td><td colspan="2">Type of coordination:
Centralised by one focal company</td></tr>
<tr><td colspan="4">Dimensions of process design:
Speculation</td></tr>
<tr><td colspan="2">Network material flow:
Decentralised network (Grid system)</td><td colspan="2">Network material flow:
Centralised network (Hub-and-spoke)</td></tr>
<tr><td colspan="4">Use AI in forecasting:
Commonly spread and fully integrated</td></tr>
<tr><td>Use of autonomous SC planning techniques:
Commonly spread</td><td colspan="3">Use of autonomous SC planning techniques:
Not widely spread</td></tr>
<tr><td colspan="2">Use of autonomous driving:
Fully implemented</td><td colspan="2">Use of autonomous driving:
Partially implemented</td></tr>
<tr><td colspan="3">Use of emerging technology blockchain:
Global process driver for the whole SC</td><td>Use of emerging technology blockchain:
Only used as data memory</td></tr>
<tr><td colspan="2">Use of AI to attack SC system architectures:
Regionally organised</td><td colspan="2">Use of AI to attack SC system architectures:
Globally organised</td></tr>
</table>

Figure 6-3: Consistent Scenarios with Selected Descriptor Variants (Tableau View of ScenarioWizard)

These four scenarios are grouped into two scenario families which express two trends: positive impact on SC performance indicators (scenario family SF1) and negative impact on SC performance indicators (scenario family SF2). The four scenarios are then assigned as different motives (M) to each family. Therefore, scenario family SF1 consists of two motives M1 and M2 as well as scenario family SF2. So, the four scenarios are renamed as outlined in Table 6-1. Additionally, each scenario is given a descriptive name to make the scenarios more tangible.

Table 6-1: Initial Scenario, Scenario Family Names a Descriptive Naming

Initial Name	Scenario Family and Motive Name	Descriptive Naming
Scenario 1	SF1M1	High SC performance with consistent autonomy
Scenario 2	SF1M2	High SC responsiveness with decentralised elements
Scenario 3	SF2M1	Low SC performance but open for new technologies
Scenario 4	SF2M2	Low SC performance with hesitating application of new technologies

It is deliberately decided to explore the two poles of the range of possible scenarios. Performances classified as ‘middle’ are limited in their explanatory power. The total impact score and the consistency factor of each scenario is shown in Figure 6-4.

```
================================================================================
Scenario No. 1
Consistency value :  0
Total impact score:  72
--------------------------------------------------------------------------------
SC responsiveness                          : Relatively high
SC efficiency                              : Relatively high
Transaction costs in the SC                : Decreasing
Interorganisational decision delegation    : More autonomy
Type of interorganisational specialisation : Process orientation
Type of coordination                       : Equally decentralised by SC partners
Dimensions of process design               : Speculation
Network material flow                      : Decentralised network (Grid system)
Use AI in forecasting                      : Commonly spread and fully integrated
Use of autonomous SC planning techniques   : Commonly spread
Use of autonomous driving                  : Fully implemented
Use of emerging technology blockchain      : Global process driver for the whole SC
Use of AI to attack SC system architectures: Regionally organised
================================================================================

================================================================================
Scenario No. 2
Consistency value :  1
Total impact score:  49
--------------------------------------------------------------------------------
SC responsiveness                          : Relatively high
SC efficiency                              : Relatively low
Transaction costs in the SC                : Decreasing
Interorganisational decision delegation    : More autonomy
Type of interorganisational specialisation : Process orientation
Type of coordination                       : Equally decentralised by SC partners
Dimensions of process design               : Speculation
Network material flow                      : Decentralised network (Grid system)
Use AI in forecasting                      : Commonly spread and fully integrated
Use of autonomous SC planning techniques   : Not widely spread
Use of autonomous driving                  : Fully implemented
Use of emerging technology blockchain      : Global process driver for the whole SC
Use of AI to attack SC system architectures: Regionally organised
================================================================================
================================================================================
Scenario No. 3
Consistency value :  0
Total impact score:  61
--------------------------------------------------------------------------------
SC responsiveness                          : Relatively low
SC efficiency                              : Relatively low
Transaction costs in the SC                : Increasing
Interorganisational decision delegation    : More autonomy
Type of interorganisational specialisation : Process orientation
Type of coordination                       : Centralised by one focal company
Dimensions of process design               : Speculation
Network material flow                      : Centralised network (Hub-and-spoke)
Use AI in forecasting                      : Commonly spread and fully integrated
Use of autonomous SC planning techniques   : Not widely spread
Use of autonomous driving                  : Partially implemented
Use of emerging technology blockchain      : Global process driver for the whole SC
Use of AI to attack SC system architectures: Globally organised
================================================================================

================================================================================
Scenario No. 4
Consistency value :  0
Total impact score:  59
--------------------------------------------------------------------------------
SC responsiveness                          : Relatively low
SC efficiency                              : Relatively low
Transaction costs in the SC                : Increasing
Interorganisational decision delegation    : More autonomy
Type of interorganisational specialisation : Process orientation
Type of coordination                       : Centralised by one focal company
Dimensions of process design               : Speculation
Network material flow                      : Centralised network (Hub-and-spoke)
Use AI in forecasting                      : Commonly spread and fully integrated
Use of autonomous SC planning techniques   : Not widely spread
Use of autonomous driving                  : Partially implemented
Use of emerging technology blockchain      : Only used as data memory
Use of AI to attack SC system architectures: Globally organised
================================================================================
```

Figure 6-4: Overview Experts' Consistent Scenario 1, 2, 3, and 4

Furthermore, the results of some experimental arrangements are explained in more detail in Figure 6-5, Figure 6-6, Figure 6-7, Figure 6-8. The expert evaluation results in four consistent scenarios. However, some experimental arrangements have been conducted to ensure that these four consistent scenarios are the most appropriate. With the value 1 of "Max. inconsistency" 34 scenarios have been calculated. A trial with the "Max. inconsistency value" 9 let the ScenarioWizard to its limits. After several minutes the calculation was interrupted manually. No results calculated. Scenario calculation with setup "Weak consistency" resulted in 283 scenarios.

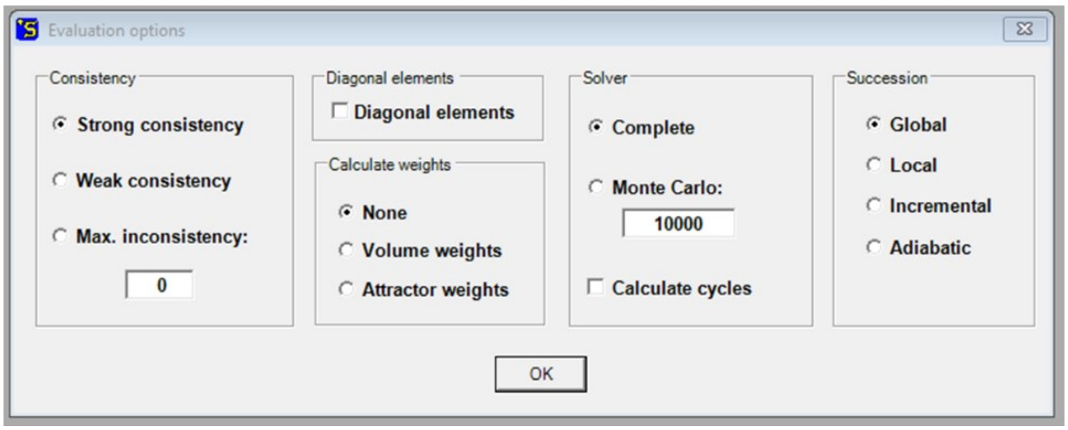


Figure 6-5: Initial option settings: experimental arrangement (ExA) 0

ExA 0 represents the option settings for the selected four scenarios.

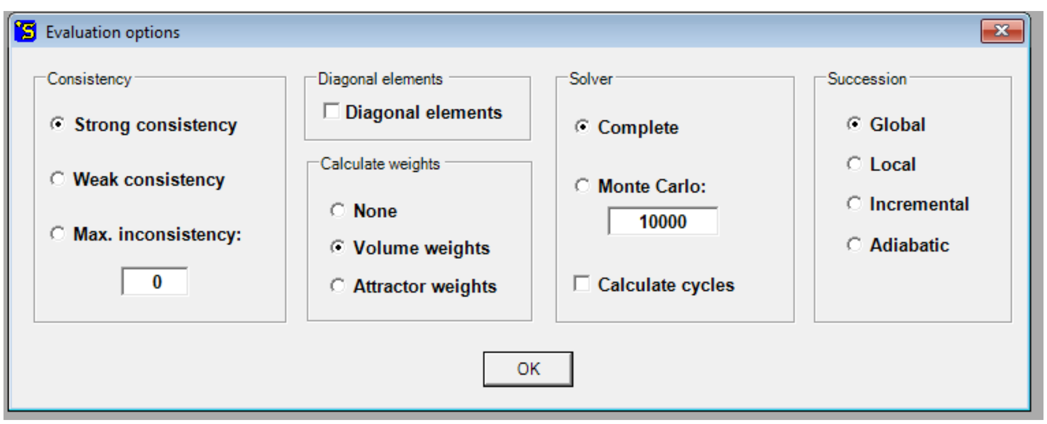


Figure 6-6: Option settings ExA 1

ExA 1 results in the same number of scenarios as ExA 0.

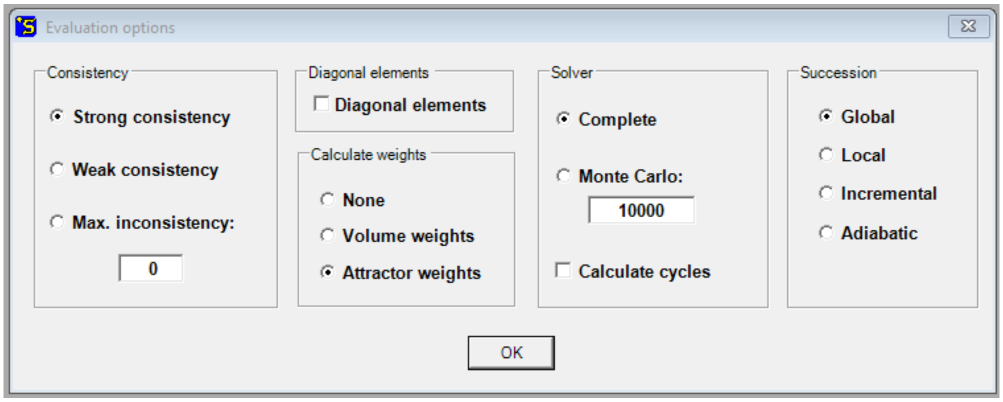


Figure 6-7: Option settings ExA 2

ExA 2 results in the same four scenarios. Initial scenario 2 has the highest score of weight: 3811. However, ExA 2 does not contribute additional value compared to ExA 1, still the same five scenarios are relevant.

ExA 3 with settings “Calculate cycles” considers cyclic solutions. Cyclic solutions are groups of several scenarios, which merge into each other through succession and therefore, build a closed cycle of inconsistent scenarios (Weimer-Jehle, 2018). It is not necessary to run “Monte Carlo” setting due to the calculation duration of setting “Complete”.

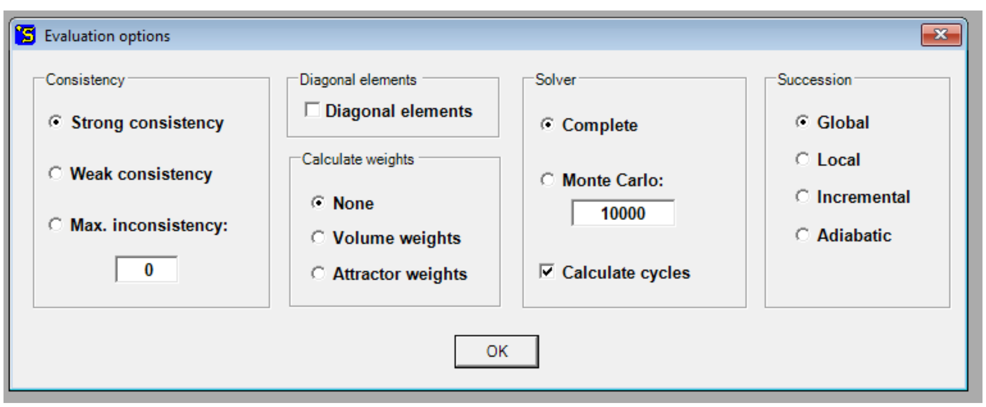


Figure 6-8: Option settings ExA 3

ExA 3 results in six scenarios. Four scenarios resulted in period 1, two in period 2. Consistent scenarios have period 1, for cyclic attractors, this value indicates the cyclic length, means the number of different scenarios, which are part of this cycle (Weimer-Jehle, 2018).

These experimental arrangements have been conducted with the purpose to meet concerns that other scenarios (even if inconsistent) might have a higher impact score and therefore might be of more relevance to be evaluated. The number of consistent scenarios is calculated using the Monte-Carlo method. The total impact score is defined as a measure of the possibility of a scenario and is the sum of the impact scores of all selected variants of a scenario (Weimer-Jehle, 2018). The total impact score indicates how stable scenarios are. 34 different scenarios have been identified using experimental arrangements. It has been found that none of these scenarios have the total impact score, which means that the further evaluation should be carried out to investigate the initial four scenarios.

Table 6-2: Scenario Comparison with Key Characteristics and Volume Weights of Each Scenario

Parameters ScenarioWizard	**SF1M1**	**SF1M2**	**SF2M1**	**SF2M2**
Total impact score	72	49	61	59
Consistency factor	0	1	0	0
Volume weight	2,351	1,781	1,661	2,368
Number of differing variants				
Iteration 1	Comparative basis	2	8	9
Iteration 2	9	7	1	Comparative basis
Iteration 3		6	Comparative basis	

The motives of each scenario family are compared to each other with the purpose to select one final scenario with a positive and one with a negative impact on SC performance. Common to all four motives are the descriptor variants ‘high autonomy’ in case of interorganisational decision delegation, ‘process orientation’ instead of ‘functional orientation’, ‘speculation’ instead of ‘postponement’ and ‘commonly and fully integrated use of AI in forecasting’. These descriptor variants compared with the respective alternative variants are strongly preferred by the experts so that they are assumed as very important and effective in each future scenario. However, these descriptor variants cannot be considered as differentiators for improved SC performance, but they rather represent the foundation for future SC system setup.

Scenario SF1M1 results in three positive SC performance indicator variants: relatively high SC responsiveness, efficiency, and decreased TC. Furthermore, this scenario is the most stable with the highest total impact score, especially when compared to the other positive scenario SF1M2 but also to both negative scenarios. One differentiator is recognised as ‘commonly spread use of autonomous SC planning techniques`. This descriptor variant contributes to relatively high SC efficiency, what is relatively low in all other scenarios. In all other attributes, Scenario SF1M2 is comparable to SF1M1. At first sight, it appears that autonomous SC planning is not of high importance for SC which are orientated to manage innovative products characterised by volatile and thus unpredictable demand as described by Fisher (1997). However, it is discussed in Section 7.7 that AI-enabled forecasting is supposed to change SC management for innovative products. SF1M1 contributes most and in general to the highest SC performance and is the only scenario which leads to relatively high efficiency. SF1M1 constitutes the strongest antithesis to both negative scenarios so that comparative analysis is most effective. Therefore, scenario SF1M1 is the selected positive scenario instead of scenario SF1M2.

Both scenarios SF2M1 and SF2M2 are coined by all three SC performance indicators with negative variants. The only attribute of SF2M1 which differentiates both scenarios is the use of Blockchain technology as global process driver for the whole SC. However, this attribute is also characteristic for both motives of scenario family SF1. Thus, it is more scientifically interesting to compare the impact of different applications of Blockchain technique on a future SC scenario. Therefore, the antithesis to the positive scenario SF1M1 is found in scenario SF2M2. A scenario with high SC performance and consistent autonomous setup is compared with a low performing scenario to which new technologies are hesitantly applied. Finally, the key selection criteria of both scenarios are compared in Table 6-3.

Table 6-3: Two Selected Scenarios Representing Positive and Negative Performance in the SC System

Attribute	SF1M1 (Positive Scenario)	SF2M2 (Negative Scenario)
SC performance	All three SC performance indicators are relatively high	All three SC performance indicators are low
Application of AI	Fully implemented and represented by high degree of process autonomy	Only partially implemented
Differentiator in process and structure setup	Decentralised coordination of SC partners and of material flow	Centralised coordination of SC partners and material flow
Framework conditions	Open for emerging technology and only regionally organised cyberattacks	Hesitant application of emerging technology but globally organised cyberattacks
Commonalities of all future SC scenarios	More decision autonomy, process design, commonly spread and fully integrated application of AI in forecasting, speculation	

The CIB-analysis applied to the CF leads to these two scenarios representing two potential future SC systems. The descriptors are clustered into scenario attributes as illustrated in Table 6-4. This classification facilitates the following discussion of the positive and negative impact on the future scenarios because it allows to consolidate the high number of event pair ratings from the CIB-analysis to the most significant statements. Furthermore, with the consolidation of all thirteen descriptors to these five attributes the SC system is represented with its basic relationships: AI application impacts SC performance within the given process and structure setup, the framework conditions, as well as the commonalities of all future SC scenarios. These attributes are coined either positively or negatively so that a root cause argumentation with applied theories is facilitated. Furthermore, the CF is intended to be applied to calculate SC use cases according to their VC in Chapter 8

Table 6-4: Descriptors Clustered to Attributes

Attribute	Descriptors
SC performance	• SC responsiveness • SC efficiency • TC in the SC
Application of AI	• Autonomous SC planning techniques • Autonomous driving
Differentiator in process and structure setup	• Types of coordination • Network material flow
Framework conditions	• Use of emerging technology Blockchain • Use of AI to attack SC system architecture
Commonalities of all future SC scenarios	• Interorganisational decision delegation • Type of interorganisational specialisation • Dimensions of process design • Use of AI in forecasting

The strength of the potential impact of descriptors on the entire SC system and therefore on the SC equilibrium depends on the ratio of powerful descriptor relationships in the system (Weimer-Jehle, Wassermann, & Kosow, 2011, p. 20). Weimer-Jehle et al. (2011, p. 20) consider the fact that about 50% of non-powerful descriptor relationships are not unusual for a system in general to represent a relatively loosely connected system. Non-powerful relationships are defined by experts' rating of 0 (no influence) referring to the Likert scale in Table 4-11. In this thesis, the ratio of powerful descriptor relationships is about 70% in the CIB-analysis. Hence, the descriptors of the SC system are relatively strongly connected to each other so that changes in the SC system which occur from changes in the environment impact the SC equilibrium significantly. This resulting quasi-equilibrium is positioned between chaos and new structure. With both scenarios, a new structure is expected. However, the new structure of the negative scenario is supposed to be less competitive because of its lower performance. Vice versa, the positive scenario is expected to create more value with its better performance and therefore achieves sustainable competitive advantage for the participating SC entities.

6.3 Disparity Between AI-enabled Performance and Value Creation in the Supply Chain

6.3.1 Supply Chain Performance and Value Creation in regard to Competitive Advantages

The scenario with positive impact on the SC claims for widely adopted and fully integrated use of AI in forecasting, as well as for commonly spread autonomous SC planning techniques. These descriptors embedded in an appropriate overall SC structure lead to relatively high SC performance. Vice versa, isolated, and not widespread application by single SC entities embedded in an overall SC structure only fosters SC performance in limited way. SC performance is expected to contribute to competitive advantages. However, with low contribution to competitive advantage the entire SC is in jeopardy to fail in the long run. This failure might happen due to commonly applied and widespread application of AI at competitors, provide comparable products or services with lower prices so that market shares of lower performing SC reduce or even completely disappear. This higher SC efficiency might lead to higher margins and higher cash flow which can be re-invested into products and services which are in line with the market. This competitor behaviour often leads to the same result that lower performing SC lose market shares. Thus, SC performance does not necessarily lead to appropriately added value in regard to competitive advantages.

6.3.2 Impact of Tangible and Intangible Value Drivers on SC Performance

Referring to interview results presented in Section 4.4, the experts propose that a SC effectively creates value only if it can be monetarised through a positive cash flow of income and expenses. This created tangible asset relies on tangible and intangible value drivers (Kalafut & Low, 2001; Wendee, 2011). Literature does not provide a clear distinction between value and value drivers. Thus, the applied distinction relies on experts' viewpoints in Section 4.4.2 to decide about the categorisation of value or value driver case-by-case appropriately to the needs of the respective research purpose. In this research, AI is considered as a value driver as well as all AI-enabled descriptors. The interviewed experts define a value driver as any variable that influences the value of a SC. This definition goes in line with prevailing definitions in literature (Pohlen & Coleman, 2005; Wendee, 2011). Resulting forecast accuracy from usage of AI in predictive analytics is therefore also seen as a value driver. This categorisation is underpinned by the proposal of one expert arguing that accurate forecast creates value in the form of cash flow, exemplarily delineated by reduced inventory accompanied by revenue growth through avoiding out-of-stock situations. Wendee (2011) distinguishes primary and secondary value drivers. Primary value drivers are directly traceable to VC for the firm either in the free cash flow or in the Weighted Average Cost of Capital (Wendee, 2011, p. 151). Secondary value drivers do not have direct relationship to tangible value (Wendee, 2011, p. 147). Thus, secondary value drivers represent intangibles. In business economics, the terminology knowledge capital, knowledge assets or intellectual capital are often applied (Duhr & Haller, 2013) to specify intangibles. Especially process capital as subcategory of intellectual capital derives value from the techniques, procedures, and programs that implement and enhance the delivery of goods and services (Edvinsson & Malone, 1997) and therefore appropriately serves for categorising the AI-enabled descriptors of the CF as intangibles. On the one hand, AI-enabled descriptors apply and produce knowledge. On the other hand, they indirectly impact tangible value through directly impacting SC performance. Low (2000) recognises an increasing importance of intangibles as driver of corporate performance so that intangibles play an important role in analysis and income estimates of institutional investors and other stakeholders. Shakina and Molodchik (2014) recognise intangibles as one of the most substantial origins of companies' excess returns and value growth. Thus, it seems likely that well-performing AI-enabled descriptors not only create relatively high SC performance but that this performance also results in tangible VC.

6.3.3 Non-financial Performance and Key Intangibles Influenceable by Artificial Intelligence

Low (2000) empirically identify nine most critical categories of non-financial performance that determine corporate VC. It has been demonstrated that more than 50 percent of company's value is based on these nine factors and that innovation has the greatest impact on market value. Intangible value drivers are assigned to these categories. Intangible resources provide most of a company's competitive advantages in today's knowledge-intensive industries (Shakina & Molodchik, 2014). An important intangible value driver in the SC is learning (Lamming, Kaplinsky, & Bessant, 2015; Willis, Genchev, & Chen, 2016). Other intangibles are quicker response to change, faster access to information, better information quality or reinforcement of organisational capabilities (Wodecki, 2019). Future SC will be coined by a large amount of data to gain information and SC learning. Elia et al. (2020) propose informational value, transactional value, transformational value, strategic value and infrastructural value as important value dimensions created by big data. For the reason that these proposed value drivers are not mutually exclusive, the author of this study consolidated the proposed intangibles to a list of intangibles which are relevant for this study as illustrated in Table 6-5. Key consolidation characteristic is whether the intangibles are influenceable by AI to support or even strengthen AI-enabled descriptors of the SC system.

Table 6-5: List of Key Intangibles Influenceable by AI

Key Intangibles influenceable by AI
Learning
Quicker response to change in the environment
Faster access to information
Better information quality

It seems surprising that only four key intangibles are accepted as directly related to AI although Wendee (2011) as well as Diefenbach (2006) identify and categorise a large number of intangibles for multiple purposes. The reason is that only these four intangibles are directly related to the value creating properties of AI and therefore, these key intangibles are causally responsible for the supposed VC through AI-enabled descriptors. Since AI allows for faster access to information with better information quality, forecast accuracy might be improved so that quicker response to market or organisational changes are possible. As typical for nonlinear systems, these intangibles influence each other to a certain degree. With faster access to information, a quicker response to environmental or SC inherent change is possible. Faster access to information and better information quality contributes to improved learning and earlier knowledge building. Improved learning allows for better decision-making and faster access to information leads to quicker response to change so that earlier adopter advantages lead to competitive advantages.

Table 6-6 shows the relation between non-financial performance categories and intangibles influenceable by AI. This juxtaposition is used in Section 6.4.4 and Section 6.5.7 to detect impact of AI on VC in negative and positive scenario and for testing the CF in Chapter 8 However, it must always be considered that the entire system in which AI acts and reacts moderates the gravity the AI impact. Table 6-6 lists categories of non-financial performance and their importance for this study. A relatively high importance is assigned if the descriptors of the SC system are supposed to have a major impact on the tangible value through these non-financial performance categories. Vice versa, relatively low importance is assigned if it is assumed that AI-enabled descriptors have minor impact through these categories on tangible value. It might be questioned why employee relations are weighted as of relatively low importance although AI will have a tremendous impact on future cooperation and collaboration between human experts and AI applications. This weighting is related to the further existing human relations as value driver for SC performance independently from their cooperation with AI applications.

Table 6-6: Categories of Non-Financial Performance and Their Key Secondary Value Drivers Influenceable by AI

Categories of non-financial performance	Key Intangibles influenceable by AI	Importance for this study
Innovation	Learning, quicker response to change of the environment, better information quality	Relatively high
Quality	Learning, better information quality	Relatively high
Customer relations	Learning; quicker response to change, accurate forecast	Relatively high
Management capabilities	Learning, faster access to information, quicker response to change, better information quality	Relatively high
Alliances	Learning through improved fitness due to common culture; quicker response to change; accurate forecast	Relatively high
Technology	Faster access to information, Better information quality	Relatively high
Brand value	No key intangibles influenceable by AI relevant for this category	Relatively low
Employee relations	No key intangibles influenceable by AI relevant for this category	Relatively low
Environmental and community issues	No key intangibles influenceable by AI relevant for this category	Relatively low

6.3.4 Supply Chain Performance and Consumer Value-in-Use

Grönroos and Voima (2012) argue that value should be recognised in the context of customer experiences. SC performance which meets the requirements of the customer such as appropriate delivery time or product and service quality as mentioned by the experts in Section 4.4, creates positive customer experience. Learning, faster access to information, and better information quality contributes to these performance indicators which gives another indication that AI-enabled SC performance creates value. Grönroos and Voima (2012) introduce value as value-in-use and inform that value cannot exist before it is created from the usage process, and therefore cannot be assessed before usage. This means that value is only materialised on consumer side in that point in time the consumer uses the product or service. However, this study refers to the definition of value as monetarised by NPV in regard to business case calculation and monetarised by net cash flow in regard to ex-post assessment of accounting figures. Against this background, and although intangible value is recognised as existing, the term 'value' is considered as tangible. This tangibility is expressed in the monetisation of intangibles through NPV or discounted cash flow (DCF). Therefore, consumer value-in-use has no significance for VC from the viewpoint of the SC. SC performance creates intangible value for the SC the moment in time, the service or product has been sold and tangible value, the moment in time, the product or service has been paid.

6.3.5 The Impact of AI Applications, AI-enabled Forecasting and Central Coordination on SC Responsiveness

The impact of event pairs between AI-enabled applications and central coordination through the focal company of the SC on the relatively low SC responsiveness are explored. Figure *6-9* informs about the impact sums between the relevant event pairs.

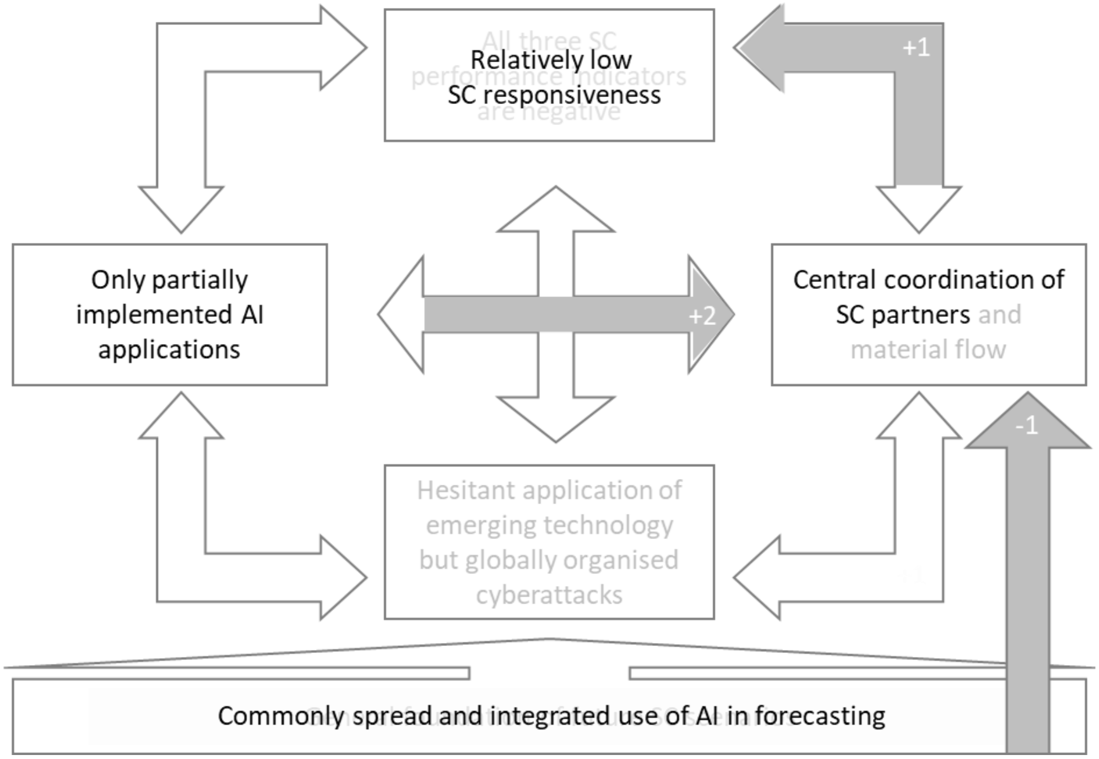


Figure 6-9: Impact of Partially Implemented AI Technologies and Central Coordination on SC Responsiveness

Experts believe that partially implemented autonomous SC planning moderately promotes (+2) central coordination of SC partners by the focal company. This centralised coordination promotes relatively low (+1) SC responsiveness whereas commonly spread and integrated use of AI in forecasting weakly restricts (-1) central coordination. Referring to the scaling interpretation of Table 4-12, the first two event pairs represent a well-established mechanism so that only relatively weak changes are expected. In the third event pair, the active descriptor ‘forecasting’ is not strong enough to initiate change impulse from central to decentral coordination as long as the overall SC performance is negative.

Central coordination refers to a focal company as decision-making unit in the SC which manages dependencies between interorganisational activities. In a typical SC structure, the focal company produces finished goods and organises the downstream flow to the customer either through distributors or directly at the last stage of the SC. Therefore, it is mainly the interest of the focal company to ensure that customer requirements are fully met. However, in a SC in which decentral decision-making units are not able to build up self-learning skills to tackle disruptive events to manage their part of the SC, the focal company keeps the coordination competency in its own hands. This is a matter of missing trust in the competency of the SC partners. Furthermore, the more complex the SC system structure is the more coordination is presumed by the focal company (Malone & Crowston, 1994). Coordination is necessary in different areas such as price coordination, capacity coordination, and coordination in case of disruptions. This coordination entails alignment effort and therefore longer reaction and adaptation time along the entire SC in all phases of the product life cycle. This human-dependant communication and semi-automated information exchange slows down the responsiveness of the SC. It is important to understand that it is a 'relatively' low responsiveness, relative to competitive SC as well as to customers' behaviour. The claim for highly flexible production due to highly individualised demand (mass customisation up to 'lot size one') and lead time as key service level stops former strategy of steady and high capacity utilisation with long-term forecasted process to operate economically (Henke, Besenfelder, Kaczmarek, & Fiolka, 2020). This outlook by Henke et al. (2020) goes in line with the experts rating that commonly spread and fully integrated use of AI in forecasting, strongly promotes (+3) low responsive SC. One expert underpins this assumption of Henke et al. (2020) by stating that "*the use of AI in forecasting is no prerequisite of being responsive*". This statement refers on the one hand to the strategy of postponement instead of speculation to enable responsive SC. On the other hand, this opinion underpins that the belief in AI according to improved forecast accuracy in fields of traditionally unpredictive demand is not sufficiently constituted.

The impact balance of the central coordination variant itself is explored on a more detailed level with the purpose to understand which event pairs do promote this variant.

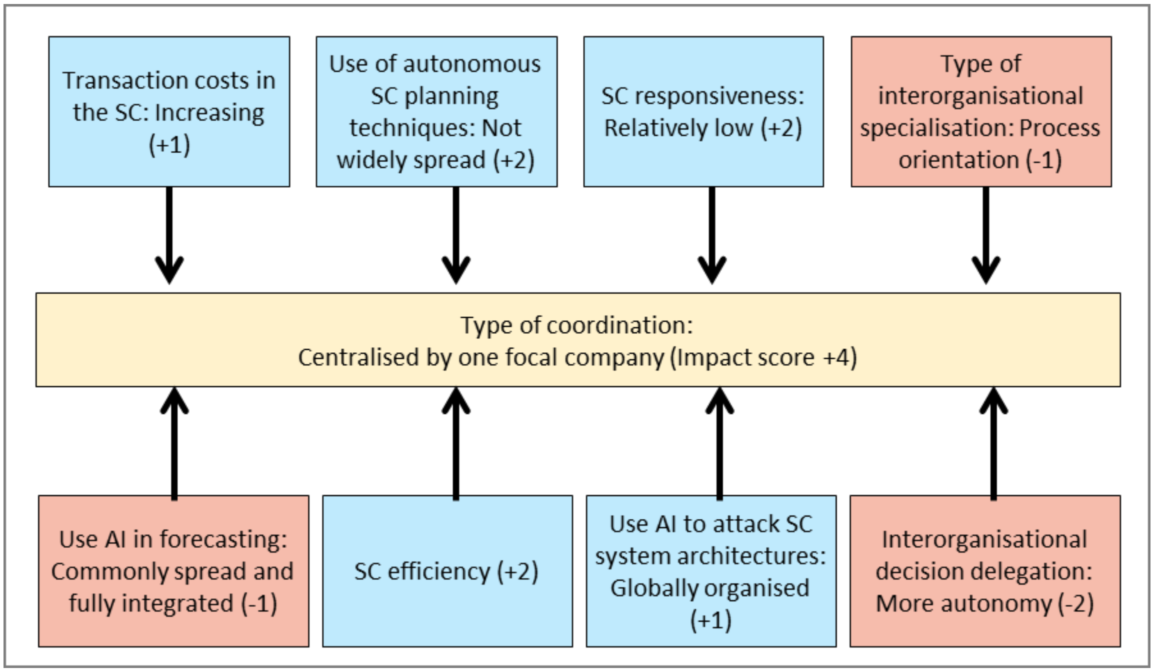


Figure 6-10: Impact Balance of Descriptor Variant 'Centralised Coordination by One Focal Company'

Figure 6-10 shows three findings according to central coordination by a focal company.

1. The moderately promoting impact of low responsiveness and low efficiency (+2) underpins the claim for a powerful entity which turns weak SC performance into strong SC performance.
2. Although use of AI in forecasting is widely adopted and fully integrated, it needs central coordination to organise interorganisational dependencies if use of autonomous SC planning techniques are not implemented along the entire SC.
3. Process orientation (-1) and more decision autonomy (-2) are not strong enough to turn central coordination into equally decentralised coordination if SC performance is rather weak and as long as the technical planning prerequisites are not fully given.

From the above three findings, it can be concluded that as long as the application of autonomous SC planning is not widespread across the SC, there is the need to centrally coordinate the SC by a focal company though this central coordination slows down the responsiveness of the SC. Commonly spread and fully integrated application of AI in forecasting only provides a competitive advantage, if combined with commonly adoption of autonomous SC planning techniques. Otherwise, SC responsiveness stays relatively low.

6.3.6 Value Creation through Supply Chain Performance with the Positive and Negative Scenario of the Conceptual Framework

A closer look on the disparity between VC and SC performance is provided with the analysis of the two scenarios selected for further exploration SF2M2 (Scenario with negative impact on SC) and SF1M1 (Scenario with positive impact on SC) from the CIB-analysis. SC performance is determined by the three descriptors SC efficiency, SC responsiveness, and transaction cost in the SC. For each scenario, the variants of each performance descriptor result in combinations for which a value can be defined or cannot be defined. Only if the combination allows an unambiguous statement either for positive or negative VC, a clear relationship between SC performance and VC can be expected. For all other combinations, only a case-by-case assessment with the aid of cost-benefit-analysis can bring full clarity.

Table 6-7 depicts that only for two performance indicator combinations an unambiguous statement of VC is possible: Either all performance indicators create positive value, or all performance indicators create negative value. For all other combinations, a prediction of total value created is not clearly possible. This uncertainty is marked with n/a in the column ‘Value created in total’.

Table 6-7: Performance Indicator Combinations of the Negative Scenario

Performance Indicators / Combination of value created negative scenario	Relatively low efficiency	Relatively low responsiveness	Increasing transaction cost	Value created in total
Combination 1 (SF2M2)	P	P	P	**P**
Combination 2 (SF2M2)	P	P	N	n/a
Combination 3 (SF2M2)	P	N	N	n/a
Combination 4 (SF2M2)	N	P	P	n/a
Combination 5 (SF2M2)	N	N	P	n/a
Combination 6 (SF2M2)	N	N	N	**N**
Combination 7 (SF2M2)	N	P	N	n/a

P: positive value, N: negative value

A comparable performance indicator combination for the scenario with positive impact on the SC is highlighted in Table 6-8. Due to the definition of efficiency as the relationship between earnings and expenses, it is suggested that relatively high efficiency always creates positive value. Thus, the combination with negative value for performance indicator efficiency are deleted so that three combinations remain among them. Combination 1 clearly creates positive value for the SC.

Table 6-8: Performance Indicator Combinations of the Positive Scenario

Performance Indicators / Combination of value created positive scenario	Relatively high efficiency	Relatively high responsiveness	Decreasing transaction cost	Value created in total
Combination 1 (SF1M1)	P	P	P	**P**
Combination 2 (SF1M1)	P	P	N	n/a
Combination 3 (SF1M1)	P	N	N	n/a

P: positive value, N: negative value

Table 6-9 shows that in max. 6 out of 35 competitive situations that the negative scenario might create better value than the positive scenario. However, SC which generate relatively high performance in the long run will create more NPV to reinvest into innovative products and services than a SC with positive but relatively low performance of the negative scenario. The reason is that the lower return of capital entails permanent shortage management compared to relatively high funds for investment from the positive scenario. This proposition will be tested in

Chapter 8 with the aid of companies' annual reports and literature-based figures related to AI as value driver.

Table 6-9: Comparison of Competitive Situations Between Positive and Negative Scenario

Combination positive scenario	**Relationship**	**Combination negative scenario**						
Combination 1	>	**C1**	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**
Combination 2	>		**C2**	**C3**	**C4**	**C5**	**C6**	**C7**
Combination 3	>			**C3**			**C6**	
Combination 2	< = >	**C1**						
Combination 3	< = >	**C1**		**C3**	**C4**	**C5**		**C7**

The potentially created value strongly depends on the setup of the SC system. This setup is represented by the characteristics of the SC attributes. Changes in the complex network of the descriptor variants impact the SC equilibrium. The first set of assumptions on the potential of VC of both scenarios are summarised in Table 6-10 and Table 6-11.

Table 6-10: Assumptions on VC in the Negative Scenario

Attribute	**SF2M2 (Negative Scenario)**	**Assumptions on VC**
SC performance	All three SC performance indicators are relatively low	Continuously increasing TC reduce the already relatively low DCF. Reinvestments in innovative products and services from the operating profit are limited.
Application of AI	Only partially implemented	The complete benefits of AI applications are not achieved. Economies of scale and economies of scope are lower than for AI applications widely adopted by all SC entities. Learning in the SC is limited due to limited access to information. Due to limited sharing of Data, information quality is relatively low. For that reason, lower number of innovations are expected, and management capabilities are only limited improved. NPV of investments in AI applications is relatively low.
Differentiator in process and structure setup	Centralised coordination of SC partners and material flow	Relatively high process costs due to management levels coordinating experts and teams. Relatively high freight and handling costs due to hub-and-spoke material flows reduce DCF.
Framework conditions	Hesitant application of emerging technology but globally organised cyberattacks	Relatively high administration costs to hedge information and finance flows reduce DCF.
Commonalities of all future SC scenarios	More decision autonomy, process design, speculation	The benefits of these descriptors do not develop their full power. The impact on positive cash flow is limited.

Table 6-11: Assumptions on VC in the Positive Scenario

Attribute	SF1M1 (Positive Scenario)	Assumptions on VC
SC performance	All three SC performance indicators are high	Continuously decreasing TC improve the already relatively high DCF of the entire SC. Reinvestments in innovative products and services from the operating profit contribute to sustainable competitive advantages.
Application of AI	Fully implemented and entirely integrated	The complete benefits of AI applications are achieved. Economies of scale and economies of scope are relatively high. Permanent knowledge sharing across all SC entities improves learning and thus management capabilities. High information quality enables quick response to change what strengthens customer relations. NPV of investments in AI applications is relatively high.
Differentiator in process and structure setup	Decentralised coordination of SC partners and of material flow	Relatively low process costs due to high degree of self-organising experts and AI-enabled decision-making units. Relatively low freight and handling costs increase DCF.
Framework conditions	Open for emerging technology and only regionally organised cyberattacks	Relatively low administration costs to hedge information and finance flows increase DCF.
Commonalities of all future SC scenarios	More decision autonomy, process design, speculation	The benefits of these descriptors unfold their full strengths and reinforce the VC of AI applications and process and structure setup. The impact on positive cash flow is relatively high.

In Section 6.4 and Section 6.5, these two opposite future states are explored according to the reasons why these system constellations lead to different performances and what aspects should be valued according to VC in each scenario.

6.4 The Scenarios with Negative Impact on the SC

The network of attributes of scenario SF2M2 in Figure 6-11 shows aggregated mutual relationships of the SC system. The details on the experts' rating for each of the relevant event pairs can be reviewed with Appendix G. .

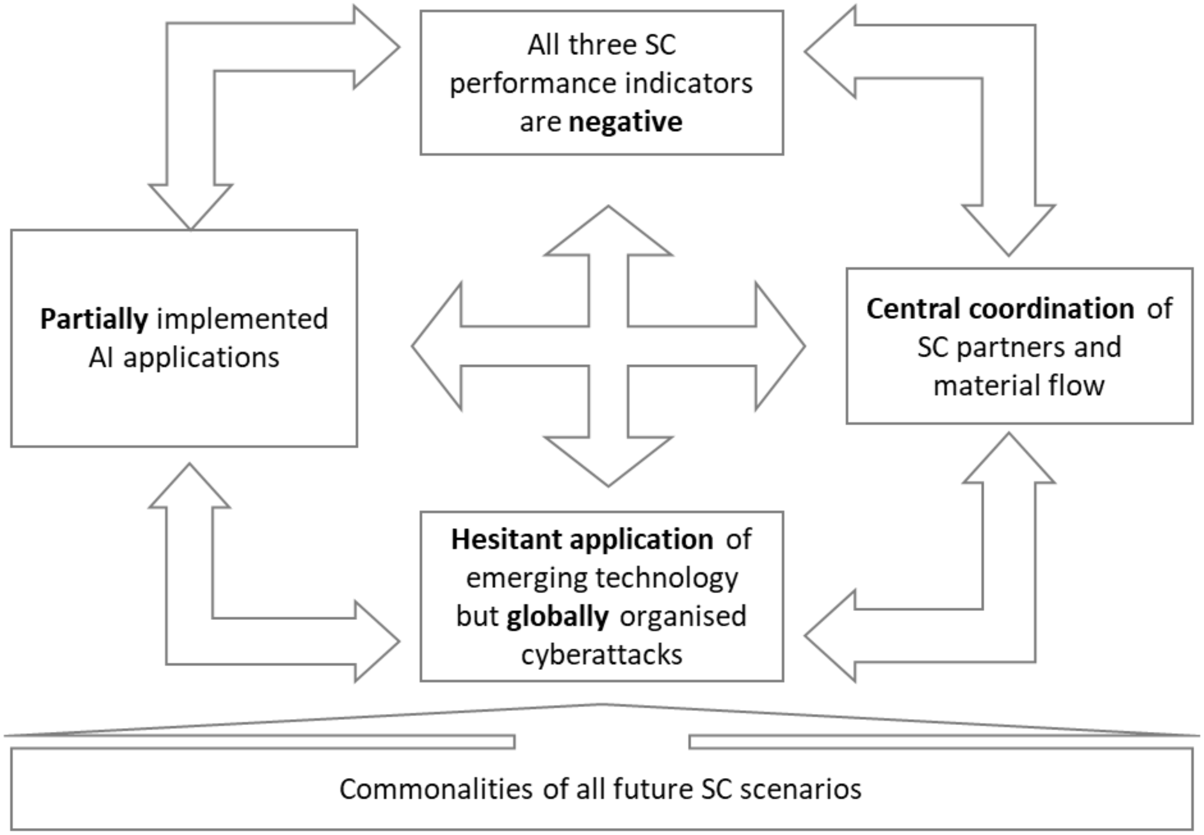


Figure 6-11: Network of Attributes of Negative Scenario SF2M2

This analysis mainly focusses on identifying direct and indirect interdependencies between the descriptors of the CF which are not obvious at first glance. One analysis objective in this section is to understand the inner, unobservable mechanisms of the negative scenario to establish an avoidance strategy of low SC performance.

The following five findings are obtained:

1. If autonomous SC planning is only partially implemented, the company which has the leading role in the respective SC (e.g., vehicle manufacturer in the automotive SC) prefers central coordination. However, this central coordination slows down SC responsiveness.
2. Relatively low SC responsiveness and SC efficiency fosters central coordination of a SC to achieve the turnaround to a more beneficial SC.

3. The reason why partially implemented AI applications have no impact on relatively low SC efficiency is that this low SC efficiency represents the current status of the SC compared with the improved efficiency of other SC with fully implemented AI applications.
4. Relatively low SC responsiveness and SC efficiency lead to increasing TC.
5. The negative scenario originates from multiple factors. Not only geographically global AI-based cyberattacks and Blockchain only used as data memory negatively impact the SC.

6.4.1 The Impact of AI Applications, Process and Structure Elements on SC Efficiency

The impact of event pairs on relatively low efficiency is explored. It is most striking that the experts do not believe in direct impact of AI-enabled applications on low efficiency (0) whereas centralised coordination by one focal company works as differentiator, which promotes relatively low SC efficiency (+2) as depicted in Figure *6-12*.

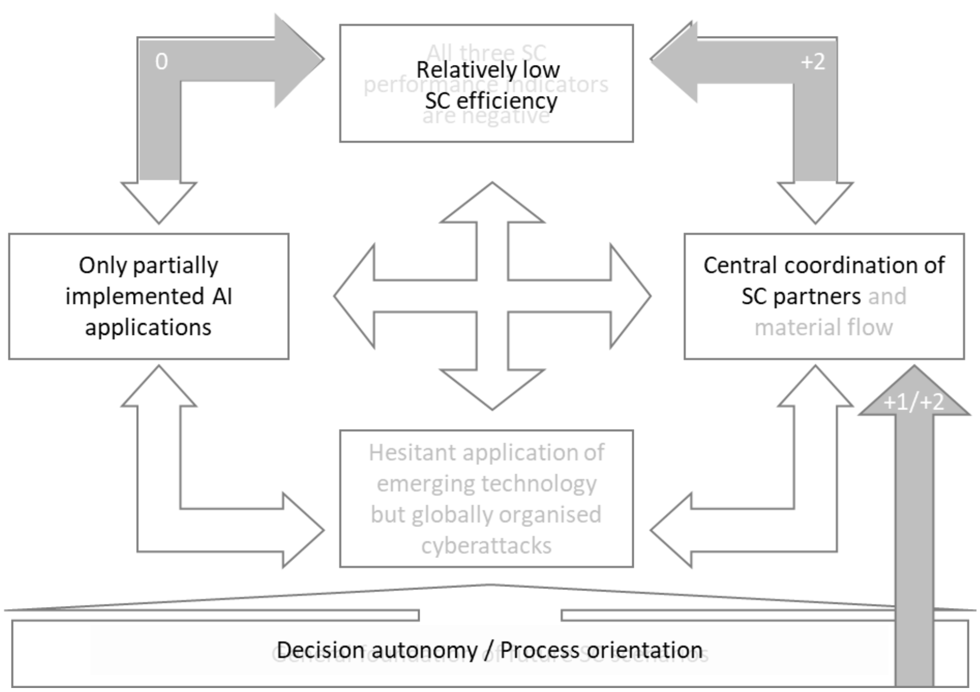


Figure 6-12: Impact of Direct Event Pairs on SC Efficiency

However, it is surprising that the experts rated central coordination as a promotor for low SC efficiency. By considering experts' qualitative statements it becomes obvious that there is an unexpected interpretation of this event pair. Experts argue that in case of relatively low SC efficiency a strong guidance and leadership have a positive impact on efficiency improvement. This effect is not expected from decentralised coordination by the experts. Thus, the experts rated the dynamics from one state to another but not the future static state of the event pair itself. Therefore, this event pair does not admit any conclusion on the initial question to explore why SC efficiency is relatively low. Referring to the interpretation of the scaling in Table 4-12, the experts believe indeed in a general promotion (+2) but they are uncertain if it is only weak or really strong impact on SC efficiency.

For interpretation of the neutral impact of event pairs of autonomous SC planning and autonomous driving, the author of this theses refers to experts' qualitative statements which only refer to positive impact to increase SC efficiency and to own reflections. Experts believe that the current state of SC efficiency will be the relatively lower future efficiency state compared to other SC which will apply AI.

Other direct event pairs assigned to framework conditions are only of minor importance in the SC system so that they are not responsible for the entire negative impact on the SC in this scenario. However, referring to experts' qualitative statements, decision autonomy has been identified as weakly promoting low efficiency. Some experts are of the opinion that design flexibility and decision autonomy are cost factors due to more coordination activities. In summary, the root causes for relatively low SC efficiency cannot be sufficiently analysed because of experts' unexpected interpretation of the descriptor correlations.

6.4.2 The Impact of AI-enabled Cyberattacks and AI-enabled Forecasting on Transaction Cost

It is obvious that the direct event pairs AI-enabled cyberattacks and Increasing TC as well as AI-enabled forecasting and Increasing TC are responsible for the negative impact in the SF2M2 scenario. As Figure 6-13 depicts, reinforcing descriptor variants are low SC responsiveness and low SC efficiency. Both leads to additional effort in organising and managing the SC through all phases of the product life cycle so that additional non-value-adding transactions and activities occur. However, referring to Table 4-12, the experts are uncertain whether the impact will be weak or strong so that they decided to rate for the general direction.

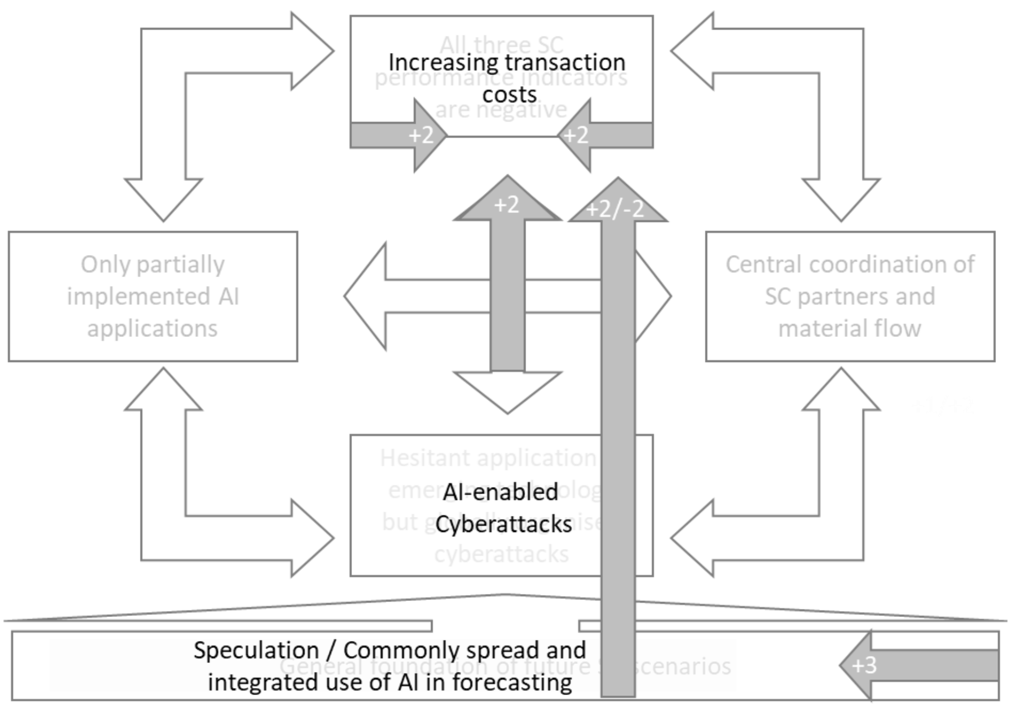


Figure 6-13: Impact of Direct Event Pairs on Increasing TC

It is also self-explaining that SC partners need additional countermeasures to defend against and repel AI-enabled cyberattacks. Of greater importance is the experts' direct rating of speculation and AI-enabled forecasting. Although the experts confirm that the commonly spread and fully integrated application of AI in forecasting restricts increasing TC, their direct rating for the speculation which is based on demand forecasting strongly promotes TC increment (+3). With this scaling, the experts on the one hand are fully convinced of the power of the active descriptor and on the other hand that the current mechanism of the event pair speculation/AI-enabled forecasting is not well-established so that significant impacts are expected in case of changes. Furthermore, the expert's explanation refers to decentralised inventories to mediate forecast inaccuracy which implicate high TC. However, AI-enabled forecasting strongly promotes descriptor variant speculation so that principally a positive impact on TC should be expected. This confusing aspect might be explained the way that the experts rated speculation independently from improved forecast accuracy due to AI applications. Therefore, both direct ratings are comprehensible.

6.4.3 The Impact of AI-enabled Cyberattacks and the Use of Blockchain Technology on Supply Chain Performance

The impact of AI-enabled cyberattacks and the use of Blockchain technology is explored. Blockchain is rated by the experts as rather less important for the SC system whereas cyberattacks are considered as having relatively more negative impact on the SC. In scenario SF2M2, both descriptors are represented with their variants which are worse for a SC system, Blockchain is only used as data memory and cyberattacks are globally organised. The experts confirm that relatively unsecured information and data flow combined with structured cyberattacks contribute significantly to negative impact on the SC. The question arises whether the negative impact primarily occurs due to these two descriptors so that all other explanations might be obsolete. For a better understanding how big these descriptors impact the scenario, the two variants are replaced by the opposite variants of both descriptors. Although this change leads to an inconsistent scenario, it is useful to temporarily explore the effect of specific changes in the SC system. The result is illustrated in Figure *6-14*. An improvement of SC performance can be observed. However, the relatively low responsibility and efficiency is not significantly improved.

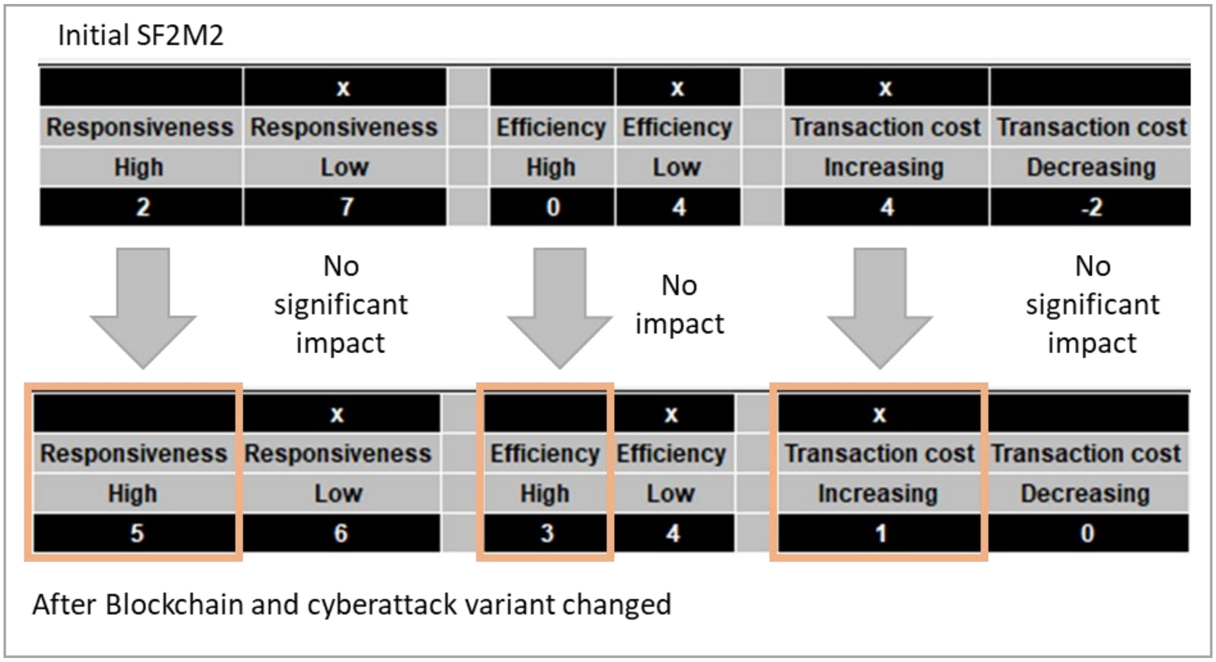


Figure 6-14: Blockchain and Cyberattack Variant Changed Results to Slightly Positive SC Performance in SF2M2

Figure 6-14 illustrates the changing impact balance sum of initial SF2M2 after having manually replaced the initial descriptor variant by the opposite variant of both descriptors. The impact balance sum of relatively high responsiveness and relatively high efficiency turns from 2 to 5 and from 0 to 3. The SC performance is still negative and changes only slightly from 7 to 6 (responsiveness), from 4 to 1 (TC) or with the same impact balance sum (efficiency). Only after changing coordination and material flow to decentral and autonomous planning over the whole SC. SC responsiveness and efficiency turn into positive impact balance sum. However, TC are still increasing. Only after changing all descriptors the scenario is completely positive and consistent. So, it can be concluded that the negative impact on the SC has more impact factors so that the previous analysis and the findings are verified.

6.4.4 The Scenario with Negative Impact and Its Value Creation

The negative scenario cannot develop the full power of AI because the key intangibles listed in Table 6-5 which are influenceable by AI are impeded. The reasons are the limited learning capability of the SC subsystems and the inefficient coordination of the SC due to isolated application of AI in SC planning and central cooperation structures. Better information quality and faster access to information do not lead to quicker response to environmental change because exchange of data is limited along the SC. This limitation is mainly caused by two descriptor variants: 'Not widespread use of autonomous SC planning techniques' and 'centralised coordination by one focal company'. Additionally, partially implemented autonomous driving limits SC efficiency and globally organised AI-enabled attacks on SC system architecture exerts strong negative impact on the SC system. The limited use of Blockchain technology opens the door for successful cyberattacks. Global cyber-physical attacks and limited use of Blockchain reinforce the inefficiency of the negative scenario and let TC increase. Although AI-enabled forecasting is commonly spread and fully integrated, this descriptor cannot develop its full penetration power. Therefore, SC performance is relatively low. SC performance is confirmed as a value driver. Thus, VC is supposed to be relatively low. The relatively low VC of these intangible value drivers affects the tangible VC of the SC constituted in financial performance such as decreasing sales, high COGS, or high fixed asset costs. As a consequence, operational performance cannot create sufficient cash flow to re-invest in long-term improvements. Table 6-12 shows how key intangibles influenceable by AI in the negative scenario hinders full development of VC for each non-financial performance category. In a nutshell, intangible value drivers such as new innovations, appropriate quality, or tight customer relationship are impeded. Sales potential, a tangible value, is not fully leveraged. Limited management capabilities due to incomplete knowledge building let the SC react slowly on environmental changes. Outdated IT, manual processes, or inappropriate organisational structures cumulated in category 'Technology' reduces SC efficiency and thus financial-performance figures such as COGS and total expenses or tangible value such as fixed assets or inventory. The combination of these limitations reduces cash flow and liquidity so that investments in necessary adjustment and renewals are limited. This limitation reduces VC through sustainable competitive advantages in the long-run.

Table 6-12: Categories of Non-Financial Performance and Key Intangibles Influenceable by AI Applied on the Performance of the Negative Scenario

Categories of non-financial performance	Key Intangibles influenceable by AI applied for the negative scenario
Innovation	Commonly spread and fully implemented use of AI in foresting detects environmental changes. Thus, the SC system would have the instruments to identify changes in the environment but the operational efficiency does not create sufficient value to re-invest into innovations.
Quality	Isolated application of AI in operational processes detects patterns for quality improvement but sharing of these findings across the SC is limited because of a missing SC-wide data platform.
Customer relations	Despite of process-orientation and better quality of information through AI applications, the SC does not sufficiently strengthen customer relations because this means among other things response to changes is slowed down due to isolated autonomous SC planning.
Management capabilities	The ability of SC entities to build management capabilities is given with faster access to information and to better information. AI-enabled forecasting improves managers' knowledge building in regard to environmental changes. However, the ability to quickly respond to these changes is limited through central coordination. Continuous knowledge sharing to improve managers operational capabilities is limited through isolated AI technologies for SC planning. Due to limited creation of cash flow, management is not able re-invest in business model improvements so that sustainable competitive advantages are limited.
Alliances	Reduced learning capabilities due to limited information exchange leads to restricted appropriate selection of SC partners. Limited strategic and/or tactical cooperation and collaboration within the SC reduces capabilities to react on environmental changes. Isolated autonomous SC planning limits new knowledge building and knowledge sharing. Thus, fitness of the SC partners through integration of all partners into common culture is reduced.
Technology	Slowed learning capabilities let SC executives fail to make appropriate decisions at an early stage or at the right time. Outdated IT, manual processes which could be automated with support of AI, or inappropriate organisational structures reduce information quality or early access to information. VC is limited.
Brand value	No key intangibles influenceable by AI relevant for this category
Employee relations	No key intangibles influenceable by AI relevant for this category
Environmental and community issues	No key intangibles influenceable by AI relevant for this category

6.5 The Scenario with Positive Impact on the SC

The network of attributes of scenario SF1M1 in Figure 6-15 shows aggregated mutual relationships of the SC system. The details on the experts' rating for each of the relevant event pairs can be reviewed with Appendix H. .

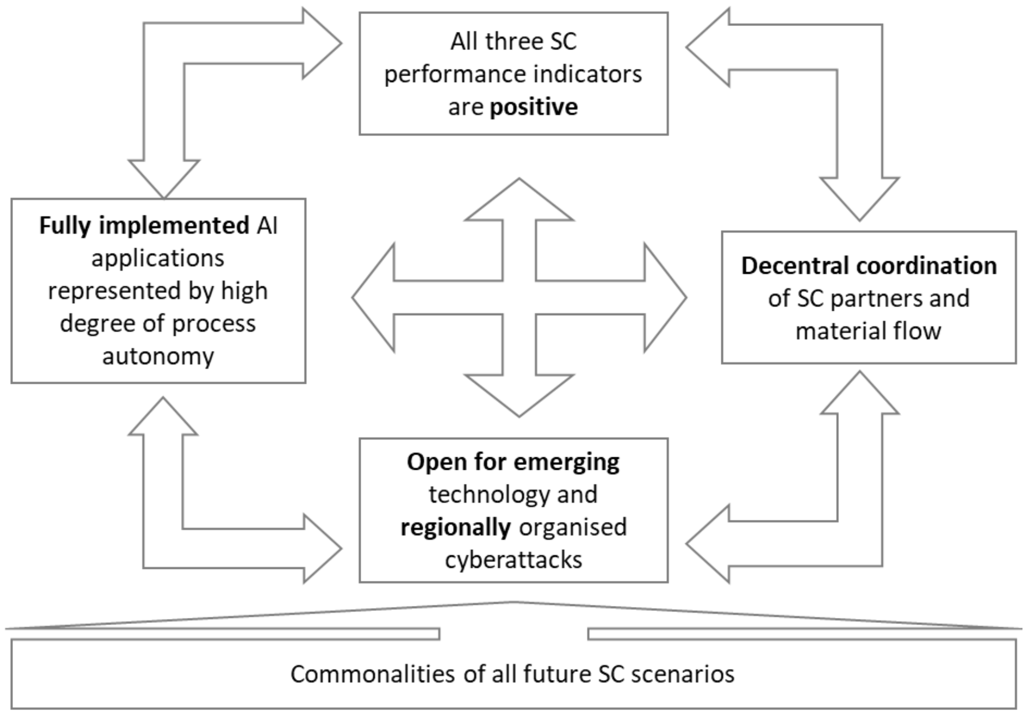


Figure 6-15: Network of Attributes of Positive Scenario SF1M1

This Section explores what factors contribute to which root causes to a positive SC scenario. It is measured with the SC performance indicators whether a scenario is positive. The experts rated certain descriptors as relatively important for the SC system having strong regulating and/or receiving substantial impact as illustrated in Appendix I. . Descriptors controlling and regulating a system have a relatively high active impact sum but a relatively low passive sum whereas descriptors having and receiving substantial impact have both relatively high active and relative high passive sum (Weimer-Jehle, 2018). The latter often generate complex system behaviour due to the mutual strong interconnectedness. Both types of descriptors exert a strong influence on the system and are usually connected with the potential emergence of complex system behaviour (Weimer-Jehle, 2018, p. 48). Therefore, event pairs with these descriptor variants are primarily explored. In the following are the 5 findings:

1. Only wide adoption of autonomous SC planning across all SC stages and SC partners positively impacts SC responsiveness and SC efficiency so that a competitive advantage can be achieved.
2. Isolated AI-enabled forecasting significantly limits the positive impact of widely adopted autonomous SC planning.
3. In autonomous, decentralised, and process-oriented settings, the future SC system achieves the best performance. Prerequisite is that all relevant process and structure elements in one SC are synchronised to each other and a commonly accepted technological standard for the entire SC is available.
4. Pure demand-driven SC have limited SC performance improvement potential. Only additionally applied and fully implemented AI-enabled forecasting brings the SC performance to its optimum. As a consequence, if the future SC is embedded in an autonomous setting, the future SC might achieve relatively high performance with descriptor variant ‘speculation’ as the preferred dimension of process design even in currently unpredictable demand environment.
5. In a SC system with positive SC performance, additional effort must be considered for applying technologies to fight AI-enabled cyberattacks.

6.5.1 The Impact of Autonomous SC Planning and AI-enabled Forecasting on SC Responsiveness

This investigation is to explore the root cause of positive impact of fully implemented AI-enabled autonomous planning and forecasting on SC responsiveness. As illustrated in Figure *6-16*, both descriptor variants promote SC responsiveness. However, referring to Table 4-12, the experts' scaling only provides the general direction and reveals uncertainty about the actual impact of widely adopted autonomous SC planning (+2).

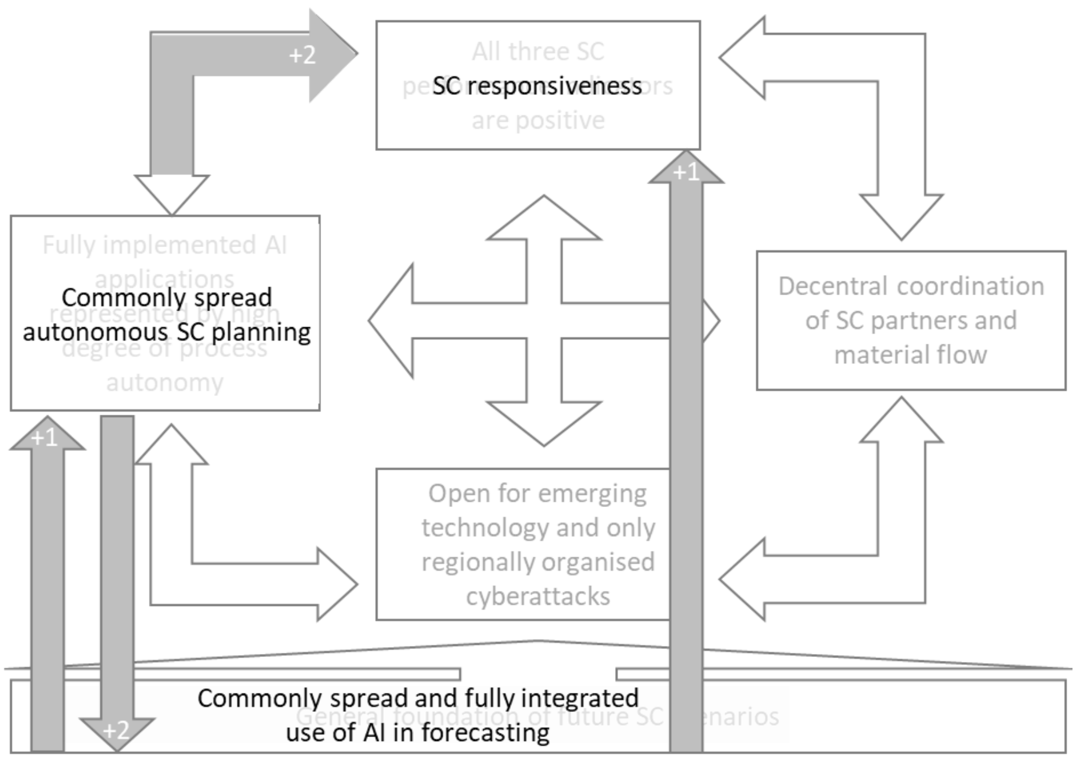


Figure 6-16: Impact of Fully Implemented AI-Enabled Autonomous Planning and Forecasting on SC Responsiveness

SC responsiveness aims to adequately react on unpredictable demand in appropriate time with the requested service level. Key competitive factor is delivery time, the time from order entry to receipt of goods at customer side considering appropriate SC costs (Christopher, 2005, p. 143 et seqq.). Christopher (2005, p. 119) provides two generic SC strategies to tackle unpredictable demand distinguishing short and long lead times across the entire SC: On the one hand, an agile SC which allows to produce make-to-order in case the lead times are shorter than the expected delivery time by the customer; on the other hand, a hybrid of lean and agile SC including a decoupling point to distinguish upstream from downstream flows (material, information, and finance flows). The downstream flows as well as the entire agile SC are predominantly demand-driven whereas the upstream material flow of the hybrid SC is primarily forecast-driven. AI-enabled autonomous SC planning is supposed to keep lead times as short as possible within the limitation of costs and therefore increase responsiveness of the SC. To meet these requirements, SC partners must be able to permanently share information respectively big data such as inventory, capacity, availability, prices, schedules of all interorganisational SC stages and combine them with external data. Experts of the Delphi Study argue that real-time transparency on data as input to AI-enabled simulation and anticipating of activities achieve the desired response target. However, only if all SC partners participate in this joint AI-enabled planning architecture, the SC will be appropriately synchronised, and all SC entities will be adequately agile. Therefore, only the variant positively impacts SC responsiveness to which autonomous SC planning is widespread. The common handling of demand changes is one argument for the positive contribution of this descriptor variant. Another key argument is the fast reaction on disturbances in the SC. In case of unexpected interruption of the SC, the root cause is similar. AI-enabled applications simulate future scenarios to meet the original delivery time and suggest or even launch measures and activities to reschedule production, delivery, or replenishment.

In contrast to this AI application field which aims to keep lead time as short as possible, AI-enabled forecasting primarily aims to reduce upstream SC costs and focuses on inventory reduction for parts and components. Thus, experts only rate a weak positive impact on responsiveness (+1). Demand-driven strategy in unpredictable environments is of high importance. The real orders (demand) are highly prioritised to be scheduled to utilise capacity. Forecast-based capacity utilisation is lower prioritised. This forecast-based capacity utilisation is supposed to be improved through higher forecast accuracy by better pattern recognition of customer behaviour based on big data and predictive analytics. However, this AI-capability is lower rated by the experts. More potential is found in improved replenishment forecasting for dependent requirements in the upstream chain. This improved forecast accuracy of parts and components is supposed to reduce inventory and therefore capital costs tied in inventory. However, each SC entity is responsible for its own spare parts and components availability and can only rely to a certain extent on forecasts from customers and their primary demand (Bullwhip effect). Therefore, the full potential of positive impact for the entire SC can only be achieved if all SC partners across all upstream SC stages apply AI-enabled forecasting. Therefore, only in case that AI-enabled forecasting is widely adopted and fully integrated, the full potential of AI will be leveraged, and the optimum of the desired target will be achieved.

Both descriptor variants mutually promote each other. Referring to the experts, autonomous SC planning moderately promotes integrated forecasting by providing the basic transparency on actual net demands over all steps of the SC. But this rating shows the experts' uncertainty of future impact of the active descriptor in this event pair. Vice versa, widely adopted and fully implemented application of AI in forecasting feeds autonomous SC planning with a lot of data to be used for simulating scenarios about necessary schedules either on each stage of the SC or seamlessly for the entire SC. Table 4-12 shows that if AI-enabled forecasting is not fully implemented at all interorganisational stages and autonomous SC planning is strongly restricted.

In other words, experts suppose that well-grounded and dispersed predictive analytics across the entire SC is crucial for simulating immediate capacity and schedule scenarios and anticipating of activities to achieve the desired responsiveness. Apparently, pure demand-driven strategy does not yield the SC to its optimum. Predictive analytics based on big data improves capacity utilisation. In contrast, experts are of the opinion that only partially implemented autonomous SC planning has no influence on AI-enabled forecasting. In other words, simulating scenarios and deriving necessary activities does not affect forecast accuracy in terms of detecting changes in customer behaviour or changing replenishment patterns. For that reason, it is crucial to fully implement AI-enabled forecasting so that autonomous SC planning optimises SC performance.

Table 6-13: Mutual Event Pair Rating of Autonomous SC Planning and AI-Based Forecasting

Descriptor Variants		Autonomous SC Planning	AI-enabled Forecasting
		Commonly spread	Commonly spread
Autonomous SC Planning	Not widespread		**0**
AI-enabled Forecasting	Isolated	**-3**	

6.5.2 The Impact of Decentral Coordination on Supply Chain Performance

This investigation is on coordination type. Scenario SF1M1 with positive impact on the SC prefers equally decentralised coordination by SC partners so that dependencies between interorganisational activities are in the responsibility of decentral decision-making units. Although equally decentralised coordination has only a minor direct impact on SC performance (see Table 4-12), it is even more surprising that this descriptor variant owns the highest cross-impact balance of all variants in scenario SF1M1.

Table 6-14: Impact of Decentralised Coordination on SC Performance

Descriptor Variants		SC responsiveness	SC efficiency	Transaction Costs in the SC
		Relatively high	Relatively high	Decreasing
Type of coordination	Decentralised by SC partners	1	0	1

Figure *6-17* underpins that all AI-enabled descriptors (strongly) promote this coordination variant showing experts' strict conviction of the impact of the active descriptor in this event pair. Furthermore, process orientation and decision autonomy also claim decentralised coordination. The question to be explored is why these descriptor variants need decentralised coordination.

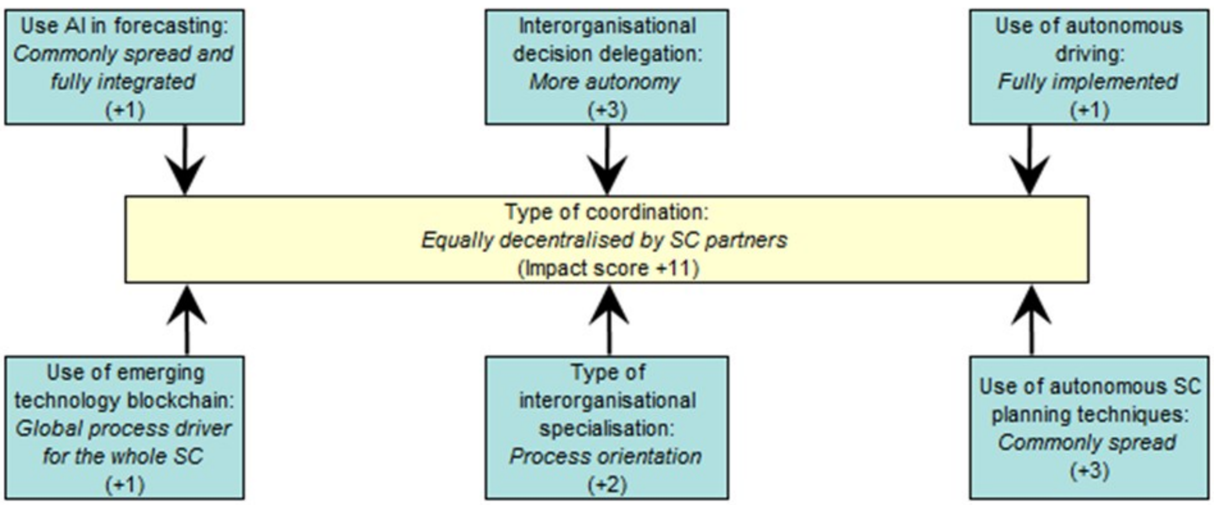


Figure 6-17: Impact Balance of Descriptor Variant "Equally Decentralised Coordination by SC Partners'

Experts state that decision autonomy is inseparably linked to decentral responsibility of decision-making units in each SC entity at each stage. And vice versa, also decentralised coordination promotes decision autonomy. However, SC entities of different firms such as a supplier for parts and components and a manufacturer as buyer need an adequate labour division which enables the units working together across firm or organisation boundaries. This labour division must allow these units to manage the dependencies of cross-organisation activities. For that reason, information flow and communication must be oriented along the material flow and not within functional organisation units so that the communication and coordination of entities and even the replacement of entities can be executed without changing the information flow structure. Therefore, process orientation is the proposed variant. Process orientation promotes decentralised coordination so that the communication and information flow can be established directly between these organisation units at the boundaries of each firm which accelerates decision-making processes.

Both AI-enabled system-substantial descriptors foster decentral SC coordination. As described in Section 2.6, the core of AI is self-learning capability. Referring to the experts' qualitative statements, a first common alignment of the technology of choice (integrated algorithms, interfaces, platforms etc.) is necessary across the SC so that the AI applications are compatible to each other and follow common targets. Having done these settings, especially autonomous SC planning, strongly promotes equally decentralised coordination whereas AI-enabled forecasting only weakly impacts it (+1). The experts suppose that the forecast figures should be aligned to each other so that the SC learns as an entire organisation to derive a clear vision and a common target in case of detected changes of customer behaviour to solve potential conflicting situations (Henke et al., 2020). In contrast, after having implemented the operational autonomous settings in all SC stages, the activities run by themselves so that a central coordination is not necessary. The overall interpretation of the experts' scaling of all event pairs of Figure 6-17 suggests that the experts have a strict conviction about the expected changes of the outlined event pairs. The experts suppose that the current mechanisms of event pair more autonomy/equally decentralised coordination are only low established so that the active descriptor 'interorganisational decision delegation' exerts strong impact on the passive descriptor type of coordination. The same interpretation as referring to Table 4-12 applies to event pair, commonly spread use of autonomous SC planning and decentralised coordination. For the two event pairs blockchain/type of coordination and autonomous driving/type of coordination, the experts rating is interpreted to mean that the two active descriptors are not strong enough, the exert sufficient change potential on the passive descriptor. This author's interpretation is underpinned by the role of both active descriptors. As illustrated in Appendix I. , both active descriptors have a relatively low active and passive impact sum and therefore, rather less impact on the system.

6.5.3 The Impact of Autonomous SC Planning and AI-enabled Forecasting on SC Efficiency

This investigation explores the positive impact of descriptors on SC efficiency. As illustrated in Figure *6-18*, widely adopted autonomous SC planning moderately promotes SC efficiency, leading to the assumption that the experts are only convinced from the rather general positive impact of the active descriptor whereas fully implemented AI-enabled forecasting only weakly promotes SC efficiency (+1). Prevailing theory is that efficiency as SC strategy focuses on cost-optimal flows and highest possible capacity utilisation with the prerequisite that the demand is highly predictable (Fisher, 1997) so that production, replenishment or distribution schedules for the entire SC are useful.

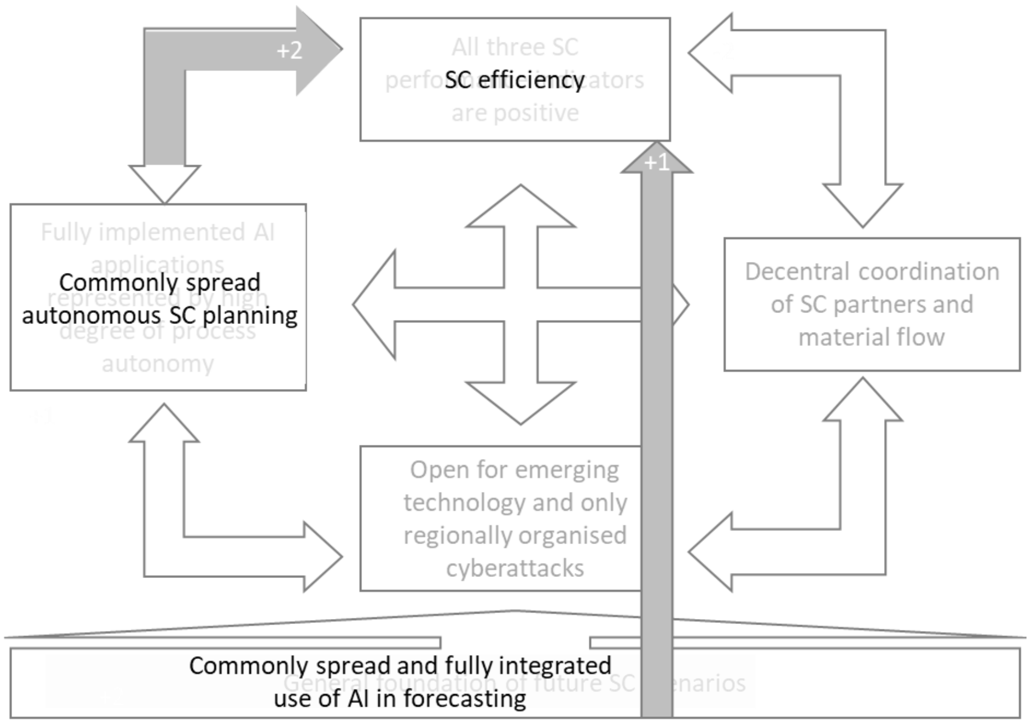


Figure 6-18: Impact of Fully Implemented AI-Enabled Autonomous Planning and Forecasting on SC Efficiency

The experts' rating for the event pair fully implemented AI-enabled forecasting/relatively high SC efficiency is highly distributed from weakly restricting to strongly promoting so that it is recognisable that the experts have very different opinions about the usefulness of forecasting. Furthermore, the qualitative experts' statements reveal a dividing into two groups of which one group (traditionalists) still thinks in experienced and acquainted mechanisms whereas the other group (visionaries) projects higher expectations onto AI-enabled forecasting. This distinction is also underpinned by referring to Table 6-15. The traditionalists agree with the assumption of Fisher (1997) that an efficient SC is not relying on forecasting for two reasons: (a) the goods are highly predictable so that forecasting in general is rather unnecessary and even AI-enabled forecasting cannot provide significant new findings; (b) forecasting in general is overrated and therefore, positive impact is of minor relevance. The group of visionaries tends to believe in the capability of future AI applications to significantly improve forecast accuracy compared to currently available and applied mainstream technology. The experts believe that the efficiency of a SC which manages unpredictable demand can be significantly improved with improved forecast accuracy.

Table 6-15: Distribution of Experts' Rating of Event Pair 'AI-Enabled Forecasting / Relatively High SC Efficiency'

Expert	Rating	Group	Average
08	-1	Traditionalists	0
33	0		
99	0		
101	0		
96	1		
68	2	Visionaries	2,4
75	2		
89	2		
98	2		
02	3		
109	3		
13	3		

According to the event pair autonomous SC planning/SC efficiency, the experts confirm the positive effect on SC efficiency through simulation and anticipation of activities but underpin with their qualitative statements that only the full implementation in all stages of the SC will provide the desired results.

6.5.4 The Impact of Autonomous SC Planning and AI-enabled Forecasting on Transaction Cost

This investigation refers to the positive impact of descriptors on TC in the SC. Experts refer to both ex-ante as well as ex-post TC. It is clearly stated by the experts that widely adopted autonomous SC planning across the entire SC decreases communication need, comprehension problems, misunderstandings or conflicts between units involved in a transaction. However, the experts suppose that techniques which are only applied by individual actors might lead to new integration challenges and costs due to other actors still applying traditional planning techniques. Hence, that application of new autonomous SC planning techniques could even increase the overall TC. For that reason, experts underpin that autonomous SC planning must be implemented as a standard across the entire SC. Then, it is supposed to help in case of highly integrated and transparent markets where supply and demand is constantly matched with need for quick offers on both sides. However, the moderate rating with +2 expresses experts' uncertainty on how the current mechanisms might be changing in the future.

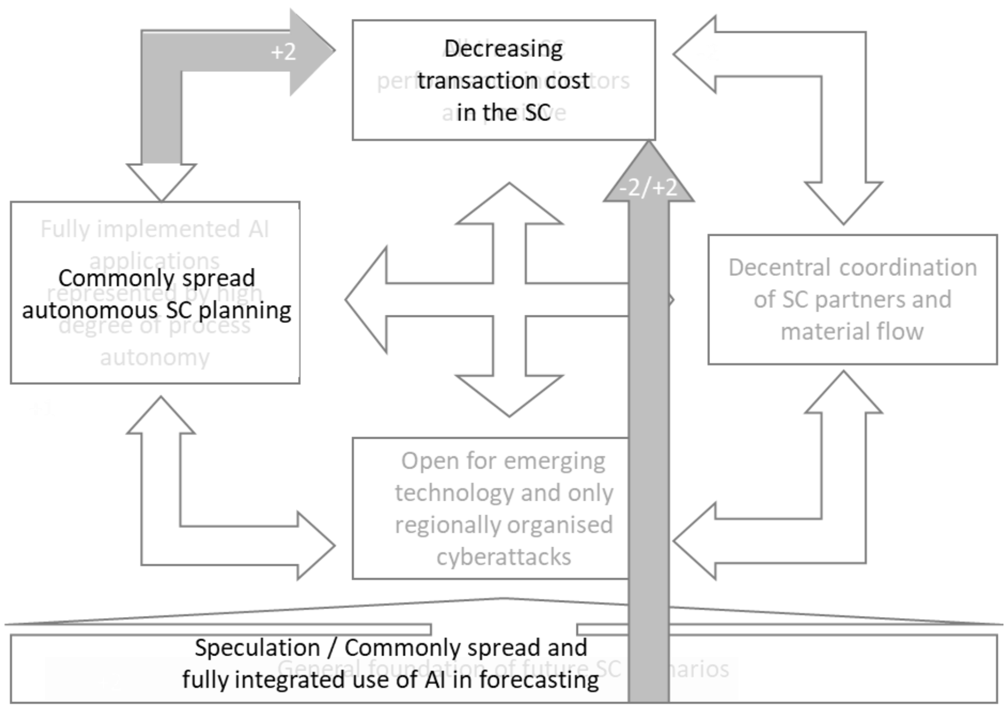


Figure 6-19: Impact of Fully Implemented AI-Enabled Autonomous Planning, Speculation, and Forecasting on TC in the SC

An experts' rating which is apparently contradictory is that speculation as the opposite descriptor variant to postponement is supposed to be restricting (-2) SC performance whereas AI-enabled forecasting is supposed to be promoting (+2) SC performance. With both ratings the experts express their uncertainty without strict commitment on the power of the active descriptor in these event pairs. Speculation is contrasted to postponement if SC is faced with unpredictable demand. However, the descriptor variant ‘speculation’ is strongly built on forecasting and therefore, the author of this thesis expects that both descriptors should go in the same direction. The resolution is given with the experts’ qualitative statements. On the one hand, descriptor variant speculation is supposed to entail relatively high decentralised inventories. The management of this multi-echelon inventory increases TC. On the other hand, the experts rate the descriptor variant speculation without AI-enabled forecasting technologies. This rating is academically comprehensible and logically correct because the improvement of prediction capability is given with the event pair speculation/fully implemented AI-enabled forecasting. As outlined in Table 6-16, widely adopted and fully integrated AI-enabled forecasting strongly promotes the descriptor variant speculation. Due to this indirect impact on decreasing TC, it is expected that TC will decrease in case that the decoupling point will be brought forward to the suppliers’ stages in the SC due to improved forecasting with AI. The experts’ strong belief in AI-enabled forecasting is confirmed by their rating according to the impact on descriptor variant ‘postponement’ which is also positive. This rating is comprehensible because a postponement strategy is demand-driven in the downstream flow and therefore, forecasting cannot serve as that strong lever for the entire SC. However, the author of this thesis supposes that AI-enabled forecasting will achieve such a high forecast accuracy that the hypothesis can be established that the implementation of descriptor variant ‘speculation’ with pulled-forward decoupling point to upstream SC decreases TC.

Table 6-16: Event Pairs Commonly Spread and Fully Integrated AI-Enabled Forecasting / Speculation and Postponement

Descriptor Variants		Dimension of Process Design	
		Speculation	Postponement
AI-enabled Forecasting	Commonly spread and fully integrated	3	1

The positive direct impact of fully implemented AI-enabled forecasting on decreasing TC is explained by the experts through potentially better decision and anticipation due to availability of more adequate information according to selection of suppliers, demand figures, and behaviour of customers so that operating SC runs smoother.

6.5.5 The Impact of AI-enabled Cyberattacks and Blockchain Technology on Supply Chain Performance

This investigation explores how strong the two descriptors Blockchain and cyberattacks impacts SC performance. Both descriptor variants of the positive scenario represent the preferred situation in a SC system. With globally applied Blockchains, data and information flow are most secured and regionally organised, AI-enabled cyberattacks are supposed to only have a limited and minor destruction factor than globally organised cyberattacks. First the cyberattack variant is changed to globally organised and therefore, more dangerous system attacks are implicated. Then the Blockchain variant is changed to 'used as data memory' only that the data security is supposed to be reduced. On the one hand, globally organised cyberattacks slightly impact SC efficiency to its disadvantage (impact balance sum turns from 4 to 3 as outlined in Figure 6-20). On the other hand, Blockchain only used as data memory turns SC efficiency to negative (impact balance sum turns from 4 to 2 referring to Figure 6-20). Both together turn SC efficiency into significant negative impact sum. Other SC performance indicators are not significantly affected.

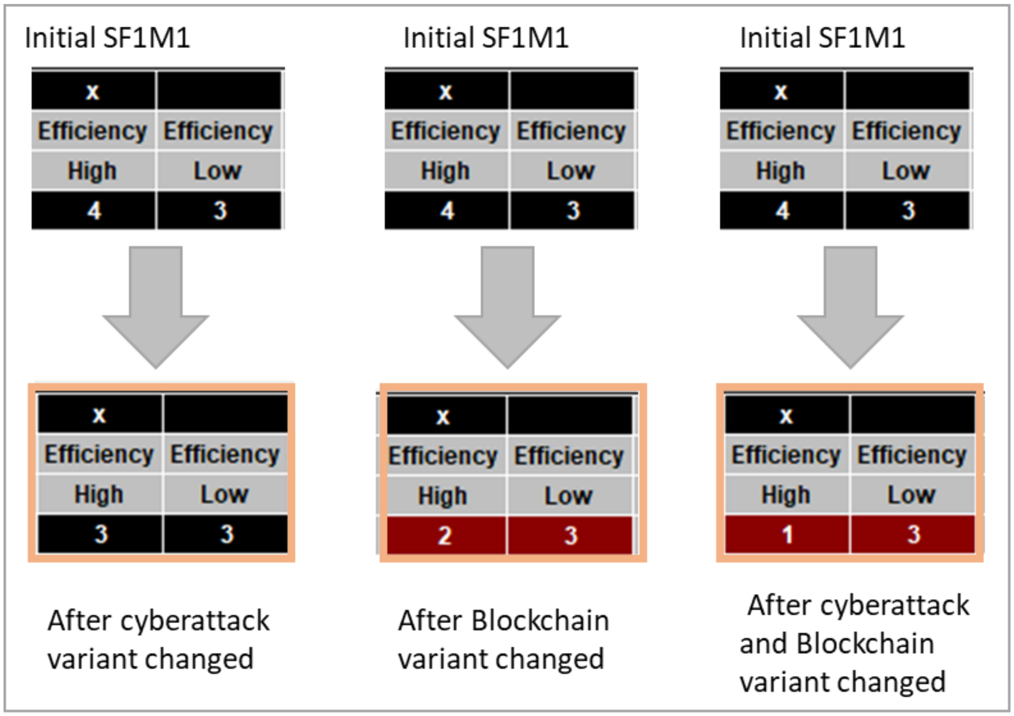


Figure 6-20: Blockchain and Cyberattack Variant Changed Results in Negative SC Efficiency in SF1M1

These changes are interpreted, that relatively unsecured data combined with globally organised and AI-enabled cyberattacks entail additional effort and cost to prepare and defend SC. Due to the fact that TC are not supposed to increase, the effort is assumed to be mainly put into technology. Furthermore, this result also shows that experts suppose Blockchain technology as a useful element to improve SC performance.

6.5.6 The Impact of AI-enabled Applications on SC Performance Indicators

Finally, a validation of the general impact of AI on SC performance in the positive scenario is conducted. For that reason, the AI-enabled descriptors ‘use of AI in forecasting (1)’, use of autonomous SC planning techniques (2)’, and ‘use of autonomous driving (3)’ are selected with the variant representing less AI application in the SC (see

Table **5-12**). All other descriptor variants contributing to a positive impact on the SC are not changed. The impact on the SC performance indicators is illustrated in Table 6-17.

Table 6-17: Impact of Changing AI-Enabled Descriptors on SC Performance Indicators of Positive Scenario

SC performance indicators	Initial Score	Score after change of (1)	Delta	Score after change of (2)	Delta	Score after change of (3)	Delta	Score after change of (1) + (2) + (3)	Delta
SC responsive-ness	**+11**	+9	**-2**	+9	**-2**	+10	**-1**	+6	**-5**
SC efficiency	**+4**	+3	**-1**	+2	**-2**	+3	**-1**	0	**-4**
Transaction Cost	**+6**	+4	**-2**	+4	**-2**	+6	**0**	+2	**-4**

Separately changing each AI-enabled descriptor leads to a slight reduction of SC performance. Changing all three descriptors at once leads to a significantly reduced but still positive SC performance. Therefore, it is concluded that (a) AI significantly impacts SC performance of the positive scenario and that (b) changes of process and structure elements contribute to a positive SC performance independently from AI-enabled applications. However, a closer look on each SC performance indicator reveals that SC responsiveness strongly contributes to overall SC performance by applying process orientation, decentral coordination, and high decision autonomy combined with a decentralised network. SC efficiency strongly depends on AI-enabled applications so that process and structure elements show no direct impact. Also, TC are significantly stronger impacted by AI than by changes of respective process and structure elements.

6.5.7 The Scenario with Positive Impact and Its Value Creation

The positive scenario develops the full power of AI because the key intangibles in Table 6-5 which are influenceable by AI are fully leveraged. Common and widespread SC planning techniques and decentral coordination enables prompt learning through permanent information sharing across the entire SC. Better information quality and faster access to information lead to quicker response to environmental change because of permanent exchange of data is along the

SC. SC Efficiency and low level of TC benefit from good data security through global application of Blockchain and therefore reduced effort for countermeasures to defeat cyberattacks. Therefore, SC performance is relatively high. SC performance is confirmed as a value driver. Thus, VC is supposed to be relatively high. The relatively high VC of these intangible value drivers affects the tangible VC of the SC constituted in financial performance such as increasing sales, reducing COGS, or low fixed asset costs. Faster access to information by big data and the accurate forecast through better information quality through AI contributes to a high quality of decision-making. Consequently, operational performance can create sufficient cash flow to re-invest in long-term improvements. Table 6-18 shows how key intangibles influenceable by AI, in the positive scenario fosters full development of VC for each non-financial performance category. In a nutshell, intangible value drivers such as new innovations, appropriate quality, or tight customer relationship are promoted. Sales potential and tangible value is fully leveraged. Well-developed management capabilities due to permanent knowledge building let the SC react as early as possible on environmental changes. Outdated IT can be substituted by emerging technology, process automation permanently increases, and appropriate organisational structures make the SC responsive and agile. These elements cumulated in category Technology improve SC efficiency and thus financial-performance figures such as COGS and total expenses or tangible value such as fixed assets or inventory. The combination of these positive impacts increases cash flow and liquidity so that investing in necessary adjustment and renewals can be made. These positive impacts increase VC through sustainable competitive advantages in the long run.

Table 6-18: Categories of Non-Financial Performance and Key Intangibles Influenceable by AI Applied on the Performance of the Positive Scenario

Categories of non-financial performance	Key Intangibles influenceable by AI applied for the positive scenario
Innovation	Commonly spread and fully implemented use of AI in foresting detects environmental changes. Thus, the SC system has the instruments to identify changes in the environment to improve operational efficiency so that value is created to re-invest into innovations.
Quality	Widespread application of AI in operational processes detects patterns for quality improvement. Sharing of these findings across the SC is possible because of a SC-wide data platform through widespread autonomous SC planning across all SC entities.
Customer relations	Process-orientation and better quality of information through AI applications allow the SC to sufficiently strengthen customer relations because inter alia response to changes is accelerated through widespread autonomous SC planning.
Management capabilities	The ability of SC entities to build management capabilities is given with faster access to information and to better information. AI-enabled forecasting improves managers' knowledge building in regard of environmental changes. The ability to quickly respond to these changes is given through decentral coordination. Continuous knowledge sharing to improve managers operational capabilities is given through widespread AI technologies for SC planning. Due to fully empowered creation of cash flow, management is able re-invest in business model improvements so that sustainable competitive advantages can be achieved.
Alliances	Improved learning capabilities due to permanent information exchange leads to appropriate selection of SC partners. Fully enabled strategic and/or tactical cooperation and collaboration within the SC increases capabilities to react on environmental changes. Widespread autonomous SC planning fosters new knowledge building and knowledge sharing. Thus, fitness of the SC partners through integration of all partners into common culture is permanently promoted.
Technology	Improved learning capabilities let SC executives make appropriate decisions at an early stage or at the right time. Outdated IT, manual processes are substituted by emerging technology and appropriate level of automation with support of AI. Appropriate organisational structures leverage information quality or early access to information. VC is limited.
Brand value	No key intangibles influenceable by AI relevant for this category
Employee relations	No key intangibles influenceable by AI relevant for this category
Environmental and community issues	No key intangibles influenceable by AI relevant for this category

6.6 Synthesising the Findings from Analysing the Two Scenarios of the Conceptual Framework

The evaluation of scenarios with positive and negative impact of AI on SC leads to the following findings:

- For all scenarios evaluated, it is ambiguous whether AI-enabled SC performance creates either intangible or tangible values that lead to competitive advantages. Which scenario creates sustainable competitive advantages cannot be derived.

- Central coordination is preferred in case that AI-enabled SC descriptors are not widely adopted across the SC. However, central coordination impedes high SC responsiveness and high SC efficiency. Low SC responsiveness and SC efficiency fosters central coordination of a SC to achieve the turnaround to a competitive SC. Further investigation is necessary to explore the root cause for this observation.
- Widely adopted and fully implemented AI-enabled SC descriptors make best use of the key intangibles that can be influenced by AI, which are: Learning, quicker response to change in the environment, faster access to information and better information quality. However, the context and dependencies between learning through knowledge building across the entire SC and information access and quality needs to be explored to generalise the findings from the scenario evaluation.
- Scenario analysis reveals that process orientation, autonomous decision-making embedded in decentral coordination best leverages the potential of AI in the SC to create value in inter-company collaboration. In order to induce a change in thinking among SC decision-maker, these findings need additional investigation to provide recommendations on how to synchronise these processes and structure elements of the SC for practical usage.
- The finding that pure demand-driven SC have limited SC performance improvement potential appears to be contradictory to the current trend of SC discussions. However, scenario evaluation figures out that AI consistently improves forecast accuracy so that a paradigm shift might be comprehensible. This finding needs more thoroughly investigation to make it more reliable.

The analysis of the scenarios evaluates the direct and indirect relationships between the SC descriptor variants and provides insights about the mutual influence of the elements, which lead to a positive or negative performance. The aforementioned findings illustrate how the components of the CF impact each other. However, it is neither argued why the SC entities and their agents behave like it is described, what are the root causes for this behaviour, nor can the findings be generalised. Thus, propositions about the analysed phenomena are established in Chapter 7 based on these findings with the purpose to build a theory about the impact of AI on VC in the SC.

6.7 Summary

In this chapter, the CF served to develop a positive and a negative scenario with the aid of CIB-analysis. Both scenarios have been explored in regard to their performance and their contribution for VC.

Chapter 7 Theory of Impact of AI on Value Creation in the Supply Chain

7.1 Introduction

In this Chapter, theory of impact of value creation in the SC is developed. As discussed in Section 3.3.2., Grounded Theory methodology is represented by an iterative process which approximates to the development of the theory through appropriate propositions about the investigated phenomena (Glaser, 1967; Lewin, 1963; Prediger, 2015; Wendee, 2011, p. 85 et seq.; Ziegler, 2003). First, the theory is presented and summarised with its key arguments and its approach and purpose then the propositions are explored and discussed to justify that the theory is meaningful for academic research and important for practical application.

7.2 Purpose, Approach, Reliability and Added Value of the Theory

7.2.1 Purpose and Approach of the Theory

The CF describes what elements constitute the SC system. The CIB-analysis evaluates the relationships of the CF and explores resulting SC scenarios. The evaluation of the SC scenarios results in six propositions. The theory systematically explains how and why the investigated interrelated phenomena of the CF create value for the SC. The propositions arising from the findings of the scenario analysis are explored. On the one hand, the findings from the Delphi Study and the expert interviews are justified with accepted theories such as RBV, KBV, and dynamic capability theory. On the other hand, the findings from the Delphi Study and the expert interviews are compared with findings from other surveys and studies with the purpose to strengthen the propositions of both sources. When necessary, refutation of existing findings with the Delphi Study data and the expert interviews is argued. The comparative analysis is a strong element of the Grounded Theory approach and is applied to elaborate how the Delphi Study results extend, corroborate, complicate, contradict, or correct other studies and surveys.

Illustrative comparisons are chosen for their illustrative value and not systematically selected to be statistically representative. Primarily, the cases that support the comparisons are represented by the descriptor variants of the positive scenario or by the combination of descriptors (e.g., Bullwhip effect).

7.2.2 Reliability and Added Value of the Theory

The theory about the impact of AI on VC in the SC meets the requirements of reliable theory building (Balzer, 1997; Gal, 2019):

- Delphi Study approach empirically anchors the theory.
- The theory has a practical use by providing recommendations for actions and by discovering and explaining inner connections of phenomena that are not directly obvious.
- The theory is not unnecessarily complicated.
- The reasoning of the propositions is compatible with older theories that have already been proven and includes them in the explanatory scope.
- The reasoning of the propositions has explanatory value and is not purely descriptive.
- Theory allows an outlook of a possible future in which certain scenarios will occur, which then confirm or refute propositions made in this thesis.
- The theory is extensive and not too particular.
- The theory intends to inspire other scientists to further research.

The added value is that the theory provides a system of rules and a coherent construct of explaining hypotheses about the VC of AI in the SC. Previous researchers have only studied the phenomena independently and isolated of each other. This theory creates new insights by bringing independent findings from former research together. The theory systematically complements known positions with new insights from the CIB-analysis and brings them into an overall context for predicting the behaviour of future SC. Behaviour predictions of an SC are processed by applying the rules offered by the theory created with this thesis. The reviewed literature underscores the stance of the author of this thesis that such a consistent theory was not previously available. Therefore, the overall theory about the impact of AI on VC in the SC builds new knowledge and offers the opportunity for other researchers to build new knowledge about the research topic by themselves.

7.3 Propositions of the Theory of the Impact of AI on Value Creation in the Supply Chain

AI-enabled forecasting will be a prerequisite to improve SC performance in future SC, but only AI-enabled autonomous SC planning creates competitive advantages. However, the resource bundles of the SC only create sustainable competitive advantages when the additional AI achieves the protection of the SC's common culture knowledge and all relevant SC entities widely adopt AI-enabled autonomous SC planning and high-frequently apply AI in forecasting. The future of the SC as a CAS is not random so that the substantially improved forecast accuracy by self-learning ability of AI will allow a cost-efficient and responsive forecast-driven SC. However, a cluster-oriented inter-company process organisation must be implemented to ensure the full potential of adaptiveness through the concept of emergence to achieve appropriate SC equilibria. This entirely applied SC framework has the potential to leverage an additional significant increasement of value for the SC. All propositions supporting the theory are listed in Table 7-1.

Table 7-1: Propositions Supporting the Theory

No	Proposition	Short description
1	AI is only valuable if the SC performance creates a certain level of competitive advantages.	It is argued that AI is a valuable, rare, and imperfectly imitable resource in the sense of RBV and keeps knowledge across the SC non-substitutable.
2	SC can only survive in the long term through the effective combination of widespread adoption and high frequent application of AI.	The SC only creates sustainable tangible value if all relevant SC entities commonly leverage the full potential of AI in all possible SC processes.
3	Fully implemented AI-enabled SC collaboration creates substantial additional value.	The qualitative findings from the CIB-analysis are quantified with the aid of surveys and studies from the body of literature.
4	AI creates value through the paradigm shift from demand-driven to forecast-driven SC.	The future of a CAS is not random, and the ability of pattern recognition of self-leaning AI allows for accurate prediction of changes in the factor and consumer market.
5	AI value creation requires the optimisation of inter-company collaboration in future SC.	Arguing the effects of inadequate synchronisation of process and structure elements of the SC, a cluster-oriented inter-company process organisation is recommended.
6	AI controls existing SC equilibria but only indirectly supports creating new SC structures.	The concept of emergence is discussed in the context that there are some limitations to apply self-organisation.

7.4 Proposition 1: AI is only Valuable if the SC Performance Creates a Certain Level of Competitive Advantages

7.4.1 Description of the Proposition

For all scenarios evaluated during the CIB-analysis, Section 6.3.5 shows that it is ambiguous whether AI-enabled SC performance creates competitive advantages. It cannot be deduced if AI applications contribute to sustainable competitive advantages. UC/APP collected by the participants of the Delphi Study gives rise to the assumption that knowledge created, acquired, and stored by AI applications is a key value driver of competitive advantages. A deductive approach referring to RBV and KBV is selected to argue that AI is a valuable, rare, and imperfectly imitable resource that creates competitive advantages. It is justified by arguing that AI protects the knowledge implicit in AI applications and shared across the SC and thus even contributes to sustainable competitive advantages.

That different scenarios can arise at all is due to the confirmation of RBV that a different mix of resources compared to other SC in the same industry are applied and that heterogeneity as well as immobility of resources are accepted (J. Barney, 1991; Steinmann et al., 2013). The descriptors of the CF are represented by resource bundles. The refutation of perfect mobility is self-evident otherwise barriers of entry or measures to protect firms' resources would make no sense (J. Barney, 1991, p. 103 et seqq.). J. Barney (1991) argue from the viewpoint of what would happen if resources in firms of one industry were all homogeneous and mobile. Thus, firms could not react with different strategies on environmental changes because no firm possesses a resource that has insights about the opportunities associated with implementing a strategy before any competing firms. The conclusion is that the degree of performance of the SC scenarios is related to the capability of the resource mix to early detect and implement an appropriate strategy which leads to competitive advantages.

7.4.2 Importance of the Discussion

The application of AI in the scenario with positive impact on the SC is only valuable if the SC performance creates at least competitive advantages if not sustainable competitive advantages. The reasoning is compatible with RBV that has already been proven so that the inferences allow for a generalisation of the theory. However, the RBV has not comprehensively been applied on the value of AI applications in the SC so that this discussion provides additional insights to phenomena that make the SC competitive. The discussion for this proposition substantially derives the reasoning of the contribution of AI to competitive advantages and builds the theoretical foundation for further propositions.

7.4.3 AI is a Valuable, Rare, and Imperfectly Imitable Resource Creating Competitive Advantages for the Supply Chain

Competitive advantage is a strong value of an SC. In RBV, it is claimed that competitive advantages can only be achieved if firms keep their resources valuable, rare, and imperfectly imitable. Referring to J. Barney (1991), the definition of resources includes e.g. assets, capabilities, organisational processes, information, or knowledge of a firm. AI possesses the capability to prepare information and knowledge from data and is inseparably connected to hardware and software assets. Hence, AI is considered a firm's resource. An SC consists of firms representing SC entities. Thus, AI is considered a resource of the SC. Resources are valuable when they enable a firm to conceive of or implement strategies that improve its efficiency and effectiveness by exploiting opportunities or neutralise threats in a firm's environment (J. Barney, 1991, p. 106). CIB-analysis and UC/APP from Poll 1 of the Delphi Study designate the descriptor use of AI in forecasting to react on threats *("… reduce risks in SC"*) and opportunities (*"Identifying … patterns and interdependencies in order to earlier warn of arising issues…"*) from the micro-economic factor market (J. B. Barney, 2012), consumer market (Makadok, 2001), and from a macro-economic environment (*"Better evaluation of interdependencies between different internal and external factors"*) such as political, sociological, or legal factors (Theobald, 2016). CIB-analysis underpins that AI-enabled descriptors improve SC efficiency and SC responsiveness what makes the SC more effective. Lichtenthaler (2019) precises this finding from the Delphi Study expanding the RBV by applying the intelligent-based view. Applied to SC, this view says that if even two SC have access to the same internal and external knowledge, they may achieve different competitive positions if one SC has superior intelligence that enables specific insights as a basis for targeted competitive moves that the other firm lacks. The experts of the Delphi Study clearly see AI as the superior intelligence compared to resources such as human experts or ICT applied with non-AI algorithms when it comes to detecting opportunities or threats from the environment. Thus, it can be confirmed that AI is a valuable resource.

A resource is defined as rare as long as the number of firms that possess this particular valuable resource is less than the number of firms needed to generate perfect competition dynamics in an industry (J. Barney, 1991, p. 107). Referring to Figure 4-3 and the qualitative expert statements in Section 4.5, the experts of the Delphi Study see AI as a promise to future SC but currently implemented only to a limited extent. This experts' opinion is confirmed by two studies reporting that only approximately 5,8% of all firms in Germany apply AI (Rammer, 2020) and about 12% of firms globally apply AI in their SC in only a few processes (Brown, 2020; Leonard, 2020). The results of these three studies outline that AI can be considered a rare resource.

Valuable and rare resources can only be sources of competitive advantage if firms that do not possess these resources cannot obtain them (J. Barney, 1991, p. 107). J. Barney (1991) claim for historically unique conditions to which resources depend, causally ambiguous links between resources and competitive advantage, and socially complex advantage. Summarising the statements of the experts from the Delphi Study on the AI definition from Section 4.5, AI is not yet interlocked with the historical path of an SC. However, the experts expect on the one hand SC starting as early adopters to implement AI applications will have historically interlocked AI within their mix of resources e.g. one decade later so that this bundle of resources of which AI applications are part, will be imperfectly imitable. On the other hand, AI expert systems such as IBM Watson, ImageNet or Google ANN for image recognition or NLP (H. Bauer et al., 2017, p. 9; Brynjolfsson & McAfee, 2017, p. 5 et seqq.) having started one decade ago with permanently building knowledge repository and developing complex self-learning capabilities supported by mature training staffs and expertise (Wilson, 2018) have a competitive advantage due to the sheer historically grown amount of data analysed for training purposes. If these AI-enabled expert systems are fully integrated into the so-called intelligence architecture with human intelligence (Lichtenthaler, 2019), then this complexity advantage is difficult to be caught up to by competitors due to the interfaces between AI and the remaining parts of the intelligence architecture which are more difficult to be imitated than stand-alone AI solutions (Lichtenthaler, 2019, p. 15). The argument can go so far as to say that the more frequently AI applications are implemented, the more inextricably they are components of socially complex SC resource bundles that are beyond the ability of firms to be systematically and directly controlled and influenced (J. Barney, 1991, p. 110 et seq.). Also, the experts of the Delphi Study see the increasing number of interrelated, autonomous, and well-coordinated AI applications as a complexity driver. Combined with the inherent adaptiveness through self-learning, and behaviour of swarm intelligence, the resource mix merges into a CAS which creates its own social complexity along the entire SC. This complexity will make the valuable and rare AI-enabled SC resource bundles imperfectly imitable and is expected to create competitive advantages.

7.4.4 AI Creates Sustainable Competitive Advantages through Keeping Knowledge Valuable, Rare, Imperfectly Imitable, and Non-substitutable

A competitive advantage is sustainable if a resource owns the aforementioned characteristics and additionally, if the advantages continue to exist after efforts to duplicate the benefits of the value-creating strategy have ceased (J. Barney, 1991, p. 111 et seq.). J. Barney (1991) declares the definition of sustainable competitive advantages as an equilibrium definition because the competitive advantage is not related to calendar periods but to an uncertain point in time, when a competitor will have achieved to build resource bundles that duplicate the benefits. Table 6-8 from the CIB analysis shows for the scenario with a positive impact on the SC that an unambiguous statement about positive VC is only possible if all three performance indicators are positive. Table 6-7 shows for the scenario with a negative impact on the SC also a positive VC for the combination of the three positive performance indicators. However, only the combination of the three positive performance indicators of the positive scenario can create sustainable competitive advantages at all. The positive VC of the negative scenario is only strong enough for competitive advantage with a limited extent because the performance of all three descriptors is relatively low. Thus, a future SC competing with the SC that deploys valuable, rare, and imperfectly imitable AI-enabled resource bundles, must try to duplicate the value created by the three positive performance indicators of the positive scenario. The competing SC needs to build knowledge about the value-creating strategies of this scenario. The principles of J. Barney (1991) applied to the positive SC scenario say, if an SC with a competitive advantage understands the link between the resources it controls and its advantages, then competing SC can also learn about that link, acquire the necessary resources, and implement the relevant strategies. In such a setting, competitive advantages are not sustained because they can be duplicated (J. Barney, 1991, p. 109). Thus, the SC composed on the principles of the positive scenario with the competitive advantage needs to avoid that the knowledge about the link between the resources and the advantages becomes comprehensible and transparent. The UC/APP collected by the participants of the Delphi Study put self-learning AI abilities in the foreground that are primarily based on knowledge created from the analytics of big data *("ML … closely linked to big data …without necessarily being programmed to do so")*. Referring to KBV, knowledge is proposed to be considered as a strategically significant resource (Grant, 1996). However, Grant (1996) argue that only human productivity is knowledge dependent whereas Lichtenthaler (2019) as well as Fenstermacher (2005) confirm the experts' opinion from the Delphi Study that computers possess knowledge that equals human knowledge and that AI applications contribute their knowledge to a firm's meta intelligence. The UC/APP collection shows that the strategies implemented based on valuable knowledge improve SC efficiency and SC effectiveness and contribute to the positive performance of all SC scenarios (see PPIM in Table 5-8 and discussion about UC/APP impact on SC performance indicators in Section 5.2.1). AI applications are not simply embodiments of knowledge but create knowledge, acquire existing knowledge, and store knowledge. This assumption implies that AI applications themselves are incapable to improve performance, but the AI-inherent knowledge produces results which contribute to value through performance improvement. Transparency of knowledge arises through codification. Knowledge codification is the conversion of tacit knowledge to explicit knowledge. But the more open and observable the knowledge, the easier it is to learn by competitors, and the less valuable it is due to risk of being imitated. Thus, valuable, rare, and imperfectly imitable resource bundles must apply tacit knowledge to manage the SC and execute activities. The collection of the UC/APP shows that AI applications learn without codified programming, establish, and adjust rules to process their algorithms without human input, and have the capability to implicitly execute SC processes. This self-learning ability of AI applications creates tacit knowledge and produces outcome based on tacit knowledge. Tacit knowledge is defined as inarticulable, or implicit that is articulable but only with some difficulty (Kimble, 2013; Nonaka & von Krogh, 2009). AI-inherent tacit knowledge is hidden from the outside observer, and it is seen as being difficult to identify and measure (Kimble, 2013). Thus, knowledge created, acquired, and stored by AI applications that is imperfectly comprehensible, makes it difficult to understand the link between the AI resources and the value created through their outcome. This argumentation is an indication that AI protects knowledge as a valuable, rare, and imperfectly imitable resource from being duplicated by competitors so that AI creates sustainable competitive advantages.

7.4.5 AI Creates Sustainable Competitive Advantages Through Effective Knowledge Sharing Across the Supply Chain

The collection of UC/APP from the Delphi Study shows that AI applications as part of subsystems of one SC entity share their knowledge with AI applications in subsystems of other SC entities to improve SC performance *("… using shared SC information …", "manufacturer will be able to ramp up production …, Logistics service provider will know in advance volume, date, peak seasons…", "Continuous monitoring of inbound and outbound shipments taking into account multiple parameters from supply chain partners, but also external like vessel schedules, weather, etc..", "Improved view on customers…", "Better evaluation … use learnings for future planning activities…"*). Kimble (2013) strengthens the experts' opinions that knowledge to be treated as an economic good and therefore serves valuable resource, must be put in a form that allows it to circulate and be exchanged. For that reason, the conjecture is discussed that not only knowledge created, acquired, and stored by single AI applications is protected, but also the shared knowledge across the SC is protected by AI. Knowledge allocation in the SC happens through compatible cooperation routines such as forms, rules, procedures, conventions, strategies, and technologies (Grant, 1996). This common schema or inter-organisational culture contains and distributes tacit knowledge as information across all SC entities. The interplay of these resources within SC subsystems is based on historical and newly-created transferable tacit and explicit knowledge (Grant, 1996). Historical and newly created knowledge as part of common culture is stored in AI applications such as expert systems, robots, bots, AGV, autonomous driving vehicles which are connected to each other and to a common platform (Kuntze et al., 2020) which is permanently fed by the input from an enormously huge data lake (Miloslavskaya & Tolstoy, 2016). The CIB-analysis proposes widely adopted autonomous SC planning to integrate decentral, autonomous AI applications and a common SC planning platform across the entire SC. The underlying concept is enabled by a multi-agent system approach (Al-mutawah, Lee, & Cheung, 2009; Fiedler et al., 2019). This AI-enabled platform edits and converts data to information and retrieves the information as common SC knowledge to all authorised SC entities. This AI-supported SC learning is justified by the general conversion and amplification process of Nonaka (1994) to which knowledge can be repeated at different levels within an organisation, moving in a growing spiral from an individual to a group level and later on to an organisational or inter-organisational level. Subsystems consisting of AI applications or human experts access this repository of knowledge but can only express to a limited extent how the subsystems process their single but interrelated activities and how the knowledge is created. This argumentation takes up both the constructivist viewpoint that supra-individual knowledge represents a phenomenon that exists only within the confines of a particular social group as common culture as well as the realist stance that understands of group knowledge all knowledge inherent of all individuals which is available in the group (Kimble, 2013). Hence, the network of individual knowledge and the tacit knowledge as part of the common culture of the SC is inseparably connected to each other through the knowledge repository of the decentral AI applications and the central AI-enabled platform. This finding is underpinned by the thesis of Luis Armando Luján (2017) which informs that only the combination of resources and their interaction makes the set of resources rare and valuable due to the non-substitutability and inimitability of the respective resource bundle. Lichtenthaler (2019) justifies this finding by highlighting that the interfaces between resources may not be imitated as easily as stand-alone AI solutions. This set of resources with inherently high amount of tacit knowledge is difficult to imitate because it is “hard-wired” in the brains of the employees (Grant, 1996), the ANN-related algorithm of AI applications and in the supra-individual knowledge of the SC. It is possible to extract single subsystems but isolated, these subsystems cannot fully unfold their potentials. Due to experts’ opinions from the Delphi Study, that employees will be significantly replaced by AI-enabled subsystems *(“…system should automatically take over low-impact decisions”,” Autonomous driving”, “Autonomous planning”, “Autonomous trucks”, “Autonomous production”, “Autonomous networks”*), a high number of tacit knowledges is stored in non-human but AI-enabled agents in the SC. The risk that employees or teams with tacit knowledge move to competitive SC is mitigated. Thus, the tacit knowledge shared by AI applications and distributed through the common culture of the SC is only partially transparent and difficult to duplicate. This argumentation is another indication that AI makes it difficult to understand the link between the AI resources and the value created through their outcome so that AI is supposed to contribute to sustainable competitive advantages.

7.4.6 Theoretical Meaning and Practical Implications

The significance of AI for VC in the SC is conclusively proven by the RBV. Thus, the discussion of this proposition underpins the theoretical meaning and the continuing importance of the RBV. Additionally, the theoretical meaning of the strong relation between AI and tacit knowledge is elaborated. Taking the findings from the discussed phenomena to the logical conclusion, this would mean that technological development is no longer necessary once only tacit knowledge controls the SC. Therefore, it must be assumed that competitors want to be able to develop AI applications that can make the link between competitive advantage and resource bundles transparent, e.g., through AI-enabled cyberattacks. Only then does the evolutionary cycle continue. From a theoretical stance, this consideration could be taken further in upcoming research with the viewpoint of the theory of evolution. The results of this proposition pave the way for the exchange of expert's opinions from different disciplines to jointly create new knowledge. For practitioners, it might implicate substantial effort to accelerate implementing technological shields against cyberattacks from competitive SC. However, the proposition underpins the strong requirement to position as an early mover regarding the protection of SC knowledge. The finding that AI capability keeps knowledge of shared culture opaque to competing SC has not yet been fully argued scientifically. Thus, this proposition has an important theoretical meaning. For practitioners, the proposition provides several instructions for actions to ensure competitive advantages for their SC.

7.5 Proposition 2: Supply Chains Can Only Survive in Long Term Through the Effective Combination of Widespread Adoption and High Frequent Application of AI

7.5.1 Description of the Proposition

The CIB-analysis determines that the positive impact on SC performance depends mainly on two intangible value drivers: The degree of widely adopted SC descriptors and the degree of how frequently applying AI with these SC descriptors. Descriptors of the CF that are directly affected by these two value drivers are:

- Application of AI in forecasting
- Application of autonomous SC planning techniques
- Application of autonomous move of equipment such as autonomous driving
- Application of emerging technology Blockchain
- Application of AI to cyberattack SC system architectures.

Widespread adoption of SC descriptors means that all relevant SC entities commonly apply the methods and instruments of the SC descriptors independently from the application of AI. For example, the instruments of autonomous SC planning and forecasting to reduce the Bullwhip effect are applied for several decades with the CPFR[iii] concept. However, the frequency of applying AI in both descriptors is limited so far. The frequency of applying AI refers to the number of AI agents applied in AI application fields illustrated in Figure 2-2 that are related to performance indicators of the PPIM in Table 5-8. Figure 7-1 generically illustrates this mutual connection between both intangible value drivers and their impact on the potential competitive advantages of a SC.

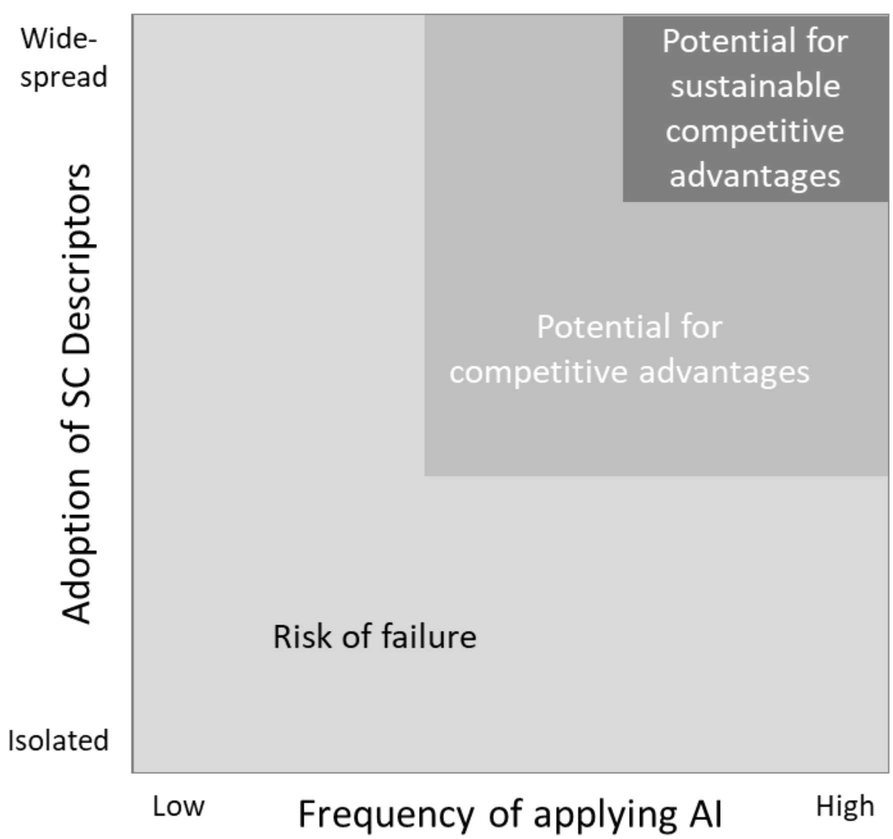


Figure 7-1: The Impact of Adoption of Descriptors and Their Application of AI on VC in the SC

The combination of degrees of each value driver results in three competitive stages of the SC from the risk of failure, the potential for competitive advantage, and potential for sustainable competitive advantages. The risk of failure refers to the non-ability of the SC to survive in the long run which is the opposite of the potential for sustainable competitive advantages. The mutual connection and their causal relationship to the competitive potential of the SC illustrated in Figure 7-1 serves to discuss the impact of relevant phenomena of VC through AI to strengthen the theory building in regard to the importance of both value drivers for the competitiveness of the SC.

7.5.2 Importance of the Discussion

This proposition provides the basic building block of the theory recognised by the CIB-analysis. Systematically, it discovers and explores inner connections of the most impacting SC descriptors that are not directly obvious in regard to the risks of failure in the long run. The two value drivers, widespread adoption, and frequency of applying AI that are integrated into each of the descriptors of the CF are disintegrated to explore the phenomena of their connections in regard to their value of competitive advantages for the SC. The scaling of the value drivers from isolated to widespread or low to high provides the practical use of the theory to classify future use cases according to their potential contribution for the survival of the SC. Especially the finding about the impact of AI on the Bullwhip effect and that a SC that will not develop the capabilities of collaborating across all SC entities will fail on the long run shows the high importance of this proposition.

7.5.3 The Potential of the Combination of Both Value Drivers to Create Value Through Competitive Advantages

Three use cases are exemplarily illustrated in Figure *7-2* with regard to the effects of combining the two value drivers. Use Case 1, Position 1 (UC1 (P1) represents a widespread adoption of autonomous SC planning commonly applying one platform across the SC by all relevant SC entities to share and exchange data and information of the common culture. However, AI is not applied although referring to the definition of the SC descriptor in

Table **5-12**, autonomous SC planning is supported by AI technologies. Use Case 1, Position 2 (UC1 (P2) indicates that the widely adopted platform is AI-enabled. However, decentral agents do not apply AI so that the maximally applicable frequency of AI is not achieved. Referring to Table 6-9, the in-between position of an SC descriptor cannot be determined precisely because too many unknowns must be considered. Use Case 2, Position 1 (UC1 (P1) shows an SC situation with all relevant SC entities applying AI but isolated without being connected to each other. Use Case 2, Position 2 (UC1 (P2) indicates an increasing number of SC entities participating in autonomous SC planning, thus connecting the AI agents with each other. One SC descriptor alone is not able to achieve relatively high performance of the positive scenario and thus is not able to achieve sustainable competitive advantages in the sense of J. Barney (1991) as discussed in Section 7.4.5. The CF requires an additive perspective on the SC system due to the complex direct and indirect relationships of the SC descriptors. Use Case 3, Position 1 (UC3 (P1) indicates that additionally to widely adopted AI-enabled autonomous SC planning the other SC descriptors such as fully implemented and widely adopted AI-enabled forecasting are also fully implemented. Only in this situation, sustainable competitive advantages can be achieved because of the protected knowledge as discussed in Section 7.4.5. The aspect of quality such as the quality of the results of the AI outcomes, qualification of the human experts applying the SC planning instruments is not considered as impacting factor. However, the entire non-substitutability of the resource bundles depends on the activities of the competing SC. One instrument of a competing SC might be the application of AI to cyberattack SC system architectures of the leading SC. Then Use Case 3, Position 1 (UC3 (P1) is pressed down into Use Case 3, Position 2 (UC3 (P2) in Figure *7-2* due to the subtractive impact of globally organised AI-enabled cyberattacks.

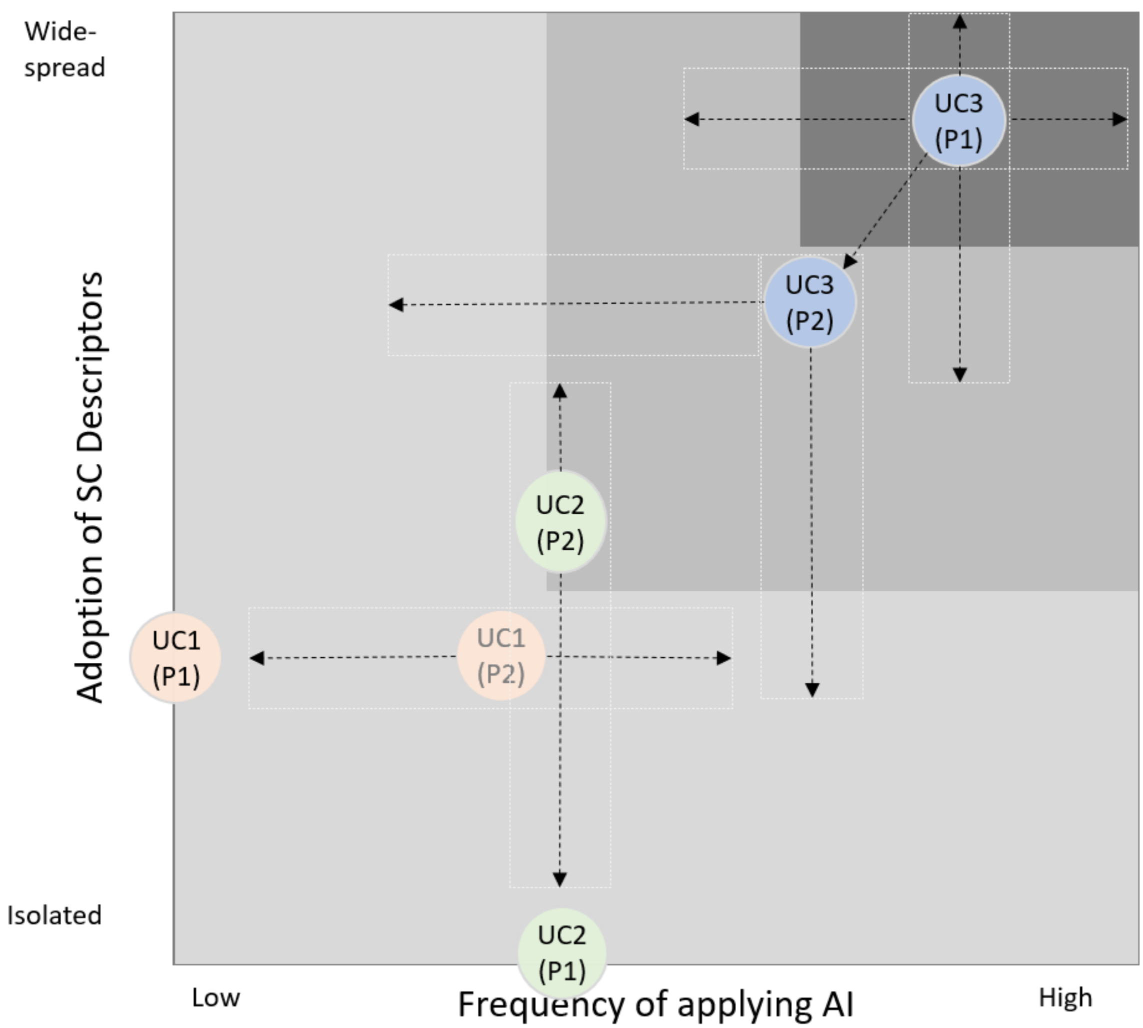


Figure 7-2: Positioning of Use Cases 1 to 3 Exemplarily Illustrated

Referring to the positive scenario of the CIB-analysis, the combination of both value drivers fosters dynamic and ordinary capabilities of the SC. Dynamic capabilities are a set of specific and identifiable processes such as product development, strategic decision making, and alliancing (Eisenhardt & Martin, 2000). With dynamic capabilities, a firm increases its adaptability towards challenges from the environment and technological opportunities (Eisenhardt & Martin, 2000; Teece, 2011; Wamba et al., 2017) with the purpose of enhancing efficiency and improving responsiveness towards consumer market changes of whatever resources the firm acquires (Makadok, 2001). Table 7-10 confirms that an SC primarily benefits in regard to efficiency and responsiveness from both value drivers, wide adoption, and frequency of AI by the combination of forecasting and autonomous SC planning. Table 7-10 also shows ordinary capabilities of the positive scenario mainly benefit from combining widely adopted autonomous SC planning, fully implemented autonomous driving, and globally processed Blockchain expressed by improved efficiency and reduced TC. Ordinary capabilities relate to the performance of particular tasks and the production of existing products/services, without reference to their current relevance to customer and competitive considerations (Teece, 2011). The collected UC/APP of the Delphi Study identify operational activities which are processed by AI applications embedded in AGV, cobots, NLP, or computer vision abilities as ordinary capabilities.

7.5.4 Widely Adopted AI-enabled Supply Chain Descriptors Create Value Through Reducing Bullwhip Effect

The experts of the Delphi Study consider the two SC descriptor variants commonly spread and fully implemented application of AI in forecasting as well as speculation as indispensable for all future SC scenarios as shown in Figure 6-3. The experts' opinion is that the

AI's ability to cope with uncertainty and volatility of the future substantially improves forecast accuracy. Even in scenarios with a negative impact on SC performance, forecasting must be widely adopted, and AI must be fully implemented to have any advantage at all. Use Case 4, Position 1 (UC4 (P1) in Figure *7-3* shows that for all other combinations of the two value drivers in regard to forecasting, the SC is doomed to failure from the outset. Detailed exploration is given in Section 7.7 with the discussion about the paradigm shift from demand-driven SC to forecast-driven SC. Even if forecasting is widely adopted and AI is fully implemented, there is still potential to fail and the competitive advantage is low at least for the application in the negative scenario as illustrated with Use Case 4, Position 2 (UC4 (P2) in Figure *7-3*.

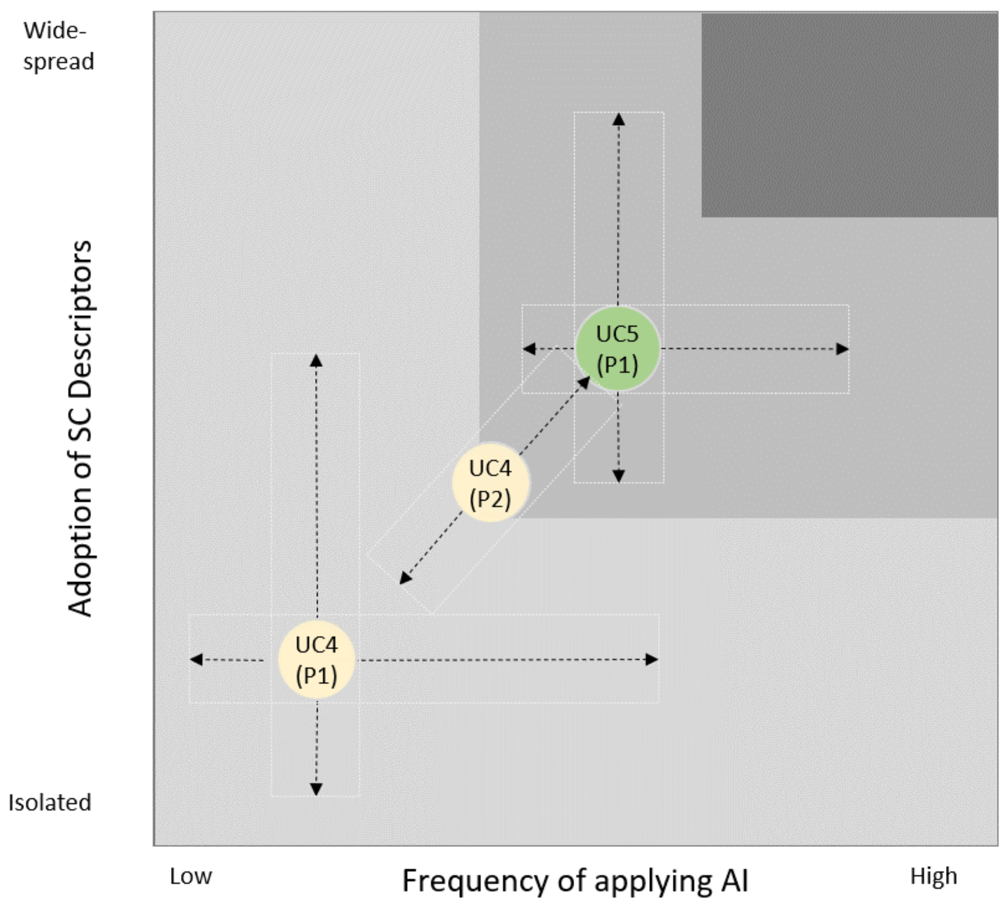


Figure 7-3: Positioning of Use Cases 4 to 5 Exemplarily Illustrated

In contrast to forecasting, widely adopted AI-enabled autonomous SC planning promotes SC responsiveness (+2), SC efficiency (+2), and decreasing transaction cost (+2) only in the positive scenario. The low performance of the negative scenario is coined by isolated adoption of the instruments of SC planning with low frequency of applying AI. Thus, the key differentiator for competitive advantage through relatively high SC performance is widely adopted AI-enabled autonomous SC planning. The combination of both value drivers for both descriptor variants provides a relatively secure competitive advantage as illustrated with Use Case 5, Position 1 (UC5 (P1) in Figure *7-3*. The main benefit from widely adopted AI-enabled autonomous SC planning comes from efficiency gains and TC reduction (see Table 7-10) because both value drivers (wide adoption and frequency of applying AI) constituting autonomous SC planning have a significant effect on Bullwhip effect reduction. The Bullwhip effect occurs if only the SC entity with direct access to consumer data applies AI-enabled forecasting and no other SC entity participates actively. The isolated application of AI-enabled forecasting has only a very limited positive impact on the forecast quality for the entire SC because entities of the downstream SC plan their production and replenishment on a forecast of lower quality. Another case could be that an upstream SC entity with no direct access to consumer data applies AI-enabled forecasting. Forecast about consumer demand is available from the SC entity with direct access to consumer data but without AI-enabled recognition of hidden patterns of consumer behaviour. The upstream SC entity applies AI-enabled forecasting for SC planning purposes on the shared inaccurate demand information. Thus, the AI-enabled forecast is only correct to a limited extent because of a reduced quality of input data. Both cases in combination with other Bullwhip-reinforcing factors such as order bundling, speculation on bottlenecks or price fluctuation during SC planning keeps inventory and storage costs across the SC higher than necessary.

The analysis of experts' rating in Section 6.4 reveals that the commonly spread and fully integrated application of AI in forecasting only creates value and therefore provides a competitive advantage if combined with common adoption of AI-enabled autonomous SC planning techniques. Vice versa, isolated AI-enabled forecasting applied only by a low number of SC subsystems significantly limits the power of wide adoption of autonomous SC planning. The detected impact of isolated forecasting from the CIB-analysis goes in line with the opinion of Ireland and Bruce (2000) that "*25 to 50 different forecasts from end to end and side to side are unlikely to be accurate*". The situation might be comparable to the end of the 1990s when CPFR[iv] concepts have been started to be implemented to strengthen collaboration between SC entities especially between consumer goods manufacturers and retailers with exactly this target to reduce the Bullwhip effect in the SC (Ireland & Bruce, 2000). In the last two decades, efforts have been made to successfully reduce the Bullwhip effect through the evolution of integrative cooperation in respect to forecasting, planning, and replenishment through promoting a single, jointly owned demand plan and a forecast throughout the total SC (Cristea & Khalif Hassan, 2018; Ireland & Bruce, 2000; H. L. Lee, Padmanabhan, & Whang, 1997; Ravichandran, 2008). Most of these efforts in the past years have been made without AI applications. Therefore, it is expected that an AI-enabled forecast which is shared with all relevant SC entities will create additional value for the SC. Inter alia, this expectation is based on a SC model by Aggarwal and Davè (2018) which deduces that AI will reduce the Bullwhip effect by centralising prescriptive analytics applying historic demand, production, and inventory data combined with current demand and other current information and previous modelling information from all SC entities as input data. This is where the insight of the CIB analysis regarding AI-enabled autonomous SC planning as the main differentiator between positive and negative SC scenarios comes into play.

The collected and retrieved big data are processed by the decentral AI agents and the central AI platform so that the outcome of the autonomous SC planning techniques the knowledge input permanently improves AI-enabled forecasting. The model of Aggarwal and Davè (2018) confirms the CIB-analysis results that centralising demand is not only for the purpose to inform the entire SC about consumer behaviours and demand fluctuation but to synchronise the available production and logistics capacity and to find optimal inventory for products of different stages with the benefit of high SC efficiency. These Bullwhip reducing impacts by collected UC/APP from Delphi Study Poll 1 are summarised as prescriptive analytics ability to simulate future demand and supply balance for better "*planning and disposition of goods supply*", "*transport planning*", "*distribution*" and "*inventory optimisation*". The concept of autonomous SC planning requires that big data and AI-enabled advanced analytics are used in every step of the SC planning to process (near) real-time data (Kuntze et al., 2020; Nishi et al., 2005; Roßmann, 2018). Autonomous SC planning processes in subsystems are permanently fed by the SC planning and execution processes of all SC entities along the SC. These processes are executed by agents of interlinked subsystems. These agents permanently provide data that serves as information for the successful projection of demand and supply matches. These data are strongly dependent on each other. If data are missing, then the decision-making either of human experts or of AI applications is limited and might lead to wrong decisions. Thus, for optimal VC through Bullwhip effect reduction, it is important that both autonomous SC planning and AI-enabled forecasting are fully and not only partly implemented.

7.5.5 Improving Common Culture of Widely Adopted and Fully Integrated Application of AI for Efficiency Gains

The analysis of the relationship between the two value drivers and competitive advantages is strengthened with the business process of recognising bad parts, a use case from the UC/APP collected by Delphi Study Poll 1, "*Fault detection in operations*". The efficiency gains are argued with knowledge creation for the common culture of the SC. The detection of bad parts in the production line of a manufacturer or in the delivery of a supplier by AI-supported computer vision does not yet create knowledge. But if the self-learning algorithms e.g of the ANN, permanently analyse hundreds of bad parts and detect a pattern that discovers the root cause for these bad parts, then new knowledge is created. On the one hand, the AI applications learn from the permanent analysis of the bad parts and the update of the agents' inherent knowledge repository. On the other hand, human experts learn from the results of AI applications. The more complementary information to be processed by the involved agents, the better the results of pattern recognition are because the newly created common knowledge circulates between the participating human experts and AI agents. Widely adopted and fully integrated information that exchange across all SC subsystems improves the provision of complementary information for exploring the root cause of any kind of defects. In the negative scenario, the complementary information exchange is limited to the individual SC entities. Therefore, a common culture of the SC develops only to a limited extent (for more details about the competitive advantages by common culture see Section 7.4.5).

This common culture or cultural fit of a specific group is necessary to reduce or even avoid that members of this group dedicate more time to communication, establishing compatible cooperation routines and developing an approximate set of common directives (Yang & Xu, 2019). Therefore, members of this group must have some common basis such as common data lake or experience from which to absorb knowledge. If the new knowledge is totally foreign to members of one group, their ability to learn is greatly reduced. If a group has no basis from which to understand the information, learning will be tedious or will not occur at all (Spekman, Spear, & Kamauff, 2002). This is correct for all agents, human experts as well as self-learning AI applications in all collaboration types. This knowledge is applied for training purposes of AI applications or as individual learning of human experts. The outcome of this learning process enriches the routines and procedures applied during the collaboration of subsystems. From the moment when subsystems apply this knowledge as a common routine, the knowledge becomes part of the common SC culture. These mental templates facilitate the creation of knowledge by providing points of reference for respective agents. Due to their own purposes, papers such as Kimble (2013), Spekman et al. (2002) or Grant (1996) discuss knowledge creation and learning from the viewpoint of human beings. However, AI applications consisting of e.g ANN are treated like human beings when it comes to learning and knowledge creation. For that reason, terms like “mental templates”, cognition, or “mind” also represent the technical body that is needed to process human-like activities in AI applications.

There is no question that AI applications create and permanently update their knowledge repository by the ability of self-learning. However, one important question in the context of the two value drivers is which agent type, human and/or AI, creates knowledge for the common culture of the SC. Is it the AI application by providing information about the pattern, and recommendations for measurements or is it the human expert who evaluates the pattern resulting and derives problem-solving measures from the result? The importance of that question is based on the discussion in Section 7.7.7 that argues the efficiency gain from self-learning AI applications. The findings of the patterns are reported by the AI application. Reporting means that a human expert uses queries provided by an IT application to retrieve the findings. The human expert transfers the findings of the AI application into codified knowledge and therefore into intangible value. This applies to Type 2 and Type 3 collaboration (see Section 7.6.1) with descriptive and predictive analytics AI abilities. Thus, it is the human experts who create knowledge for the common culture by bringing this knowledge into routines of the SC that are applied by all agents of relevant SC subsystems. The value comes from the value driver wide adoption and from the relatively high frequency of applying AI (see Section 7.7.7). As long as the new knowledge is not applied in the SC by implementing these routines to avoid the root cause for the bad parts in the common culture (Grant, 1996) of all participating SC entities, only limited value for the SC is created. Potentially, this value contributes to competitive advantages, but not to sustainable competitive advantages (see the discussion in Section 7.4.5). The created tangible value of the reported findings depends on the effort needed to (a) codify this knowledge and (b) implement it as norms and routines in the common culture of the SC.

In Type 4 collaboration, the AI application with the computer vision ability provides the findings of the pattern to the AI-enabled platform which shares the knowledge with the respective subsystems in the production and R&D organisation and with the supplier and recommends action alternatives. In the negative scenario, this exchange of knowledge enhancing information across SC entities is limited and slowed down due to not widely adopted SC planning. In the positive scenario, this tacit-knowledge-based interaction between decentral AI applications and the AI-enabled platform is primarily autonomously coordinated. Codification autonomously happens the moment, prescriptive analytics capability of the platform recommends measures to human-based subsystems. With the last step, Type 3 collaboration happens. The next step, the adjustment of the parts (might be that raw material needs to be substituted or an assembly routine needs to be aligned) is processed as Type 2 or even Type 1 collaboration and the communication of these adjustments as norms and rules by human experts flows into the common culture as codified knowledge. It is expected that with the implementation of measures to avoid bad parts, fewer costs for rework, less material waste, and fewer process costs occur. These effects positively impact the cash flow and tangible value is created for the SC. The underlying assumption is that only AI applications can to identify these patterns or at least identify these patterns faster, more precisely and with less effort than human experts are able to do. Type 4 collaboration creates knowledge for the common culture of the SC. The efficiency gain is argued as in Section 7.7.7. However, even in this strongly data-driven Type 4 collaboration human experts are the drivers for the implementation of the intercompany adjustments so that the efficiency gains from a high frequency of applying AI are limited. In conclusion, the interplay of tacit specialist knowledge of AI applications, the enrichment of common culture through this knowledge across the entire SC and the limited need of codifying of a common culture for the usage of human experts make the difference between the positive or negative impact on VC in the SC.

7.5.6 Theoretical Meaning and Practical Implications

The impact of the value drivers, degree of adoption of SC descriptors across all relevant SC entities and the degree of application of AI on competitive advantages has not yet been sufficiently explored in the literature reviewed. The CIB-analysis with the qualitative statements of the participating experts detects one important new aspect of the dependencies between both value drivers of SC descriptors which contribute new knowledge to academic discussions. This aspect that only commonly applied widespread adoption of SC descriptors and high degree of AI lead to sustainable competitive advantages provides a clear recommendation to practitioners regarding initiatives to improve a SC. The proposition emphasises the significance of further researching in reducing the Bullwhip effect with support of these value drivers. Thus, the discussion has a strong theoretical meaning that implicates the decision-making of executives in operating SC. Exploring the exemplarily illustrated five use cases from the background of the CIB-analysis' results provides a well-prepared reasoning that adds new knowledge to academic discussions. Most importantly, the finding that the key differentiator in future SC will be AI-enabled autonomous SC planning has never been so clearly elaborated in existing literature. The exemplarily illustrated and explored classification of five use cases offers the possibility for academics and practitioners to understand the findings, to test the results, and to apply the approach to own use cases.

7.6 Proposition 3: Fully Implemented AI-enabled Supply Chain Collaboration Creates Substantial Additional Value

7.6.1 Description of the Proposition

This proposition discusses the quantification of the qualitative findings from the Delphi Study. The experts of the Delphi Study underpin with the collected 72 UC/AP (see Appendix C.) four types of inter-company collaboration between agents of different kinds. The collaboration types and their shares in current SC are outlined in Table 7-2. The collaboration types represent the collaboration between non-AI-supported subsystems (Type 1), Mixed subsystem (Type 2 and Type 3), and pure AI subsystems (Type 4).

Table 7-2: Share of Types of Collaboration Between AI Applications and Human Experts in Current Supply Chains

No	Types of collaboration	Principal	Agent	Share of current SC
1	Non-AI-supported subsystems	Human expert	Human expert	88%
2	Mixed subsystem with human expert in leading role	Human expert	AI application	6%
3	Mixed subsystem with AI application in leading role	AI application	Human expert	4%
4	Pure AI subsystem	AI application	AI application	2%
Total				**100%**

For each collaboration type, a leading role (Principal) and a supporting role (Agent) are defined. A literature review exposes Type 1 collaboration as the predominant one with 88% and that collaboration with AI in total has only a ratio of 12% of the entire collaboration in current SC. Based on an index of 100 for non-AI-enabled collaboration, the AI-enabled collaboration types create additional value for an SC as shown in Table 7-3.

Table 7-3: Impact of AI on Value Creation of Collaboration Types

No	Types of collaboration	Index of contribution to VC
1	Non-AI-supported subsystems	100
2	Mixed subsystem with human expert in leading role	117
3	Mixed subsystem with AI application in leading role	125
4	Pure AI subsystem	136

Type 2 collaboration increases value of 17% compared to Type 1 collaboration. The UC/APP indicate that AI in the role of the principal is supposed to create more value than in the agent role due to the high amount of proposed UC/APP with autonomous elements and efficiency gain argumentation. For that reason, Type 3 collaboration increases value by 25% compared to collaboration without AI support. The efficiency gain for Type 4 collaboration is expected to be 36% compared to the initial situation of non-AI-supported subsystems. In future, the ratio of each collaboration type will change due to increasing importance of AI applications as presented in Figure 4-3 and Figure 4-4. Results from the Delphi Study Poll 1 as shown in

Table 5-8, the findings from the CIB-analysis combined with available surveys from other researchers allow to precise assumptions about future fields of applying AI. The resulting shares of future collaboration types are shown in Table 7-4. A significant reduction of Type 1 collaboration is expected from 88% to 36%. The total share of AI-enabled collaboration types increases from 12% to 64% (Sum of Type 2,3, and 4 collaboration).

Table 7-4: Share of Collaboration Types in Future Supply Chains

No	**Types of collaboration**	**Share of future SC**
1	Non-AI-supported subsystem	36%
2	Mixed subsystem with human expert in leading role	19%
3	Mixed subsystem with AI application in leading role	19%
4	Pure AI subsystem	26%
Total		**100%**

The performance of the scenario with positive impact on SC performance is significantly higher than the performance of the negative scenario (see Table 7-10). The CIB-analysis shows that one predominant reason being the cooperation across all relevant SC entities of the entire SC instead of dyadic inter-company collaboration or collaboration that is mainly driven by a focal company and central coordination, but isolated application of AI. This additional VC potential is expressed in Column “Range of cooperation” in Table 7-5. Cooperation which is more related to the scenarios with a negative impact on the SC has no or minor additional value potential (factor 1,0 and factor 1,3) whereas full cooperation proposed by the positive scenario has the potential to leverage additional value with a factor of 2.5. The future share of each collaboration type is respected in future value calculation in the Column “Weighted AI impact on VC” (Share of future SC multiplied by AI impact on VC). Exemplarily depicted for Type 4 collaboration, the weighted VC potential of 9% (share of future SC of Type 4 collaboration of 26% multiplied by the absolute AI impact on VC with the amount of 36%) is multiplied with the factor 2,5 for a full range of cooperation. The result is a Type 4 collaboration VC potential of 23%. The total VC potential in a future SC for that the positive scenario is implemented is 43% which sums up the VC potential for all collaboration types.

Table 7-5: VC Potential Through Ranges of Cooperation

No	Types of collaboration	Share of future SC	AI impact on VC	Weighted AI impact on VC	Range of cooperation		
					No	**Partial**	**Full**
					1.0	*1.3*	*2.5*
1	Non-AI-supported subsystem	*36%*	*0%*	0%	0%	0%	0%
2	Mixed subsystem with human expert in leading role	*19%*	*17%*	3%	3%	4%	8%
3	Mixed subsystem with AI application in leading role	*19%*	*25%*	5%	5%	6%	12%
4	Pure AI subsystem	*26%*	*36%*	9%	9%	12%	23%
Additional value potential					***17%***	**23%**	**43%**

7.6.2 Importance of the Discussion

The explanatory value of the theory is strengthened by quantitative statements. It is meaningful for the reliable theory building that the qualitative findings from the CIB-analysis are comprehensibly quantified to apply the theory for testing purposes. This discussion provides the foundation for the understanding of the generic SC situation and the significance of appropriate activities regarding the application of the descriptor variants of the positive scenario. The discussion shows the substantial changes of collaboration in future SC and emphasises the opportunity to create additional value by early reacting on these changes but also the risk to fail in case that a positive scenario cannot be achieved. Both perspectives make the discussion important for the reliable theory building.

7.6.3 The Four Collaboration Types

The participating AI experts highlight that AI applications are able to collaborate independently and autonomously whilst transferring information from one subsystem to another. In contrast, domain experts are rather of the opinion that AI focuses on the support of human activities in currently known fields such as simulation, robotics, and deep learning. Collaboration happens in all AI application fields depicted in the PPIM from Table 5-8. The taxonomy shown in Table 7-2 is based on the typical cooperation and collaboration characteristics between technology and human experts framing that technology can support humans partially and only executes an activity if human experts confirm before or technology acts autonomously but human experts can use veto. AI technology interacts with human experts and autonomously informs only if human experts consciously ask or technology ignores human experts (Gerst, 2019, p. 111; Wilson, 2018). Table 7-2 informs about four types of collaboration. The sequence of the collaboration types (Type 1 to Type 4) represents a ranking of significance of AI involvement. Type 1 collaboration is based on subsystems with non-AI-supported agents, mainly human experts but also mechanic devices such as conveyor belts in production or automated high-rack storages. These mechanic devices are subordinated to human experts' control. Type 2 collaboration represents mixed subsystems with experts in leading role whereas in Type 3 collaboration the role assignments are reversed. Type 4 collaboration only includes AI applications exemplarily outlined in Satoh (2013) or Lang, Moonen, Srour, and Zuidwijk (2008). The leading role that equals to the customer, client, or contracting authority is the principal of the collaboration whereas the agent is the subordinated role equal to the delegate, contractor, or supplier. Both terms are borrowed from PAT to underpin the relationship within or between subsystems. Both principal and agent represent either a human expert or an AI application. The term 'agent' in PAT should not be confused with the general usage of the term 'agent' in this thesis. In general usage, an agent represents the role of a principal as well as the role of the agent from PAT. Column "Share of current SC" in Table 7-2 shows the shares of each collaboration type in current SC.

7.6.4 The Sharing of Collaboration Types in Current Supply Chains

Literature provides insights into how AI is applied in current SC. However, the literature review has not revealed precise shares for types of collaboration. Thus, assumptions based on available data are made that allow the most accurate result possible. A survey authorised by Deloitte (Anonym, 2020e) informs that 12% of firms globally apply AI in their SC. Conversely, it is derived from this value that Type 1 collaboration has a share of 88% because Type 1 collaboration per definition has no involvement of AI-enabled subsystems. Anonym (2020e) limit the informative value by distinguishing between AI, autonomous driving and Blockchain. It has not been respected that AI is a technology applied in autonomous driving and in Blockchains (Kreutzer & Sirrenberg, 2019). However, this information value is sufficient for the accuracy level needed to propose VC of the positive scenario because already applied Blockchain use cases, as well as inter-organisational autonomous driving, is negligible. The AI-enabled descriptors of the positive scenario are supposed to have a certain ratio of Types 2, 3, and 4 collaborations. These ratios are calculated based on available studies explained below. Korn et al. (2019, p. 19) provide the first indication by having asked companies which of their AI deployments have been found to be most useful in their companies (see Table 7-6).

Table 7-6: Ratio of AI in Collaboration Types

AI Solution	As of 100%	Mixed subsystem with human expert in leading role	Mixed subsystem with AI application in leading role	Pure technical subsystem
ML	21%	14,94%	2,13%	4,27%
Smart robotics	14%	5,66%	5,66%	2,83%
NLP	13%	6,33%	5,06%	1,27%
Neural networks and deep learning	14%	2,83%	7,07%	4,24%
Text analysis	14%	11,32%	1,41%	1,41%
Virtual agents	3%	1,04%	1,39%	1,04%
Speech recognition	11%	5,33%	4,27%	1,07%
Computer vision	7%	2,16%	1,44%	3,60%
Biometrics	2%	0,00%	2,01%	0,22%
Percentage of AI in SC	**12%**	**5,95%**	**3,65%**	**2,39%**

Type 4 collaboration is currently represented by intelligent -often virtual- agents visualising physical material during SC execution and AGV in intralogistics processes. Both application types communicate with other -often AI-enabled- technical subsystems, such as a central cloud platform to exchange e.g. coordination data with other AGV or material flow data with other intelligent agents (use cases exemplarily shown in Gesing, Peterson, and Michelsen (2018, p. 27 et seqq.)). The four-field matrix of Kersten et al. (2020, p. 15) brings technologies in relation to each other with the characteristics ‘relevance’ and ‘implementation status’. Kersten et al. (2020, p. 15) show that for cross-company machine-machine communication representing Type 4 collaboration both characteristics are relatively low compared to well-established technologies such as mobile data access for employees or ERP systems. On the one hand, this comparison shows that the relatively low percentage of Type 4 collaboration is justified. On the other hand, it suggests that the relevance is relatively low rated because interviewees have less experience with this technology. Both ratings underpin the correctness of its relatively low share. Compared to cross-company machine-machine communication, predictive analytics representing Type 2 collaboration is relatively higher rated in both characteristics. This rating leads to the suggestion that predictive analytics is already more experienced due to the higher implementation rate. Thus, the relatively higher share of Type 2 collaboration is justified. In contrast, prescriptive analytics is relatively lower rated what justifies the lower share of Type 3 collaboration technologies. This argumentation is emphasised by material flow related technology matrix of Kersten et al. (2020, p. 14) which shows comparable low ratings for robots and autonomous driving (Type 4 collaboration) and relatively high rating for well-established technologies such as 2D-codes and sensor technology. It is concluded that the shares of current SC of each collaboration type can be considered justified although the author of this study is aware that the allocations are vulnerable.

The impact of AI in Column "Index of contribution to VC" in Table 7-3 is derived from the significance of the role of AI in each collaboration type. To give an example from the UC/APP of the Delphi Study, AI applications to provide prescriptive analytics are principals because the human expert is only the operator of the proposed measures by AI. Vice versa, predictive analytics by AI provides information that needs to be analysed and evaluated by the human expert as principal to derive appropriate measures and decisions. Table 7-8 exemplarily lists some use cases for each collaboration type. Examples for Type 1 collaboration are found in the body of SC literature. These use case examples serve to better illustrate the theoretical discussion.

With the purpose to justify potential AI impact on VC of each collaboration type in Column “Index of contribution to VC” in Table 7-3, the collaboration between pure human expert subsystems serves as index value 100. This statistical measure allows to consolidate a multitude of data and to put all other collaboration types in relation to an initial value to derive and analyse percentage key figures for changes in the composition of these collaboration types. Kurzlechner (2017), Ashayeri and Lemmes (2006), Chui et al. (2018), F. Chen, Drezner, Ryan, and Simchi-Levi (2000) along with Anonym (2019a) provide studies about improvement potential through AI applications in SC (details see Table 7-6).

Table 7-7: AI Impact on Value Creation

Literature Reference	**Impact on VC**	**Impact on VC**		
		Mixed subsystem with human expert in leading role	Mixed subsystem with AI application in leading role	Pure technical subsystem
Chiu (2018), Ashayeri (2005)	forecasting accuracy	15,00%		
Kurzlechner (2017)	Productivity improvement through automation potential in production			20,00%
Kurzlechner (2017)	predictive maintenance	10,00%		
Kurzlechner (2017) / Bauer (2017), related to Kurzlechner (2017) / Pohlen (2005	Collaboration between workers and cobots / robots			20,00%
Kurzlechner (2017)	Automated quality tests increases productivity			50,00%
Kurzlechner (2017)	Automation of support functions	40,00%	60,00%	90,00%
Cognizant (2019)	Data analytics solution to increase throughput	4,00%	6,00%	8,00%
Chen (2000)	Increase profitability by centralising demand information		10,00%	30,00%
Average value creation potential		**17,25%**	**25,33%**	**36,33%**

VC has been mainly proposed by improving ordinary capabilities (Daspit, D'Souza, & Dicke, 2016; Teece, 2011) through improved demand forecast accuracy, leveraging automation potential, predictive maintenance, or collaboration between workers and cobots or robots. Information from these studies leads to the suggestions about AI impact on VC per Type 2,3, and 4 collaborations in Table 7-2. These papers support the justification of the suggestions of the Delphi Study Poll 1 in regard to the VC of SC performance categories outlined in Table 4-7 and Table 5-8.

Table 7-8: Types of Collaboration and Examples of Use Cases in SC

#	Types of collaboration	Examples of use cases
1	Non-AI-supported subsystem (1)	• Brainstorming between human expert teams from different companies in research and development (R&D) processes. • Internet research to identify and evaluate best-fitting suppliers. • Negotiation between suppliers and purchasing experts. • Determining demand based on data collected from SC partners and calculated with non-AI applications and shared with SC partners. • Trucks driven by human drivers sending telematics data to logistics service provider company which are analysed by dispatching expert. • Retrieving MRP data from APS system of focal company and sharing these data via EDI with supplier production department. • SC planner of supplying plant uses email and phone calls to inform and discuss options with SC planner of receiving plant about delay of truck. • Customer informs production asset supplier about downtime of production line and asks for technician to install spare part.
2	Mixed subsystem with human expert in leading role	• Predictive analytics application prepares report which serves as basis for human experts to make a decision about next step in a business process. • Central AI-enabled forecasting application provides data to human experts in SC entities. • Training of AI applications with data retrieved across the entire SC.
3	Mixed subsystem with AI application in leading role	• Prescriptive analytics application recommends the most promising scenario in case of material flow interruption to meet customer delivery date. • Chatbot with NLP abilities at customer service desk communicates with calling party in regard to changing delivery address.
4	Pure technical subsystem	• Decentral AI application explores capacity and workload data and sends result to central AI platform to process S&OP. • Autonomously driving trucks permanently sharing data with SC entities to track ETA versus ATA.

7.6.5 The Sharing of Collaboration Types in the Positive Supply Chain Scenario

Figure 4-4 underpins that all experts are strongly convinced of the future importance of AI and that in future SC the amount of AI subsystems will significantly increase. The PPIM in

Table 5-8 illustrates the SC processes and the Performance indicators to which future use of AI is expected. On the one hand, it shows that SC planning processes are supposed to be most affected by AI applications in the future. On the other hand, lowering activity cost is strongly expected value from AI applications. Combined with the experts' opinion that significant growth of direct interaction between AI applications characterises future SC collaboration, the significantly increasing percentage of Type 4 collaboration outlined in Table 7-4 can be justified. Literature review supports precising the Delphi Study results. Recent studies confirm a significant change in the structure of employment towards a relative reduction of Type 1 collaboration and an increasing relative number of Type 2, Type 3, and Type 4 collaboration (Gerst, 2019, p. 114; Rammer, 2020; Zika, Helmrich, Maier, Weber, & Wolter, 2018, p. 25 et seqq.). The total number of human expert workplaces is only moderately affected in the case of general economic growth (Zika et al., 2018). However, the number of human experts related to Type 1 collaboration is expected to relatively decreasing whereas the number of human experts working in Type 2 and 3 collaboration will increase in future SC. Surveys underpin this outlook by informing that robots can take over up to 20 M factory jobs and that 46 M Americans whose jobs have high exposure to automation can have 70% of their tasks done by robots by 2030 so that about 10% of US jobs can be lost from the use of automation (Gilbert, 2021) but AI-enabled processes also entail new job roles (Wilson, 2018)[v] so that the entire number of human experts might remain nearly constant. The results of these surveys strongly correlate with the 72 UC/APP gathered by Delphi Study Poll 1 that underpin the move from human expert collaboration to a high amount of AI-enabled collaboration (see Appendix C.). Wilson (2018) identifies five characteristics of business processes generally and of collaboration particularly that companies want to improve: flexibility, speed, scale, decision-making, and personalisation. PPIM in Table 5-8 shows overlapping results of the Delphi Study: higher flexibility and SC responsiveness, higher service and lower activity time corresponds with the characteristics of speed and flexibility of Wilson (2018) whereas lower SC cost can be mapped with scale and speed. The underlying study of Wilson (2018) confirm the findings of the Delphi Study outlined in Table 5-4 by detecting significant AI-driven performance improvement the more of these five characteristics are adopted and combined. Adoption of one collaboration principle leads to an improvement factor of about 3.5 whereas the adoption of all five collaboration principles increases performance by a factor of 6,5. This improvement claim leads to the change in the ratio of collaboration types reducing the number of relatively low VC of Type 1 collaboration and increases relatively high VC contributed by Type 2 and 3 collaboration so that an absolute number of human experts is involved in processes with relatively higher value contribution in the SC. The fact that more human experts are involved in processes underlying collaboration types with higher VC leads to a higher VC per each human expert. With the reasoning that value is a result of improved performance, the performance of human experts which are part of Type 2 and 3 collaboration increases so that key performance indicators (KPI) that are workforce-related are expected to improve. The expectation of relative growth of Type 2,3 and 4 collaboration is supported by the study of Rammer (2020, p. 28) which detected a significant growth of job vacancy in the field of AI in all industries. This finding leads to the assumption that companies intend to invest in AI-enabled capabilities what is underpinned by the study of Gesing et al. (2018, p. 12) which detected "precipitous spikes in venture capital investment in AI start-ups and corporate funding for AI R&D and acquisitions". Venture capital investment is a strong indication in the belief in long-term growth potential (Hayes, 2021). An approximation of future shares of collaboration types for the AI-related descriptor autonomous planning, AI-enabled forecasting, autonomous driving, Blockchain and AI-enabled cyberattacks is illustrated in Table 7-9.

Table 7-9: Future Sharing of Collaboration Types Related to AI-Enabled Descriptors of Positive Scenario

Types of collaboration	**Other activities**	**Auto-nomous SC planning**	**AI-enabled forecasting**	**Auto-nomous driving**	**Block-chain**	**AI-enabled cyber-attacks**	**Total**
	OA	ASCP	AFC	AD	BC	ACA	
Non-AI-supported subsystem (1)	30%	1%	1%	1%	1%	2%	**36%**
Mixed subsystem with human expert in leading role (2)	1%	2%	12%	2%	1%	1%	**19%**
Mixed subsystem with AI application in leading role (3)	2%	7%	2%	5%	2%	1%	**19%**
Pure technical subsystem (4)	2%	12%	2%	3%	6%	1%	**26%**
Total	**35%**	**22%**	**17%**	**11%**	**10%**	**5%**	**100%**

The findings outlined in Table 5-8 underpin these ratios. In future SC, the ratio of pure human expert subsystems is supposed to be significantly lower than in current SC. This means that in all subsystems AI applications replace human experts. For descriptor ‘autonomous SC planning’, it is expected that AI will take over the leading role in all subsystems. Therefore, Type 3 and 4 collaboration are dominant and the share of mixed subsystems with human experts in the leading role is low. In forecasting, AI applications are supposed to mainly assume the role of the assistant whereas the human experts evaluate the AI findings and make the decision. This assumption corresponds to the UC/APPs collected in Poll 1 of the Delphi Study. For autonomous driving, Blockchain technology, and AI-enabled cyberattacks, the shares of subsystems with AI applications in the leading role are supposed to significantly increase. With increasing number of AI applications, the SC performance increases (Brynjolfsson & McAfee, 2016) (Chui et al., 2018; Kreutzer & Sirrenberg, 2019). This assumption is underpinned by the ability of AI to amplify and scale it competences in collaborating subsystems (Wilson, 2018). Poll 1 of the

Delphi Study comes to a comparable result. Primarily the future planning process will contribute to a significant SC performance improvement. The processes make, deliver, and source will also contribute to SC cost reduction, and lower activity time which justifies the contribution of the descriptor Blockchain in Table 7-9. Chui et al. (2018) detect VC potential of $1.2 – 2.0 trillion in SC management and manufacturing through AI-enabled analytics in the fields of predictive maintenance, yield optimisation, procurement and spend analytics, inventory and parts optimisation, logistics warehouse optimisation and sales and demand forecast. The findings of the Delphi Study confirm the VC potential for the SCOR processes 'Plan, 'Source', 'Make' and 'Deliver' correspondingly to Chui et al. (2018). Such huge value expectation automatically leads to investments in areas in which the highest return is suggested. A recent PriceWaterhouseCoopers (PwC) survey amongst 1,000 executives in the US already using AI (Anonym, 2021a) provides the key areas in which significant AI investments might be taken: workforce planning (58%), simulation modelling (48%), scenario planning (43%), and demand projection (42%.). With these investments, executives expect to create better customer experience (67%), improve decision-making (54%), achieve cost savings (50%), or operate more efficiently and increase productivity (52%). The figures in brackets show the percentage of agreement by the interviewees. The fields of improvement correspond to a high degree with the Delphi Study results. The strong overlapping of the key areas with the 72 UC/APP confirms the Delphi Study findings. The same PwC survey ranks among the top five AI objectives helping employees making better decisions, automating routine tasks, and analysing scenarios using simulation models. Most of these objectives are strongly related to the defined descriptors of Poll 2 of the Delphi Study autonomous SC planning and AI-enabled forecasting. The survey of Kersten et al. (2020, p. 36) for German SC underpins the results of the US-focused PwC survey and the Delphi Study results of this study detecting that the highest potential of AI is seen in advanced data analytics in planning. The PwC study (Anonym, 2021a) also reveals that executives rank managing risks, frauds, cybersecurity threats as number one of all AI-related activities in the upcoming period of time. This finding corresponds to the descriptor ‘Use of AI to attack SC system architectures’ which is detected by Poll 2 of the Delphi Study as one important element of the CF. Risk of cyberattacks are the reason why 48% of the executives plan significant investments in SC resilience and plan to protect AI systems from cyber threats and manipulations (35%). Referring to Kreutzer and Sirrenberg (2019, p. 206), a share of about 30% of autonomous driving cars underlies the collaboration types for autonomous driving in Table 7-9. This finding justifies the descriptor ‘use of autonomous driving’ in the CF. All these VC aspects might be a reason why 86% of executives support that AI will become mainstream technology at their companies in 2021 (Gilbert, 2021).

7.6.6 Quantifying the Value Creation Through the Positive Supply Chain Scenario

Common value as proposed with the positive scenario of the CIB-analysis can primarily be created through collaboration in the field of autonomous SC planning or forecasting. If the SC entities decide to cooperate only partially or even not at all then the value created is lower. Full value can only be created with full range of collaboration. However, the aspect of range of collaboration can only be covered as a model in this thesis. The reason is that the number of SC entities cannot be generalised and therefore it cannot be clearly specified what ‘partial’ and what ‘full’ exactly means. Table 7-10 summarises the results of a detailed analysis based on the ratings of the experts in Delphi Study Poll 2. Appendix K. illustrates the details of the experts’ rating of the Delphi Study in regard to the promotion of relatively high or relatively low SC performance.

Table 7-10: Total Difference of the Impact of AI-Enabled Descriptors on Performance Indicators of the CF.

Performance indicators/AI-enabled descriptors	**SC responsiveness**	**SC efficiency**	**Transaction cost**	**Total**
Widely adopted AI-enabled forecasting	4	1	2	7
Widely adopted Autonomous SC planning	3	3	4	10
Fully implemented Autonomous driving	1	2	4	7
Globally processed Blockchain	2	1	4	4
Total difference between positively and negatively promoting impacts				**28**

The analysis includes all AI-enabled SC descriptors except the use of AI to attack SC system architectures. The reason for deliberately omitting this descriptor is that it would distort the own performance of the two scenarios. The analysis aims to calculate a value that represents the difference between positive and negative SC performance based on the pure interpretation of the Delph Study ratings. This value is 28, which can be applied as an amplification of the performance that can be achieved from changing a negative scenario to a positive one. The question is how to interpret this figure with the aim to derive a useful amplification factor for further analysis. The experts of the Delphi Study consider 19 event pairs with an impact. For all other event pairs, the experts see no impact (value is 0). The maximum possible sum of all event pairs in Appendix K. for which the experts have rated an impact is 57 because the maximum rating is +/-3. The experts have awarded half of the available points to the positive impact of the widely adopted descriptors on SC performance. Translated to the Likert scale, it is a value of 2 (equals to moderate promoting influence) or qualitatively expressed with reference to Table 4-12, the experts are of the opinion that the impact of widely adopted descriptors is important for the performance of the system. The experts suppose that the mechanisms of these event pairs are not yet well-established (1) but also not very low-established (3). Widely adopted AI-enabled descriptors are capable to exert a moderate impact on the SC performance. But how to translate moderate impact to a value creating quantifiable factor to be applied for testing purposes? A retrograde approach is applied. With the assumption that full range of cooperation as shown in Table 7-5 should be moderate (equals to approx. 50% of the possible value) a conservative value creating factor of 43% is defined. With the already identified AI impact on VC for all collaboration types and the share of AI-supported collaborations (see Section 7.6.5), a factor of 2.5 is detected as an amplification factor. The amplification factor for the partial range (1.3) of cooperation is conservatively defined by the author with the sole aim to have a factor for calculation purposes in Chapter 8 . However, the derivation of these amplification factors is certainly a weak point of this exploration. This weak point is owed to the fact, that existing literature does not provide sufficiently valid empirical analyses on this context which offers starting points for further research. The rating of the Delphi Study participants shows that cooperative behaviour of SC entities is an amplifier for the positive influence of AI. Therefore, it is imperative to also consider this reinforcement aspect when assessing VC by AI in the SC. The AI impact on VC of each collaboration type and the factor of each range of cooperation is multiplied by each other. The result is summed up to the contribution of VC of each range of cooperation:

- All SC entities implement the descriptors isolated: 17% created value.
- Some SC entities cooperate to implement the descriptors: 23% created value.
- All SC entities cooperate to implement the descriptors: 43% created value.

Table 7-5 illustrates the explanation. Both aspects of VC in the SC are consolidated in Table 7-11. The experts of the qualitative interviews summarised in Section 4.4 confirm the understanding of SC performance as a value driver for non-financial performance of the SC. The CF applies three SC performance indicators: SC responsiveness, SC efficiency, and transaction cost. The value created through the aspect of cooperation and the aspect of AI as part of collaboration types is assigned to these SC performance indicators. This assignment of created value to SC performance indicators facilitates the allocation of the created value to the tangible assets of a value determining concept.

Table 7-11: Value Created with the Positive SC Scenario

SC performance indicators	Weighting of VC impact	Range of cooperation		
		No	Partial	Full
		17.3%	*22.5%*	*43.3%*
SC responsiveness	*0,4*	6,9%	9,0%	17,3%
SC efficiency	*0,5*	8,7%	11,3%	21,7%
Transaction cost	*0,1*	1,7%	2,3%	4,3%

Non-AI-supported subsystems' shares in future SC are reduced by 52% to 36%. Subsystems with AI increase their shares by 52% to 64%. Additional VC of 43% is possible in a SC in which all SC entities collaborate in the relevant descriptors of the CF. VC in other areas in which AI can be applied is not considered. The following Sections explore the root cause of this VC through AI in the SC.

7.6.7 Theoretical Meaning and Practical Implications

No comparable detailed and consisting derivation of quantifiable results of VC through AI in the SC from an existing CF is known with the available literature. A different perspective is introduced to analyse collaboration between human experts and AI applications. This perspective allows for improved theoretical discussions because it strictly refers to the VC across the entire SC that is in the focus of the future SC scenarios. Particularly the derivation of the quantified additional value potential contributes knowledge to the field of the SC. Both, academics, and practitioners can apply that information in their respective areas. Quantifying the qualitative results of the CIB-analysis opens possibilities for further research to test and refine the findings because the quantifiable results serve as comparison for further calculation of implemented use cases. The findings from the proposition allow practitioners to calculate tangible VC for own business cases.

7.7 Proposition 4: AI Creates Value Through the Paradigm Shift from Demand-driven to Forecast-driven Supply Chains

7.7.1 Description of the Proposition

CIB-analysis reveals that AI used in forecasting is a strong active descriptor, controlling and regulating the SC system (see Appendix I.). AI used in forecasting promotes SC efficiency (+1), SC responsiveness (+1) and decreasing of transaction cost (+2). The experts of the Delphi Study identify "*improvement of customer demand forecasts along the complete product life cycle'*" as a strong value driver. However, the Delphi Study discloses two groups of experts with very different opinions about the usefulness of forecasting. Table 6-15 distinguishes the group of traditionalists and the group of visionaries. The visionaries' group believes in the power of AI to significantly improve forecast accuracy. The experts of the Delphi Study also expect that the descriptor variant 'Speculation' instead of 'postponement' will prevail in the SC system in the long term, so that SC planning and scheduling will be more related to forecast-driven instead of demand-driven approach. The combination of AI-enabled forecasting and variant 'speculation' is one element of the CF is to positively impact SC services, lowering activity time and increasing flexibility of the SC as shown by the PPIM in Table 5-8. Primarily, visionaries' group of experts expect from the forecast-driven approach, that the order-to-delivery cycle accelerates and the reduction of SC costs due to less inventory and logistics cost[vi]. The group of traditionalists from the Delphi Study support the demand-driven approach by arguing that today's volatile markets served by ever more complex SC make accurate forecasting impossible (Packowski & Francas, 2014). Therefore, delivery capability must be ensured despite of longer delivery times due to assembling customer-required product variants only after order-entry (Swaminathan & Lee, 2003), taking into account necessary costs. However, the key competitive factor of SC is shortening order-to-delivery cycles considering appropriate SC costs (Christopher, 1998; 2005, p. 143 et seqq.; Tiedemann, Johansson, & Wikner, 2016) and thus, demand-driven SC provide potential to improve. The two fundamentally opposite assumptions are that the lowest possible order-to-delivery time can only be ensured with high inventory or that low inventory only allows for relatively higher order-to-delivery time prior to that production time is not lower than the required delivery time by the customer. These two opposite poles so far seemed unresolvable. The visionaries' group of experts are now breaking down these two opposites by proposing to bet on the ability of AI to significantly improve forecast accuracy and to ensure the highest possible delivery capability despite of relatively low inventory. It is discussed if the self-learning ability of AI is strong enough for recognising the smallest relevant patterns of a CAS through big data analytics in order to provide early information about changes in consumer behaviour.

7.7.2 Importance of the Discussion

Referring to the word frequency analysis in Section 5.2.2 based on UC/APP from Delphi Study Poll 1, the aspect of 'learning', 'data', and 'forecasting' is considered a key value driver of the SC. The CIB-analysis of Delphi Study Poll 2 reveals that forecasting and autonomous SC planning are key value drivers for SC performance. These important findings are discussed with the target to discover and explain inner connections of future SC which have a large impact on VC by AI. The discussion about inner connections of future SC is of high importance for root-cause analyses to correctly evaluate the VC by AI. One important outcome of this discussion is the argumentation for a forecast-driven SC with low inventory and high accuracy. The discussion is important because it discovers that a forecast-driven SC is only possible with strong big data analytics capabilities of AI applications and argues the reliability of this hypothesis. The discussion reveals that the performance of the future SC strongly depends on the self-learning ability of AI and comprehensibly argues the root-causes.

7.7.3 Big Data as Value Driver for AI-enabled Forecasting improves Supply Chain Efficiency

The visionaries' group of the Delphi Study believes that AI used in forecasting exerts significant impact on the passive descriptor SC efficiency (+2,4). The positive impact mainly comes from the better information quality and improved learning capability discussed in Section 6.3.3 and highlighted as key intangibles influenceable by AI. Based on multiple empirical studies collected by Kreutzer and Sirrenberg (2019) the opinion of the Delphi Study experts is confirmed that AI is supposed to significantly improve forecast accuracy, so that the outlook to future situations comes closer to prediction than to forecasting. Prediction is understood in the sense that the occurrence probability of the assumed or simulated scenarios is very high, and that the limitation of available data is steadily reduced in the sense of applying the principles of big data approach. CIB-analysis shows that widely adopted autonomous SC planning is a strong enabler of permanently applying big data in forecasting (+2) and therefore significantly contributes to improve AI ability of pattern recognition in the SC. Blackburn, Lurz, Priese, Göb, and Darkow (2015) empirically confirm with a case study in the chemical industry that the accuracy of demand forecast with predictive analytics in the field of big data is up to 96%. The case study of Blackburn et al. (2015) informs that the applied predictive analytics outperforms statistical methods based on historical demand data for almost all investigated forecast situations in various business environments and production settings. These results refer to tactical and operational decisions on production planning, inventory levels, transportation, and scheduling of commodities with high pressure on margins and the need to manage an SC highly efficiently. Blackburn et al. (2015) even consider their market volatile and their SC complex. The experts of the Delphi Study underpin that widely adopted autonomous SC planning permanently exchange big data across the entire SC, so that AI-enabled forecasting is supplied with the latest real-time data. The highlighted opportunity by Blackburn et al. (2015) is the availability of the enormous amount of data in companies as well as in the public sphere of the internet. Blackburn et al. (2015) refer to one bn gigabytes of data created every day in 2012. This amount of big data has been increased to 2.3 bn gigabytes in 2018 with an expected growth rate of about 70% until 2019 (Kroker, 2018, 2019). The total data volume in 2025 is expected to have 175 Zettabyte (Anoym, 2018) which is 175,000 bn gigabytes. It is supposed that the data lake consisting of environmental information and internal data will significantly increase and will become continuously more precise due to common and inter-organisational platforms across all SC entities. UC/APP collected by Delphi Study experts justify the large potential of big data to improve "*planning and disposition of goods supply*" "[…] *to apply machine learning algorithms in manifold areas being related to demand forecastin*g", and to evaluate "*risks on a higher detail level and with higher event prediction rate*." The aforementioned figures about the sheer volume of available data suggest that recognising previously hidden patterns of behaviour by discovering detailed correlations between previously inaccessible data structures will bring forecasting more to the fore. Blackburn et al. (2015) confirm with the empirical study the ability to process covariate information such as economic indicators, expert opinion, market variables, public sphere data, public holidays, industrial value chains, or company internal data.

The following case study to which Gast (2018) reports, is part of a project which was conducted by the author of this thesis in 2017. It shows the limitations in regard of the feasibility of big data analytics. Gast (2018) informs about a situation that is characterised by a demand-driven SC with the challenging service level of a 4-hour order-to-delivery time. The necessary logistics network of a large number of regional warehouses (RWH) to ensure appropriate inventory is questioned due to its high amount of fixed logistics costs. The goal of the case study is to figure out if the turn from the demand-driven SC to a forecast-driven SC with the aid of anticipatory shipping (Spiegel et al., 2013), allows to significantly reduce the number of RWH and therefore the amount of inventory while respecting the 4-hour delivery time. Two product types are subject of investigation: Products of product type A are ordered either as a single product or combined, with a toolkit composed of different types of equipment. For orders of product type B, it is necessary to blend products according to an individual recipe to create a new product variant. Demand for both product types is relatively volatile. The number of products is relatively high. The number of blended products is countless. Prerequisite for successful anticipatory shipping of both product types is that self-learning AI is trained with sufficient and appropriate data. For product type A, the number of available historical data and (near) real-time data has been too low so that a reliable training of the AI application was not possible. However, cost-benefit analysis conducted during the project revealed that with a higher number of data sets, a reliable result would have been feasible, and the cost reduction would have increased SC efficiency. Case studies having demonstrated the VC potential of comparable anticipatory instruments can be found in Baniwal et al. (2019), C. K. H. Lee (2017), and Viet, Behdani, and Bloemhof (2019). For product type B, the number of variants of blended products is too high and the number of new products makes the situation too dynamic so that a reliable forecast accuracy is not feasible. Therefore, the SC of product type B remains demand-driven with relatively high SC costs and the risk to miss order-to-delivery service level.

Finally, the question arises whether a forecast accuracy of 96% informed by Blackburn et al. (2015) in the beginning of this section is sufficient to carry out far-reaching changes in the SC to fully bet on forecast-driven SC. Chui et al. (2018, p. 22) informs that a forecast accuracy improvement of 10% to 20% is translated into a potential of 5% reduction in inventory costs and revenue increases of 2% to 3%. Additionally, H. Bauer et al. (2017, p. 9) highlight that a forecast error reduction between 20% and 50% might lead to reduced lost sales by up to 65%. In a case that an initial forecast accuracy of 85% can be improved by 11% to 96%, then sales improve by 2.1%, inventory reduces by 30% and inventory cost reduces by 3.3% (see Table 7-12). The figures in Table 7-12 are based on papers by Chui et al. (2018, p. 22) and H. Bauer et al. (2017, p. 9), the correlation between forecast accuracy and sales, inventory, and inventory cost is extrapolated.

Table 7-12: Forecast Accuracy Impact on Sales, Inventory, and Inventory Cost

FA	Sales	IC	INV
x	y	y	y
1%	1,1%	-0,33%	-5,0%
2%	1,2%	-0,33%	-7,5%
3%	1,3%	-0,33%	-10,0%
4%	1,4%	-0,33%	-12,5%
5%	1,5%	-0,33%	-15,0%
6%	1,6%	-0,82%	-17,5%
7%	1,7%	-1,30%	-20,0%
8%	1,8%	-1,78%	-22,0%
9%	1,9%	-2,27%	-25,0%
10%	2,0%	-2,75%	-27,5%
11%	2,1%	-3,30%	-30,0%
12%	2,2%	-3,60%	-32,5%
13%	2,3%	-4,23%	-35,0%
14%	2,4%	-4,78%	-37,5%
15%	2,5%	-5,00%	-40,0%
16%	2,6%	-5,66%	-42,5%
17%	2,7%	-6,16%	-45,0%
18%	2,8%	-6,67%	-47,0%
19%	2,9%	-7,17%	-48,5%
20%	3,0%	-7,50%	-50,0%

FA: Forecast accuracy, IC: Inventory cost, INV: Inventory

This impact on tangible value leaves the possibility of a paradigm change to forecast-driven SC. The discussion shows that an appropriate forecast accuracy based on big data analytics for tactical and operational decision-making within an existing product portfolio, in general, allows for a forecast-driven approach. However, case-depending analysis is necessary.

7.7.4 Big Data as Value Driver for AI-enabled Forecasting Improves Dynamic Capabilities of Supply Chain Responsiveness

The dynamic capability of strategic decision-making is expected to being improved, especially towards decision-making in high-velocity markets. In high-velocity markets, change becomes nonlinear and less predictable because ”market boundaries are blurred, successful business models are unclear, and market players are ambiguous and shifting" (Eisenhardt & Martin, 2000, p. 1111). Eisenhardt and Martin (2000) are of the opinion that this uncertainty cannot be modelled as probabilities because it is not possible to specify a priori the possible future states. However, for the firm to successfully compete in a dynamic marketplace, the capability to understand the market mechanisms is necessary to ensure the firm remains in congruence with the environment (Daspit et al., 2016). Eisenhardt and Martin (2000) argue that the set of processes represented by dynamic capabilities in high-velocity markets is simple, highly experiential and fragile with unpredictable outcomes. For that reason, SC managers have little opportunities to create appropriate and useful new knowledge. Thus, managers rely on existing knowledge and simple routines with the disadvantage that managers overgeneralise from past situations that lead to wrong or at least too late decisions in case of uncovered disruptive changes due to inappropriate early warning mechanisms (Eisenhardt & Martin, 2000, p. 1111). High-volatile and high-velocity markets of that kind correspond to CAS. However, referring to Pathak and Dilts (2002, p. 656), also CAS have observable patterns. This is possible because in CAS future is non-random (Pathak & Dilts, 2002). These smallest but observable patterns, no matter how hidden, which would never be recognised by a human expert, might be discovered and displayed by AI applications. With the observation of these patterns through permanent access to big data and well-trained mature ANN-related applications, AI-enabled forecasting detects weak signals of changes in the behaviour of consumers which have been unobserved yet. Even if these non-linear changes cannot be predicted accurately, AI-enabled prescriptive analytics is able to provide options for future scenarios to which managers can rely with their decision-making.

Thus, the insights into formerly uncovered smallest changes allow for further development of possible options for action by consumers in a delimited space of possibilities. And while changes in the environment can cause the entire system to go for an unpredictable pattern, the system can then stabilise into predictable patterns. Patterns of change in the market can be recognised at the very earliest stage. These smallest indications which cannot be identified by human experts are useful to create new knowledge to improve dynamic capabilities. Wamba et al. (2017) empirically proves a positive correlation between big data analytics impact on dynamic capability and firm performance. The findings of Wamba et al. (2017) are meaningful in this context due to an appropriate number of participating companies from supposed high-velocity markets (e.g. agriculture, information and communication, transportation and storage, wholesale and retail trade (Wamba et al., 2017, p. 359)). It has been argued that AI-enabled big data analytics will be faster than firms with simple rules so that they will be earlier in hitting market windows and reinventing or applying technical solutions. With these findings, Wamba et al. (2017) justify the correctness and the importance of faster access to information and quicker response to change in the environment, two of the four key intangibles influenceable by AI discussed in Section 6.3.3. These value drivers are related to proposed UC/APP from the Delphi Study ("*Identify more complex patterns and interdependencies in order to earlier warn of arising issues*.") Priore, Ponte, Rosillo, and de la Fuente (2019) underpin these findings with their empirical study about applied ML to improve replenishment in fast-changing as well as chaotic SC. A literature review by Kamilaris, Kartakoullis, and Prenafeta-Boldú (2017) for the application and benefits of big data in high-velocity market agriculture shares these findings. These examples suggest that AI-enabled detection of dynamics in the environment will be faster and more precise than simple routines or experiential knowledge so that adherence to deadlines may be even better. Nevertheless, it is supposed that engaging in testing and prototyping actions to learn quickly to create new knowledge (Eisenhardt & Martin, 2000, p. 1112) cannot be avoided even with AI-enabled analytics. However, prototyping and early testing to quickly gain new knowledge might be more precise, even earlier and with reduced TC because the number of scenarios might be reduced. Almost two decades after Eisenhardt and Martin (2000, p. 1112) have argued managers' emotional inability to cope with uncertainty because they primarily refer to their existing knowledge from the past, the availability of permanent analytics of real-time information is expected to significantly strengthen forecast accuracy. Thus, it is expected that AI-based learning mechanisms will improve the evolution of dynamic capabilities so that also high-velocity markets can be faced with more stable and better analytics capabilities. These AI-enabled improved dynamic capabilities allow for forecast-driven approach in the SC.

7.7.5 Forecast-Driven Supply Chains Create Value Through Managing Innovative Products with Efficiency Instruments

The PPIM from Table 5-8 demonstrates that the experts of the Delphi Study expect that AI technologies will most probably contribute to SC planning processes to reduce SC costs so that SC efficiency is fostered. Even in the delivery process, AI is supposed to significantly reduce SC cost compared to the rating for increasing flexibility and SC responsiveness. Fisher (1997) distinguishes functional and innovative products in regard to the accuracy of demand predictability. The demand of functional products can be predicted very accurately whereas the demand of innovative products is only predictable with certain limitations. For that reason Fisher (1997) proposes SC segmentation principles which allow to apply a cost leadership strategy for functional products flows to focus on SC efficiency whereas a responsive SC should allow for appropriate management of innovative products flows (see Section 2.2 and Subsection 5.3.1).

Fisher (1997) informs about a contribution margin of functional products of between 5% to 20% whereas the contribution margin of innovative products is about 20% to 60%. The main reason identified by Fisher (1997) is that functional products are faced with strong price pressure due to competitive situation whereas innovative products gain early-mover margins. The average margin of error in forecast for functional products is located with 10%, for innovative products between 40% to 100%. Stockout rate for functional products lies between 1% and 2%, for innovative products between 10% and 40%. With increasing new product variants (see case studies of Ben & Jerry's, Mrs. Fields, and Starbucks informed by Fisher (1997, p. 2 et seq.)) the SC deals with kinds of innovative products. For that reason, the experts of the Delphi Study inform that "if *AI predicts consumer demand for a new product, then the manufacturer will be able to ramp up production with reasonable certainty […]* ". Having earlier options by stable and reliable forecasting based on AI abilities to recognise patterns of consumer behaviours on innovative products, might keep a higher contribution margin not only by later competitive pressure on pricing but additionally through efficiency gains. The SC can reap the benefits of reduced inventory, less risk from out-of-stocks, and the average margin of forecast errors for functional products. This approach allows the SC to manage innovative products as a functional one on an earlier stage and to apply efficiency increasing instruments such as lean and automated processes during autonomous SC planning to leverage economies of scale by expanding market share through the early interplay of marketing campaigns and price reductions. SC that efficiently manage functional products have a higher impact on tangible VC than SC that are necessary to manage innovative products. Thus, it is beneficial for tangible VC to apply AI to increase the percentage of functional products of the product portfolio. Therefore, using AI in forecasting is to switch initially innovative products to functional products so that instruments of

SC efficiency can be applied. Instead of applying demand-driven SC instruments to innovative products to mitigate demand uncertainty at the expense of delivery time, it makes sense to adopt a forecast-driven approach as early as possible.

7.7.6 Self-learning Ability of AI is the Value Driver for Forecast-driven Supply Chains

The collected UC/APP from the Delphi Study revolve around the technological aspects of supervised or semi-supervised training, deep learning, ML, learning of typical *"repetitive, but more complex behaviours to improve predictive analytics*" and data modelling. Experts of the Delphi Study highlight the "*concept of computer learning to make sense of patterns from data analysis* ..." that is "*... closely linked to big data trend*". With "*focus on algorithm instead of data*" and the developing of algorithms "*without necessarily being programmed [...]*", the experts of the Delphi Study lead the discussion about value drivers in the direction of the self-learning abilities of AI. Elia et al. (2020) confirm that successfully applying the self-learning ability of AI in the field of forecasting improves VC through improved market responsiveness by enhancing the ability to respond quickly to market needs. Both Elia et al. (2020) as well as Burkhardt (2017) emphasise that big data is the prerequisite to leverage the full self-learning potential of AI in the field of improving accuracy of demand forecast. However, as the experts of the Delphi Study propose, it is not only the access to these data volume which might improve forecast accuracy but also the ability to interpret data correctly and to provide appropriate information to other agents. CIB-analysis shows that AI-enabled forecasting and widely adopted autonomous SC planning based on the multi-agent system architecture represent a strong CF to enable dynamic capabilities to fully leverage competitive advantages from self-learning ability of AI. Widely adopted autonomous SC planning, including all relevant SC entities allows for permanent exchange and update of real-time data.

It could be said that it is enough to learn structures and correlations once from this enormous amount of data in order to gain new insights into demand patterns. As a consequence, one time training might be sufficient to enable AI applications to produce correct results. But as the UC/APP from the Delphi Study outline, the key benefit of interpreting big data by self-learning AI applications is the ability to permanently adjust former results due to updated data input. Vallverdú (2014) confirms the Delphi Study findings that self-learning is the ability of AI to recognise patterns, learn from data, and become more intelligent over time. Self-learning in the narrow sense is a learning with no external rewards and no external teacher advice (Bozinovski, 1982). However, for this study it is useful to follow the experts of the Delphi Study to apply a broader view on self-learning comprising learning approaches such as supervised learning, unsupervised learning, semi-supervised learning and reinforcement learning. All these methods are used to train algorithms which are applied e.g., in ANN with the target to make their applications more intelligent. Self-learning AI improves the ability of an SC to identify best-fitting resources in strategic factor markets by replacing or complementing existing resources with its pattern recognition ability. Likewise, self-learning ability of AI improves the ability of managers to identify changes in the consumer market at the earliest possible stage (Kreutzer & Sirrenberg, 2019, p. 131 et seqq.). In conclusion, self-learning ability of AI in combination with big data ensures the appropriate forecast accuracy to support the decision of a paradigm change to a forecast-driven SC.

7.7.7 Self-learning Ability of AI Creates Efficiency Gains in Forecast-driven Supply Chains

The data-driven Type 4 collaboration will significantly change the nature of cooperation as depicted in Table 7-13. The substantially increasing share of Type 4 collaboration shown in

Table 7-9 is accompanied by an increasing frequency of applying AI, not only but as argued in Section 7.6.5 to a significant extent at the cost of human experts.

Table 7-13: Comparison of Type 1 and Type 4 Collaboration Activities

Activities	Type 1 (Pure human expert subsystem)	Type 4 (Pure technical subsystem)
Predict	Experience based	Detect data patterns
Collaborate	Verbal/written communication	Coordinate/inform with data
Operate	Perceive objects with human senses	Identify objects with data
Decide	Bounded-rational, based on a mix of intuition and preferences	Rational, purely based on data
Organise labour	Enrich, enlarge, motivate	Disintegrate to smallest Decision-Making Units (DMU)

A remarkable efficiency gain due to self-learning ability of AI for the entire SC is expected. Some problems with human beings' learning are avoided to which Lamming et al. (2015) refer such as motivation problem, challenge problem, or reinforcement/reward problem. These learning problems often increase TC or process cost and hence negatively impact tangible value. Therefore, it is comprehensible that experts of the Delphi Study are of the opinion that AI-enabled descriptors decrease TC and improve SC efficiency. Other inherent problems of the individual learning human being that creates TC or process cost such as the elicitation problem, completion problem, parochial/not invented here problem or sharing problem (Lamming et al., 2015) are not related to the self-learning process of AI applications. Once AI applications are installed and prepared for self-learning, the application permanently collects and shares information and knowledge. This relatively automated procedure reduces process costs which makes it comprehensible that the Delphi Study rating of AI improvements results in lower activity time and lower SC cost (see Table 5-8). Nevertheless, challenges such as elicitation problems are a matter of the organisation which is interested in knowledge building. Problems of that kind are relocated from the individual learning subsystem to the human beings organising learning processes so that the impact on tangible VC is unclear. Other problems with self-learning AI applications occur mainly in regard to training approach of the algorithm and the applied training data (bias in – bias out (Kreutzer & Sirrenberg, 2019, p. 10)). However, this concern is countered by the quality of the results of correctly trained AI applications. It is proved by multiple use cases that results of AI-enabled expert systems exceed the quality of the results of human experts (Chui et al., 2018; Kreutzer & Sirrenberg, 2019). The ability of AI to add new knowledge to existing knowledge (Daspit et al., 2016) is proved to be significantly more efficient than that of human experts e.g. in case of pattern recognition (Kreutzer & Sirrenberg, 2019; Schmidhuber, 2015). The fact that there is no need to codify this implicitly applied knowledge to make it valuable increases the efficiency of the AI application as informed by the Delphi Study result. The default probability of AI learning systems compared to human beings (sickness, leave the company) is expected to be lower and underpins the CIB-analysis results in regard to the impact of AI on improving SC efficiency. The results of self-learning AI applications are explored and applied by human experts. These activities contribute to the individual learning process of human agents so that both AI-enabled agents and human agents are qualified to learn. Thus, the learning process of both kind of agents contributes to efficiency improvement and thus to VC in the SC.

7.7.8 Theoretical Meaning and Practical Implications

The proposition proposes a rethinking of existing SC doctrines with substantial impact on implemented SC mechanisms in regard to IT system architectures, information exchange, qualification of employees, and process organisation. The proposition to bet on a forecast-driven SC as the strongest competitive advantage in future SC is of high theoretical meaning because it claims for a substantial shift in the former argumentation of SC theories. The author of this thesis considers this proposition as thoroughly discussed with a comprehensible derivation of the arguments. However, at the time of the thesis' completion, there are still insufficient case studies that demonstrate the AI capability of pattern recognition at this high-sophisticated level. At this point, the argument is vulnerable. On the one hand, this vulnerability creates opportunities for further research. On the other hand, it might be a sufficiently convincing starting point for SC executives to take the early mover advantage of preparing the necessary activities for exploring the feasibility of the forecast-driven approach for their individual SC.

7.8 Proposition 5: AI Value Creation Requires the Optimisation of Inter-company Collaboration in Future Supply Chains

7.8.1 Description of the Proposition

CIB-analysis reveals that in autonomous, decentralised, and process-oriented settings, the future SC system achieves the best performance, if all relevant process and structure elements in one SC are synchronised to each other and a commonly accepted AI standard for the entire SC is available. Customer-orientation is a strong integrative element and will serve more and more as a coordination instrument for inter-organisational collaboration of autonomous subsystems because decentral decision-making units act and react primarily autonomously, without a central instance to manage and coordinate. Thus, the agents need a common goal to which all data is gathered, explored, and retrieved for further use in cascading approach from process to process. Explained from a technical viewpoint, the parameters of the ANN-related application must be set so that they focus on data, which provide output related to the needs of the following process and not for the needs of the functional area the AI applications are used. Therefore, CIB-analysis figures out that process orientation fosters all three SC performance indicators (+1). To achieve the foundation for

VC with AI-enabled SC descriptors, a cluster-oriented inter-company process organisation is recommended.

7.8.2 Importance of the Discussion

Synchronising elements of inter-company process organisation is the normative part of the theory building in this thesis. This discussion underpins the importance to harmonise dynamic and ordinary capabilities through exploring how to improve absorptive capacity of the SC so that the theory about VC through AI has a practical use. The discussion explores the reasons for the feasibility of this proposition and argues the benefits of the substantial shift in the collaboration of SC entities at the interface between companies. It is of high importance that the reasoning for this significant shift in organising a future SC is well-understood so that SC executives believe in the benefits of the effort that must be undertaken.

7.8.3 Value Creation Through AI Requires Synchronisation of Complementary SC Descriptors

Business process re-engineering initiated in the 1990s (Hammer & Champy, 1993) to implement end-to-end business process thinking, brought verifiable intra-organisational performance improvement. The key argument of this concept that the alignment of all activities towards customer requirements improves agility and reduces delivery time, so that services are more efficient, effective and also worthwhile for inter-organisational performance improvement (Wattky & Neubert, 2005). Parallelly, a trend towards more personal responsibility became visible in the 1990s accompanied by increasing degree of freedom to make decisions on an expert level to increase performance through improved employees' motivation (Aghion & Tirole, 1997) and to avoid inefficient vertical communication with functional managers. With the IoT in the 2010s, a data-driven business model approach has been initiated and decentral coordination by integrated autonomous devices occurred (K. Bauer et al., 2020; Winchcomb, Massey, & Beastall, 2017). Although all three concepts have proved performance improvements, process orientation, decision autonomy, and decentral coordination have often been observed as isolated instruments, independently implemented with different individual objectives. However, the CIB-analysis resulting in the positive scenario shows a strong interdependency between these descriptor variants so that it is necessary to synchronise these concepts to each other. Primarily Type 3 and 4 collaboration enforce the data-driven approach of the IoT and considerably increases the aspect of autonomous decision-making, compared to the current software-hardware coordination. Parallelly, the initial target of employee motivation moves into the background. The sheer number of autonomous decision-making units of Type 4 collaboration makes the concept of decentral coordination indispensable, not only for horizontal communication between AI applications on operational level as in current IoT, but also for vertical communication from and to the integrating platform and adds the inter-organisational aspect. Process orientation aligns AI-enabled data collection, data preparation, evaluation of information, and knowledge sharing with full focus on end consumer needs and keeps the SC lean and agile.

The positive scenario of the CIB-analysis also provides widely adopted and fully implemented AI-enabled descriptors. A recent survey of Mikalef and Gupta (2021) confirms that complementary resources such as inter-dependent coordination, organisational change capacity, data, and technology jointly contribute to the emergence of an overall AI capability. However, it cannot be clearly distinguished to what extent AI-enabled descriptors or other descriptors impact VC with their contribution to positive SC performance. With the purpose to clarify if the non-AI enabled descriptor variants alone allows for relatively high SC performance, the impact balance sheet of the ScenarioWizard is adjusted accordingly (see Appendix I.). Table 7-14 shows that the impact on SC performance is relatively low if the SC is not supported by widely adopted and fully implemented variants for all AI-supported descriptors. The AI-enabled descriptors are manually adjusted to configure the scenario for the purpose to analyse the impact balance of the SC performance descriptors. (For impact balance see Section 6.2). Columns “Selected variant” and “Impact balance selected variant” show that the system prefers the SC performance descriptor variants with the relatively low performance in case that AI-enabled descriptors are set on the disadvantageous variant. Compared to columns “Initial variant” and “Initial impact balance positive scenario”, which contain the SC performance figures from the initial positive scenario with widely adopted AI-enabled descriptors, SC efficiency and SC responsiveness is considerably lower, TC are strongly decreasing instead of increasing. Conclusion is that SC efficiency and SC responsiveness is fostered by decision autonomy, decentral coordination, and process orientation but the contribution to SC performance improvement without support of AI is relatively low. This relatively low SC performance goes hand in hand with increasing TC what reduces the overall SC performance. These three descriptor variants only weakly promote SC performance. The process and organisational as well as the AI-related SC descriptors are complementarily interlinked and need to be synchronised. Thus, the discussion for the need of changing inter-company process organisation should be opened.

Table 7-14: Low AI Support Embedded in Descriptor Variants of Scenario with Positive Impact on SC

Attribute	**Descriptors**	**Selected variant**	**Impact balance selected variant**	**Initial variant**	**Initial impact balance positive variant**
SC performance	SC efficiency	Relatively low	-2	Relatively high	4
	SC responsiveness	Relatively low	5	Relatively high	11
	Transaction cost	Increasing	7	Decreasing	6

7.8.4 Need for Changing Inter-company Process Organisation in Future Supply Chains

A SC is fragmented and VC is split up between multiple companies (Döpgen & Göpfert, 2019, p. 307). The nearly autonomous vertical collaboration between decentral AI applications and central (Cloud-) platform(s) only requires supervisory activities by human experts. The tremendous replacement of human decision makers by AI applications will significantly change the process of decision-making, primarily in operational processes but at the same time also improve ordinary capabilities of the SC. This reasoning makes it comprehensible, why CIB-analysis reveals a strong impediment in further applying centralised coordination (+2 on low efficiency and +1 on low responsiveness) and cumbersome functional orientation (-2 on both high responsiveness and high efficiency, and -2 on autonomous decision-making). Dynamic capabilities of the SC are mostly related to Type 2 collaboration and partly to Type 3 collaboration (see Table 7-2). Dynamic capabilities are strongly related to R&D activities as well as to decisions in regard to the business model of SC entities. R&D activities depend on creative thinking and associated methods such as brainstorming, design thinking, or ideation (2006; Eisenhardt & Martin, 2000). Adjustments of business models rely on data from the SC environment. These environmental data are collected from multiple global data sources and well-prepared by AI applications. Both activities are only supported but not primarily led by AI so that human experts continue to play an important role in coordination and content. Thus, Type 2 and Type 3 collaboration rely on process organisations that strengthen cooperation between human experts and that enables orientation towards a common goal. Aghajani, Amin, and Abasgholipour (2014) empirically specify that ease of mutual communication, accompanied by mutual trust, mutual interests, and group thinking are important variables to improve inter-organisational coordination between experts of the same level. Davenport (1993) empirically prove that process orientation reduces parochial thinking and brings more action orientation that is permitted by functional structure. This action orientation in inter-organisational collaboration leads to a direct horizontal communication and decision-making on experts' level from different SC entities in contrast to functional structure in which communication and decision-making goes vertically to the functional head of each organisation unit. This kind of vertical communication strongly impedes the fast and direct exchange of data and information (Hülsmann, Grapp, & Li, 2008) between AI-enabled systems, whereas process orientation requires that experts focus on the common process goal which does not differ between functions, so that the overall performance of the collaboration increases (Wollersheim, Leyer, & Spörrle, 2016, p. 147 et seqq). The positive impact on the SC of process orientation and decentral coordination is confirmed by the results of the CIB-analysis. Decentral coordination promotes decision autonomy (+2), process orientation promotes all three SC performance indicators (+1) and fosters decision autonomy (+2). Miri-Lavassani and Movahedi (2018) argue that a business process goes beyond connecting entities and that this process illustrates a series of actions or activities from beginning to an end for directly or indirectly achieving a common goal. However, the principle of connectivity says that internal relations are more intensive than external relations (Goepfert, 2006, p. 72) due to tighter and more binding commitments between principal and agents in hierarchical relationships (Williamson, 1975). Nevertheless, process-oriented inter-organisational cooperation necessitates that external relations are at least comparably strong as internal relations to fully leverage SC mechanisms towards a common goal because knowledge work, which contributes to problem solving is not centralised in one company but disintegrated in smallest decision-making units across the entire SC (Getto, 2016). Tight and stable inter-organisational interaction especially within Type 4 collaboration let the boarders blur between market mechanisms and firm hierarchy through usage of same data lake, same (Cloud-) platform consolidating and sharing information, and the need of short response times to react on disruption. Agents of SC entities interact in a quasi-firm-hierarchy but in legally independent companies. Due to significantly improved transparency through commonly and mutually shared data pools, and joint investments in AI applications, teams from different firms at the interface between two firms especially in operational processes, are welded together more strongly. This tight and daily collaboration builds an informal common culture at both individual and organisational levels. An inter-company process organisation is necessary which fosters the formal building of a common culture because common culture fosters data-driven knowledge creation and AI-enabled SC learning to ensure competitive advantages. The principle of Nonaka (1994) is that knowledge creation within an organisation is initiated by the enlargement of an individual's knowledge is applied on inter-organisational SC mechanisms. It has been stated that these individual perspectives of experts from different SC entities remain personal unless they are articulated and amplified through social interaction. The SC is a mechanism used to coordinate social interaction associated with distributed entities (Al-mutawah et al., 2009). It is suggested to consider collaboration between AI applications and human experts in Type 2, 3, and 4 collaboration as social interactions. Social interaction is a process of mutual interaction (Bergius, 2019) and AI agents are active parts of this process. Firms accumulate knowledge over time learning from their members (Grant, 1996). So do SC entities and thus the entire SC. The SC learns from the agents of the subsystems which are spread across different SC entities. Yang and Xu (2019) identify through their literature review that relational characteristics that lead to greater collaboration among SC partners lead to greater learning. Willis et al. (2016) state that SC learning positively correlates with SC performance flexibility and that SC integration positively mediates this correlation. In case of Type 2 and 3 collaborations, the cooperation happens between human experts and AI applications. In case of Type 4 collaboration, only AI applications collaborate with each other. The inter-company process organisation sought must therefore foster flexibility, integration and learning of all collaboration types.

7.8.5 Recommendation of an Inter-company Process Organisation to Improve Value Creation in Future Supply Chains

The aforementioned justification on why the process-orientation, decentral coordination, and autonomous decision-making proposed by the CF have positive impact on the SC leads to the questions what inter-company process organisation efficiently empowers autonomous AI-enabled processes, best supports knowledge building to detect changes in the environment, enables agents of respective subsystems to apply creative processes to develop appropriate measure for the business model, and provides sufficient flexibility to implement adjustments in the operating model identified by dynamic capabilities. In other words, an inter-company process organisation has to be found which leverages the full potential of the different types of collaboration between human experts and AI applications in the SC.

Process-orientation clusters the SC along inter-organisational business processes whereas all clusters are oriented to one process goal. Each cluster consists of sub-processes which contain activities. These activities represent a sequence which delivers an outcome for the sub-process. The sub-process again serves as input for a subsequent sub-process. Each cluster represents a sub-system of the SC. Each sub-system is self-organised to an appropriate extent. This self-organisation is facilitated through decentral coordination respectively through autonomous decision-making of and within each cluster. In general, this autonomous decision-making is independent from the constitution of the agent be it a human expert or an AI application. From organisational aspect, each cluster should be composed so that it can be adjusted or even substituted in case of need due to SC learning. The effectiveness of an adjustment depends on the absorptive capacity of the SC. This dynamic capability acquires, assimilates, transforms, and exploits new knowledge (Daspit et al., 2016) with the purpose to improve ordinary capability by re-organising the set of resources of clusters so that a competitive advantage can be achieved. The idea to organise the inter-organisational sub-processes in clusters is derived from Daeberitz (2019). In contrast to the general characteristic of geographical proximity, clusters as understood in this study the proximity of the clusters is virtually established. Clusters are defined as connected through vertical and horizontal relationships (Daeberitz, 2019, p. 53 et seqq.). Instead of using the clusters with the macroeconomic purpose the term cluster is applied for organisational purposes. In contrast to Daeberitz (2019), vertical perspective refers to the hierarchy between operational experts, middle and top management. Horizontal perspective refers to the material, information, and finance flow between suppliers, focal companies and customers. However, the original purpose of clusters such as exchange of resources or one-sided transfer of resources, cost-effective adaptation of other firm's solutions, reduced risk of know-how loss, facilitating trust building or increasing innovation potential (Daeberitz, 2019, p. 79 et seq.) is still useful for the interpretation of clusters applied in this thesis. The reason for this cluster-building lies in the agility of its exchangeability in case of business model adjustment. As illustrated in Figure 7-4 inter-organisational cluster-building is plausible to consolidate dynamic (cluster 1) as well as ordinary capabilities (cluster 2). Each cluster is coordinated by a cluster owner. This cluster owner should not be interpreted as a hierarchical manager but more in the sense of the interpretation of Nonaka (1994) as the role of middle-up-down management. This leadership style takes all members as important actors who work together horizontally and vertically. It facilitates the parallel knowledge creation process taking place simultaneously at top, middle, and lower levels between human experts and/or AI applications. Originally introduced to manage knowledge creation between top, middle, and lower management, this study considers the Middle-Up-down model of Nonaka (1994) to be used for knowledge distribution in the cluster-oriented concept, either through communication or through analysing available data bases. Referring to Getto (2016) and Christopher (2005, p. 291 et seq.) such middle management claims for an ideal skill profile consisting of managers merging general business knowledge, technological breadth, social skills and technological and functional depth. Middle managers synthesise the tacit knowledge of both frontline agents (human experts and AI applications) and top management, make it explicit when necessary, and initiate to incorporate it into new technologies and products (Nonaka, 1994). Clusters can be organised according to the characteristics of their inherent process interdependencies as pooled, sequential, reciprocal or team interdependent (Grant, 1996). Cluster 1 in Figure 7-4 representing an R&D process, is team-and project organised (Getto, 2016) whereas cluster 2 is more characterised through sequential and pooled interdependencies.

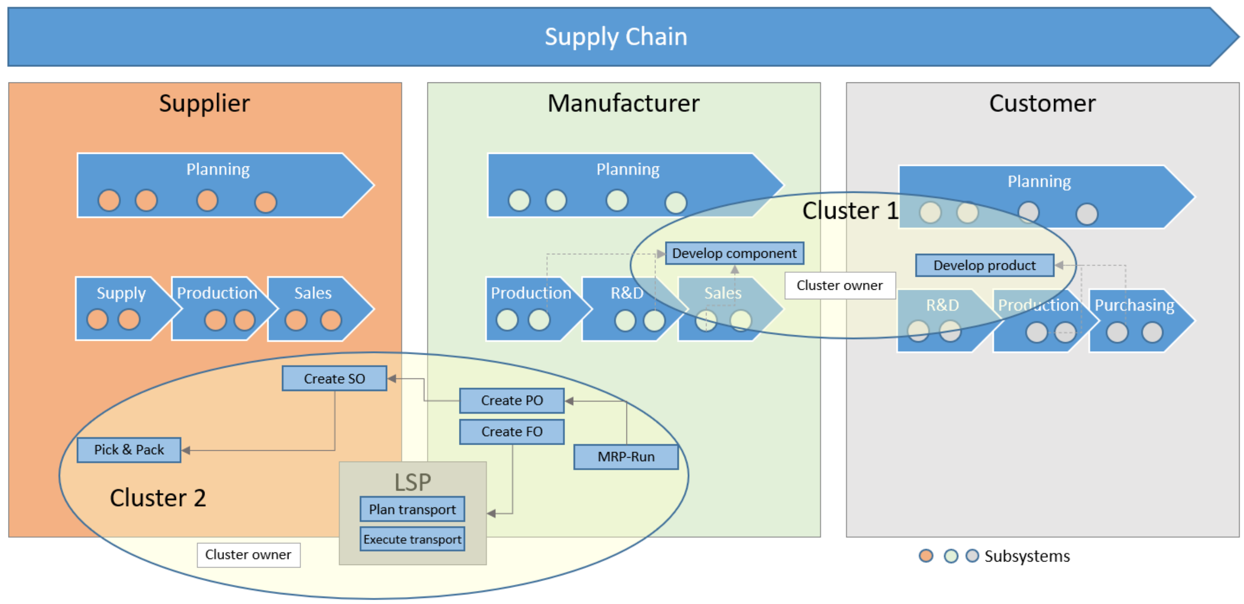


Figure 7-4: Exemplary Illustration of Inter-Organisational Cluster-Building

With this inter-organisational setup, the positive scenario enables flexible structure with permeable boundaries due to process orientation allowing to adjust actions of teams and team structure to the needs of the process instead of promoting goals per function (Wollersheim et al., 2016). Since all activities are process-goal-oriented, the ordinary capabilities can be flexibly adjusted by replacement of single resources, groups of resources or even entire clusters. Referring to Wollersheim et al. (2016), process-orientation makes the employee feeling more responsible for the solution of his task because he is aware of the influence of his activities on the process steps that follow. Due to the fact that process orientation ensures strong responsibility of each employee to obtain the process goal, self-organisation is expected and due to autonomous decision-making also enabled. A coordinating cluster-responsibility supports the process-oriented goal achievement. These entities are embedded in a hierarchically organised labour division which provides the framework for strategic decision-making. Although this future inter-company process organisation is inspired by Nonaka (1994), the underlying concept of a hypertext database is considered as outdated and replaced by the concept of an AI-enabled

SC platform. The role of the cluster-manager is more related to the line of reasoning of Surana et al. (2005) and Choi et al. (2001) that requires an appropriate balance of how much to control, and how much to let emerge. Especially in case of prevailing AI subsystems, a more supervisory interpretation of the role is proposed.

7.8.6 Theoretical Meaning and Practical Implications

The proposition summarises the weaknesses of implemented process organisations and thus reveals that the academic discussions must emphasise the benefits of the recommended changes. The discussion brings together complementary elements of an SC that have not yet been explored in a CF so that academics and practitioners gain a better understanding of phenomena under investigation. Particularly the concept of clusters at the interfaces between SC entities is of high theoretical meaning. It is the first time that VC through AI in the SC is argued in regard to related organisational requirements. Therefore, the theoretical meaning is high. The concept is not entirely proven by the body of literature and thus needs additional research to confirm the correctness of the value expected. The practical implication is relatively high and strongly related to the academic discussion. The recommendations and the reasoning about inter-company collaboration increases executives' implementation power and the potential to gain competitive advantages.

7.9 Proposition 6: AI Controls Existing Supply Chain Equilibria but Only Indirectly Supports Creating New Supply Chain Structures

7.9.1 Description of the Proposition

After having defined the descriptors of the CF, the applied instruments such as CIB-analysis and scenario development requires a static composition of the structure of the established system. It is not intended by the methodology to change or even add new structural elements. However, CAS theory provides the reasoning that the behaviour of and in SC systems can be discussed with the assumptions that agents are adaptive towards new situations and that the concept of emergence can be applied. However, it is argued that AI applications are denied to directly contribute to self-organisation but support human experts in doing so. This limited AI ability affects the establishing of equilibria in the SC through positive feedback loops. The contribution of AI is presented, and it is argued how AI abilities nevertheless ensure competitive advantages.

7.9.2 Importance of the Discussion

The concept of emergence and the impact of feedback loops to establish SC equilibria are key elements of system theory which are important in the explanatory scope of VC through AI. Thus, the discussion is important for arguing how to achieve competitive advantages by creating value in the quasi-equilibrium of all stable situations. It is found out with this discussion that AI is only indirectly supportive for creating new structures in the SC. This finding is not prevailing in the reviewed literature. Thus, it is important that the reasoning is comprehensible and convincing to allow for reliable new knowledge. From theoretical perspective, this discussion argues that human experts are the agents that directly create adaptiveness in the complex system of the SC. This viewpoint substantially impacts the theory building for VC through AI, and therefore must be well-derived with this discussion.

7.9.3 AI Applications Enable Self-Organisation by Adaptive Human Agents in the Supply Chain but are Denied to Directly Create Value Through the Concept of Emergence

Emergence is the formation of new characteristics or structures of a SC system as consequence of the interplay of system elements not directly described by the defining constraints and instantaneous forces that control the system (Pathak & Dilts, 2002; Surana et al., 2005). Self-organisation is a process where some form of overall order arises out of the local interactions between parts of an initially disordered system (Heylighen, 2001). Coming from the cybernetics, self-organisation refers to closed systems whereas the concept of emergence refers to open systems. Both concepts are applied in this thesis when negative and positive feedback loop is discussed. It has to be clarified to what extent the analysis of the impact of AI on the established SC system is limited by the static CF when it comes to dynamic changes in the structure of the SC system. Based on the initial argumentation of Surana et al. (2005) in regard to emergence further thoughts are put into the question whether AI impacts how SC with complex process organisation and function organisation structure arise and develop. AI applications support emergence, in the SC but are not causally responsible for new SC structures and adjusted characteristics. This means that AI does not create new structures in the SC through collective behaviour but only informs human experts that organisational market patterns or patterns of consumer behaviours change. For a better understanding of this proposition, the findings of Pathak and Dilts (2002) are consulted. Pathak and Dilts (2002) apply a simulation model without pre-defined structure to show how SC are formed and how they evolve over a period of time. The simulation shows that SC self-organise an additional structural layer of subcontractors without central coordination as a reaction to environmental dynamics. This additional structure represents additional subsystems in the SC system. These subsystems arise when environmental demand exceeds production capacity of first tier in the SC. The corresponding SC reality is that agents of existing subsystems react on environmental dynamics and decide in case of capacity restrictions to subcontract for additional production capacity. It is difficult to imagine applications of weak AI generating a new layer of subsystems without any involvement of human experts negotiating contracts and defining cooperation rules. Meanwhile, it is conceivable that AI applications subcontract capacities to existing layers of subsystems with contracts already negotiated and rules of cooperation already defined. This study is subject to the assumption of weak AI, and therefore AI is denied the ability of directly contributing to self-organisation of the SC. This conclusion should not be confused with the understanding of AI as disruptive technology (Vyas, 2016). AI as technology changes the characteristics of SC by replacing other technologies and by making SC more efficient and effective. The installation of a SC-wide AI platform with Type 4 collaboration will build a new structure in the SC and this new structure will give the SC new structural characteristics. It is a useful discussion if the installation of a central AI-platform is a controlled activity by dependent agents or if it arises due to the collective behaviour of independent agents aiming independently from each other for the same objective of sustainable competitive advantages. The hypothesis of a controlled new structure is supported by the observation of current SC, mainly in the automotive industry, where focal companies such as Volkswagen have started to implement comparable platforms with the key target to harmonize and consolidate all data in real-time from the shopfloor of all SC entities to generate KPI of any kind to coordinate and manage the SC (Anonym, 2019c). Self-learning AI is primarily applied for data analytics purposes. The target of such platforms is to become faster, more transparent, and safer (Anonym, 2019c). With AI to support these targets, the expectation of the decision-makers is to create value. Such a platform changes the structural characteristics of a SC through consolidating data-driven collaboration of multiple subsystems. To decide whether a platform is implemented with central control or through emergence, relevant SC characteristics are evaluated. Systems are characterised by complex behaviours that arise as the result of nonlinear spatio-temporal interactions among a large number of components or subsystems. This interaction happens during AI platform implementation and application. But the initial idea and initial provision of the platform is given by central control of the focal company. The SC does not act as a social organisation in which agents independently develop patterns of behaviour within given rules. The focal company coordinates the integration of other agents to the platform. Referring to the line of argumentation of Surana et al. (2005), emergence is seen when new structures arise from highly structured collective behaviour over time from the interaction of simple subsystems without any centralised control. It is still proposed to consider the focal company as the central control. This viewpoint fits better to what CIB-analysis reveals. There is the need of a central coordinator to achieve the turnaround from a weak SC to a relatively high-performing SC.

But what if the observer takes a bird's eye view from a very high altitude, analysing activities in different SC? Then, the hustle and bustle of agents within dependent subsystems in independent and parallel SC is similar to the behaviour initiated by swarm intelligence and stigmergy mechanisms (Soni et al., 2019; Susi & Ziemke, 2001). However, even then the activities creating new structures occur through the behaviour of the human experts and not through the behaviour of AI subsystems.

Satoh (2013) describe bio-inspired self-adaptive agents in distributed systems which emulate cellular differentiation ability of multicellular organisms in nature, by which a less specialised cell develops or matures to possess a more distinct form and function. Applied to self-adaptive agents, agents are differentiated according to demands from other agents and are able to delegate functions which may be initially provided by them, to other agents that can provide the functions. The agents self-organise these adaptations of characteristics of involved agents. However, it seems that the structure and the number of agents is pre-defined and only the deployment of functions of each agent adapts in regard to the demand occurring. A new structure e.g. a new layer in the SC does not emerge. Other literature providing concepts of emergence purely based on collaboration between AI agents have not been found. As a conclusion, it is hard to imagine from the belief in weak AI that AI will build the ability to foster emergence and therefore, direct VC is not expected from emergence through AI. Thus, applying the methodology to create a static CF with a stable network of descriptors is not limiting for the scope of this thesis.

7.9.4 The Contribution of AI to Enable Supply Chain Equilibria

Prerequisite of the CF is the coevolution between the SC system and its environment. The interplay of the SC system elements is required to remain stable despite of changes in the environment. However, optima and steady states as a form of overall order are at best, short-lived in CAS so that subsystems of the SC are most of the time in a state of disorder due to turbulent environment (Gell-Mann, 1994a; Holland, 2006). CIB-analysis underpins this understanding of a CAS as illustrated in Table 6-8 and Table 6-9. Only a small number of all combinations of SC performance indicators leads to an unambiguous equilibrium of the SC system and thus to potential sustainable competitive advantages. The environment of a SC is represented by the needs of the consumer market and by the technological changes in the factor market. Although a CAS such as any dynamic system automatically evolves towards a state of equilibrium through self-organisation (Ashby, 1956), the application of AI in situations of disorder allows to provide competitive advantages for the SC. As already argued in Section 7.9.3, AI-enabled agents as part of collaborating subsystems, are not able to actively create new structures in a SC system. This means that AI applications are only able to support positive feedback loops as described in Section 2.4 but the establishing of a new equilibrium emerging from behaviour of stigmergy in SC systems needs the active contribution of human experts. The question raises to what extent AI contributes to negative feedback loop which controls the SC to stabilise the SC system in the initial stable quasi-equilibrium (Choi et al., 2001). An equilibrium can be described as an attractor in a basin of surrounding states to which the attractor represents a stable state of the system (Ashby, 1956; Levy, 2000). AI applications foster detecting the structures which lead to an equilibrium. However, after having detected these structures, the rules and regulations (Choi et al., 2001) given in the SC to which the AI applications are trained to allow these AI applications to recommend or execute only measures which lead the system back to the former order of the system. This re-establishing of the former equilibrium happens if the AI applications are focused on efficiency targets. SC applying AI in negative feedback loops contribute to reduce TC, increase customer relationship through improved customer services such as on-time deliveries and improved productivity. Due to a relatively high number of these rationally decision-making agents permanently applying big data analytics and improved knowledge through self-learning, the SC equilibrium will be achieved earlier compared to SC not applying AI. Therefore, AI creates value through causing earlier and more frequently equilibria in the SC.

However, new technologies in the factor market or changing consumer behaviours that require adaptation of the range of products or services call for positive feedback loops (see Section 2.4), to establish other equilibria than the existing ones to achieve sustainable competitive advantages and long-term survival of the SC. Adaptive agents are constantly changing their inner properties to better fit in changing environments (Strogatz, 1995) due to a strong desire to survive (Choi et al., 2001, p. 359; Gell-Mann, 1994a, p. 21). In a SC system, survival means that the adaptive agents of the SC must coevolve with the turbulent environment to achieve sustainable competitive advantages (Gell-Mann, 1994a). AI increases the adaptiveness of subsystems by providing covered insights to changing patterns in the environment. Human experts collaborating with AI agents become more adaptive through these insights and trough proposals for action by scenario simulations of prescriptive analytics. From the perspective of swarm intelligence, the SC system due to its capability of self-organisation moves to a new equilibrium. The value created by AI is either that a new equilibrium is faster established than without AI support or that of a new equilibrium at all. Thus, AI either accelerates the activity of finding a new order or even ensures survival of the SC. If an equilibrium is not achieved, the SC system not only remains in a state of disorder but will fail because it produces past the market. Thus, AI creates value through effectively supporting the establishing SC equilibria.

Strogatz (1995) refers with the concept of adaptiveness of inner properties to living organisms and natural systems. Satoh (2013) provides a concept of self-adaptive AI-enabled agents in distributed systems which balance the demand between the capacity of available agents and their functionalities to achieve an equilibrium between workload and capacity. This concept leads to the belief that subsystems of Type 4 collaboration also have the ability to create value through establishing SC equilibria. However, the concept focusses on SC efficiency and moves back between order and disorder to the former equilibrium but is not able to contribute to positive feedback loops.

Choi et al. (2001, p. 364 et seqq.) underpin the importance of knowing when to control a SC in a deterministic manner through negative feedback and when to let it emerge by positive feedback. AI applications are supportive to managers to strike an appropriate equilibrium by strengthen dynamic capabilities. However, what if managers are reluctant to these insights by AI applications? The question should be asked differently: In what cases might it be possible that managers stick too long to negative feedback loop and are not willing to let the SC strive for a new equilibrium? The answer is already given by the CIB-analysis and the resulting scenarios. Scenarios which restrict self-organisation through low decision autonomy, central coordination and functional orientation give managers a strong authority and risk to restrict behaviour of stigmergy. This is difficult because CAS system elements exist in a quasi-equilibrium (Surana et al., 2005) which emphasises the importance of self-organisation. The concept of the edge-of-chaos (Schwartz, 2014) states that a quasi-equilibrium is positioned between order and disorder. Physics has shown that edge of chaos is the optimal setting for control of systems with positive and negative feedback processes (Pierre & Hübler, 1994). Feigenbaum (1976) mathematically illustrated that a range exists which provides no mathematical structure. Within this range a mathematical prediction of an interval value is not possible. The closer the system moves to chaos, the more the agents want to find stability by moving back to a situation of order. The agents need sufficient flexibility, creativity, agility, and innovation near the edge of chaos to self-organise until the subsystems have adapted to the environment (Levy, 2000). The positive scenario provides the sufficient decentralised, non-hierarchical network structure claimed by Levy (2000) to ensure appropriate degree of self-organisation. Self-organising collaborative human experts or AI applications such as autonomous SC planning techniques or AI used in forecasting automatically evolves towards the new (quasi-) equilibrium.

The equilibrium of the SC system can be disturbed through interventions, disruptive events or interferences. In the CF, interferences are mainly respected by descriptor use of AI to attack SC system architecture. On the one hand, these attacks represent interferences entailing a quasi-equilibrium which needs control through negative feedback. On the other hand, it is expected that improvements of AI applications increase the penetrating power of these attacks so that the SC system needs positive feedback which drives the emergence to bring the system to a new equilibrium, for sustainable defence against these improved AI-enabled attacks. This example shows that mutual impact of AI applications as agonist and antagonist also leads to SC equilibrium and that the agonist creates value through this equilibrium by improved security for the SC. However, the VC of this new equilibrium must be viewed critically due to the total cost of economics. Table 7-15 exemplarily shows four events to which AI applications create value by establishing equilibria. Each event is assigned to processes which are affected by the event and is classified according to the feedback loop and the impact on the value.

Table 7-15: AI and Its Impact on Value to Establish Equilibrium

No	**Event to which AI applications create value**	**Exemplary use case**	**Process**						**Feedback loop**	**Impact on value**
			P	**S**	**M**	**D**	**T**	**R**		
1	Predictive analytics identifies imbalance during SC execution. Delay of delivery detected.	Accident on the road, waiting time at loading point, traffic jam	OP			X	X	X	Negative	Total expenses
2	Supported MRP-run identifies imbalance between stock and demand	Capacity bottleneck due to increasing demand	TA	X	X	X			Negative	Sales
3	Innovation process to adjust product portfolio	Disruptive product of competitor reduces market shares	ST			X			Positive	Sales
4	Pattern recognition to adjust SC resources	Disruptive technology enters factor market	ST	X					Positive	COGS

Legend: P: Plan, S: Source, M: Make, D: Deliver, T: Transport, R: Return, ST: Strategic, TA: Tactical, OP: Operational, S&OP: Sales & Operations Planning

7.9.5 Theoretical Meaning and Practical Implications

The findings of this proposition expose new insights on the phenomena discussed. The conceptual solutions for managing the SC are exhausted. SC resilience as an example is ultimately only an umbrella term for concepts that have already been discussed for decades such as vulnerability analysis, supplier network, segmentation, collaboration, reliability, efficiency, or monitoring. The focus of these concepts remains on the operational and tactical level of the SC, thus has only limited contribution to the strategic evolution of the SC. Therefore, the author of this study perceives an extension of currently existing discussions of academics and practitioners. The viewpoint that AI only directly forms new structures of the SC and therefore the concept of emergence is primarily supported by human agents' adaptiveness is deduced and well-reasoned but has a strong theoretical meaning because literature review shows that prevailing opinion appears to be different. The practical implication is relatively weak regarding change impacts, but SC executives need to be aware of the further importance of human experts as the adaptive element that creates new structures of the SC.

7.10 Summary

In this Chapter, an approach was presented to establish a theory about the impact of AI on VC in the SC. In this course, the purpose, the approach, the reliability, and the added value of the theory was discussed and the building of the theory of this thesis was justified. Six propositions were described and discussed. The structure of the discussion is always the same, starting with the description of the proposition, arguing the importance of the discussion, continuing with the sections containing the exploration and investigation, and concluding with the theoretical meaning and the practical implication of each proposition. The findings from the discussions revealed the necessity of a comprehensive and coherent theory about the impact of AI on VC in the SC to be applied with the purpose to create competitive advantages.

Chapter 8 Testing of the Theory – An Attempt at Case Studies

8.1 Introduction

In this chapter, the validation test of the quantifiable Proposition 2, and Proposition 3 from Chapter 7 is conducted. Due to limited time and resources, the author of this thesis decided not to directly test the other four propositions. The results of the other propositions are largely incorporated into the testing of these two propositions. Proposition 1 confirms that AI is a valuable, rare, and imperfectly imitable resource and discusses the non-substitutability of AI-enabled resource mixes. These prerequisites are respected in testing proposition 2. The discussed paradigm shift from a demand-driven to a forecast-driven SC of Proposition 4 is covered by the evidence of increasing value through improved forecast accuracy of testing proposition 3. Proposition 5 that discusses the need to optimise inter-company collaboration is emphasised by Proposition 2 and thus incorporated in the test of Proposition 2. Generally, Proposition 6 argues the need of human and AI-enabled agents, and qualitatively proves evidence that the quantifiable tests are theoretically sound. Thus Proposition 6 provides the foundation for the testing of Proposition 2 and 3. Standard criteria of scientific validation such as empirical approval and logical deduction are not directly applicable to future research (Grunwald, 2013). However, the validation of knowledge is one central methodological challenge of scientific work. The credibility of the previous conceptual work is strengthened by the sensitivity analyses in this chapter by an attempt at case studies. Both Section 8.2 and Section 8.3 start with explaining the target and approach, followed by the testing of the propositions, and ended with the conclusion of the validation.

8.2 Test of the Proposition 2: Supply Chains Only Survive in the Long Term Through the Effective Combination of Widespread Adoption and High Frequent Application of AI

8.2.1 Target and Approach

In this Section, Proposition 2 is tested with a case study based on an SC model of three entities. Proposition 2 claims that sustainable competitive advantages are primarily achievable with the high performance of the positive scenario. Use Case 3, Position 1 (UC3 (P1) in Figure 7-2 represents the positive scenario of a SC system that resulted from the CIB-analysis. Use Case 1, Use Case 2, and Use Case 4 (see Figure 7-3) with their positions are more related to the low SC performance of the negative scenario (see Table 6-3). The recommendations of the expert interviews from Section 4.4.2 to apply the concept of EVA to calculate a tangible value that results from the different scenarios of the CF is followed. Despite of disadvantages discussed in the literature (see e.g. Rose (2010)), the EVA concept includes KPI such as net profit and asset costs that are often applied to inform about companies' financial situation. A sensitivity analysis is applied to test the EVA resulting from the positive scenario and the negative scenario. It is described how the coalition benefit from the positive scenario compared to isolated activities in the SC can be applied to achieve sustainable competitive advantages.

8.2.2 The Results of the Economic Value Added (EVA) from the Supply Chain Model

Three publicly accessible annual reports from 2019 substantiate the basis for the figures. The three SC entities BASF (Anonym, 2020d), BMW (Anonym, 2020j) and Continental (Anonym, 2020n) are part of a common SC in reality. These three companies represent a model section of a real SC. This model is illustrated in Figure 8-1.

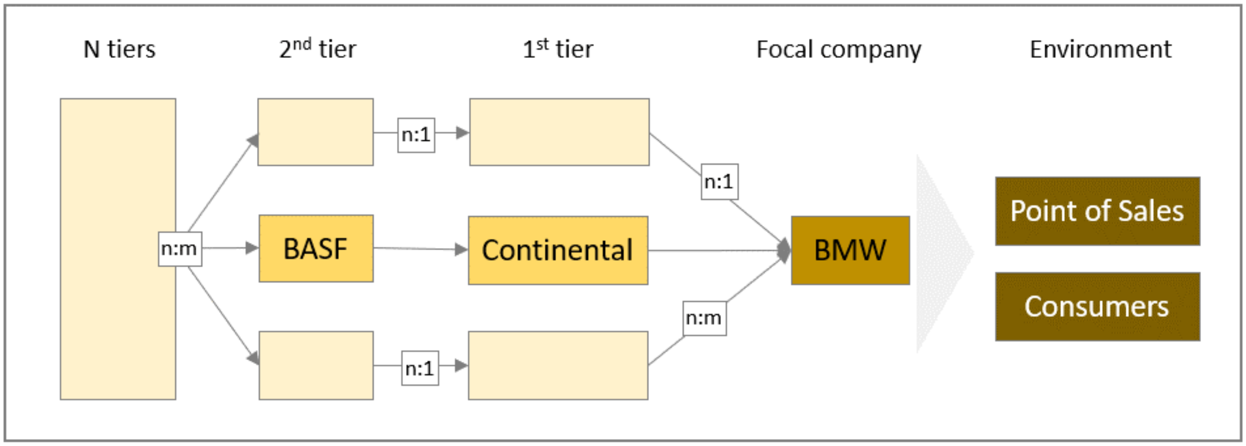


Figure 8-1: Illustrative SC Model for Testing Purposes

Hofmann and Wessely (2013) give a general framework of how SC initiatives can be estimated and considered by the economic value added (EVA) approach. The EVA approach is applied on this SC model. Figure 8-2 illustrates the EVA tree (Ashayeri & Lemmes, 2006; Pohlen & Coleman, 2005) fed by the descriptors of the CF.

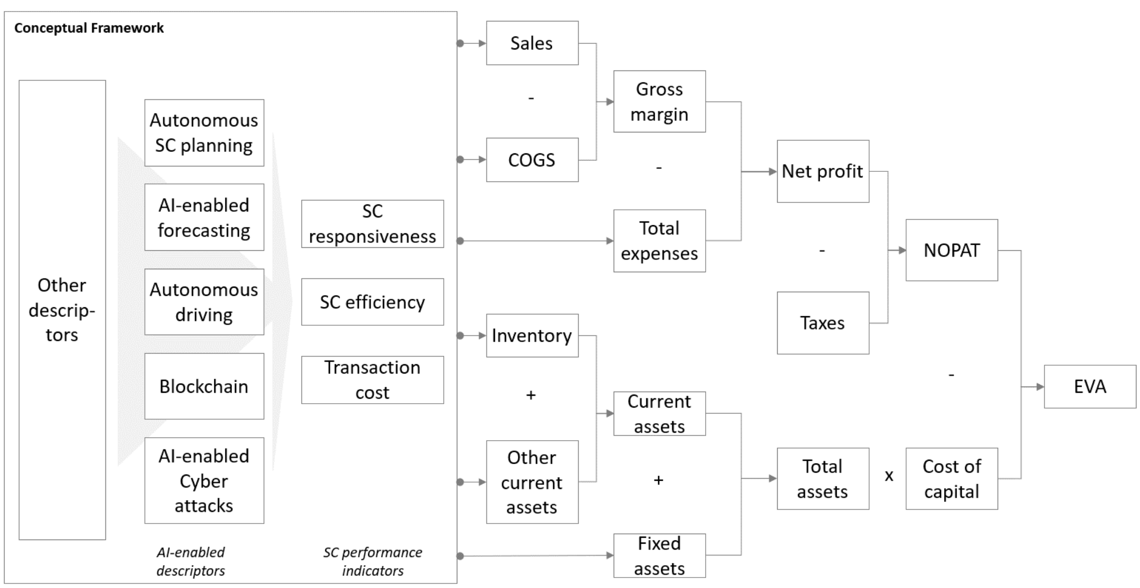


Figure 8-2: Economic value added (EVA) tree fed by CF and its descriptors

COGS: Cost of Goods Sold; NOPAT: Net Operating Profit After Taxes

The EVA for three situations is calculated:

- Situation 1: Initial situation of the year of the annual reports without any impact by the value drivers.
- Situation 2: Value drivers are applied in isolation by each SC entity of the model.
- Situation 3: Applying the value drivers of the positive scenario.

All three allocated EVA results for the SC model for all three SC entities are outlined in Table 8-1. The results of Situation 2 and Situation 3 are calculated with the aid of Table 7-5 that shows in Column 'Range of cooperation partial' the potential for additional value of 23% and the potential for additional value in Column 'Range of cooperation full' of 43%.

Table 8-1: Comparison of EVA Results of the SC Model

Input Parameter	**Situation 1**	**Situation 2**	**Situation 3**
	Initial Value in Euro	**Value of no SC cooperation in Euro**	**Value of the positive scenario in Euro**
Sales	208,004,400,000	222,070,905,554	237,970,553,886
COGS	163,101,400,00	157,162,225,620	148,253,464,051
Gross Margin	*44,903,00,000*	*64,908,679,934*	*89,717,089,835*
Total Expenses	35,071,600,000	34,463,458,456	35,304,826,140
Net Profit	*9,831,400,000*	*30,445,221,478*	*54,412,263,695*
Taxes	3,067980,000	9,133,566,443	16,323679,109
NOPAT	*6,763,420,000*	*21,311,655,035*	*38,088,584,587*
Inventory	21,911,400,000	21,075,523,913	19,821,709,782
Other current assets	64,957,300,000	64,619,392,125	64,112,530,314
Current assets	*86,868,700,000*	*85,694,916,038*	*83,934,240,096*
Fixed assets	97,324,500,000	96,480,696,585	95,214,991,463
Total assets	*184,193,200,000*	*182,175,612,623*	*179,149,231,558*
WACC	9,99%	9,99%	9,99%
Cost of capital	18,407,040,453	18,205,416,221	17,902,979,874
EVA	**-11,643,620,453**	**3,106,238,813**	**20,185,604,713**

The sum of the initial EVA of the SC entities represents the total initial EVA of the SC model (Situation 1). This initial EVA is negative with an amount of -11.643 M Euro. The EVA of 3.106 M Euro for the SC model when the value drivers are applied in isolation by each SC entity is already positive (Situation 2). The EVA of 20.185 M Euro by applying the value drivers for the positive scenario (Situation 3) is significantly higher than the EVA of the negative scenario. The calculation procedure for Situation 1 is as follows:

- The relevant figures to calculate the EVA such as sales, COGS, or inventory (see Figure 8-2) are taken from the annual report of each SC entity of the SC model.
- Consciously, the conversion rules for EVA calculation as proposed by Hosch, Hürzeler, Isenschmid, and Koller (2020) are not applied to avoid bias from personal evaluation because the conversion rules provide a large number of choices that make the desired comparability more difficult and complex.
- The Gross Margin results from the formula Sales minus COGS.
- The Net Profit results from the formula Gross Margin minus Total Expenses.
- The Taxes are calculated with 30 Percent for all SC entities to facilitate the comparison of the EVA.
- The Net Operating Profit After Tax results from the formula Net Profit minus Tax.
- The Current Assets result from the formula Inventory plus Other current assets.
- The Total Assets result from the formula Current Assets plus Fixed Assets.
- The Weighted Average Cost of Capital (WACC) is given in each annual report. For the total EVA calculation of the SC model, the average WACC of 9.99% is applied.
- The Cost of Capital results from the formula WACC multiplied by Total Assets.
- The EVA results from the formula NOPAT minus Cost of Capital.

The calculation procedure for Situation 2 and Situation 3 is as follows:

- The figures of the EVA tree calculated as described in the calculation path of Situation 1 are multiplied by the weighing factors outlined in Figure 8-3.
- The weighting factor in Column Impact VD[vii] represents the weighting of the SC performance KPIs SC responsiveness, SC efficiency, and transaction cost. It shows that SC efficiency has the highest impact on the VC (0.5), followed by SC responsiveness (0.4) and TC (0.1). These weighting factors primarily result from the CIB-analysis but should be adjusted for further individual research regarding to individual cases for their own purposes.
- A weighting factor for each EVA tree element outlined in Figure 8-3 is defined and shown in Columns Weighting. These weighting factors primarily result from the CIB-analysis but should be adjusted for further individual research regarding to individual cases for own purposes.
- One calculation is illustratively explained: The weighting factor for the performance KPIs (Column KPI) in column Impact VD is multiplied with the respective cooperation type. Illustratively shown in Figure 8-3 with the example of calculating the weighting factor for the SC responsiveness and no cooperation (Column No). The formula 0.4 multiplied by 17% (the precise figure is 17.3% as shown in Table 7-11) results in the weighting factor of 6.9%.
- The figure 6.9% that stands for the VC through non-cooperation, is multiplied by the weighting factor 0.7 and results in the rounded value 5% (4.83%). The value of 5% expresses the value contribution of SC responsiveness to the EVA tree element Sales.

- For each of the EVA tree elements that are positioned on the first level so that they are directly influenceable (Sales, COGS, Total Expenses, Inventory, Other Current Assets, Fixed Assets), the calculation is processed.
- This calculation results in the EVA for each SC entity of the SC model.

Conceptual framework		**No**	**Partial**	**Full**
KPI	**Impact VD**	17%	23%	43%
SC Responsiveness	0,4	$\boxed{6{,}9\%}$	9,0%	17,3%
SC Efficiency	0,5	8,7%	11,3%	21,7%
Transaction Cost	0,1	1,7%	2,3%	4,3%
	100%	**17%**	**23%**	**43%**

Fixed assets				**Other current assets**				**Inventory**				**Total Expenses**				**COGS**							**Sales**
Value			**Weigh-ing**	**Value**			**Weigh-ing**	**Value**			**Weigh-ing**	**Value**				**Value**			**Weigh-ing**	**Value**			Weigh-ing
No	Partial	Full		No	Partial	Full		No	Partial	Full		No	Partial	Full	Weigh-ing	No	Partial	Full		No	Partial	Full	
0%	0%	0%	0	0%	0%	0%	0	2%	3%	5%	0,3	0%	0%	0%	0	0%	0%	0%	0	$\boxed{5\%}$	6%	12%	0,7
1%	1%	2%	0,1	0%	0%	0%	0	2%	2%	4%	0,2	1%	1%	2%	0,1	3%	5%	9%	0,4	2%	2%	4%	0,2
0%	0%	0%	0	1%	1%	1%	0,3	0%	0%	0%	0	1%	1%	2%	0,5	0%	0%	0%	0,1	0%	0%	0%	0,1
1%	**1%**	**2%**	**0,1**	**1%**	**1%**	**1%**	**0,3**	**4%**	**5%**	**10%**	**0,5**	**2%**	**2%**	**4%**	**0,6**	**4%**	**5%**	**9%**	**0,5**	**7%**	**9%**	**17%**	**1**

Figure 8-3**:** Illustrative Allocation Logic of Value Created

8.2.3 Distribution of the Jointly Created Value in the Supply Chain

The tangible value for each SC entity can be calculated from the explained input parameters in Section 8.2.2. The results of the impact of different ranges of cooperation on the EVA tree elements are shown in Appendix J. . However, these results per SC entity that are shown in Column 'Additional value full cooperation in Euro' are calculated based on the EVA initial tree figures of each annual report so that the different value that is created by each SC entity depends on the different size of the company such as the percentage of sales, percentage of COGS. This kind of arithmetical derivation of additional value does not express a fair contribution of each SC entity to the common value created. Therefore, the chosen approach to distribute jointly created value derives from cooperative GT (Myerson, 1991; Thun, 2005). In contrast to conventional decision theory, decisions of SC entities in GT mutually influence each other so that interdependent decision situations occur. Exemplarily, the discussed Bullwhip effect reduction from Section 7.5.4 is only possible if all SC entities interdependently collaborate. The calculated Shapley value represents the fairest allocation of commonly created values (Thun, 2005). It is the additional value that a cooperation of all SC entities creates. The Shapley value calculated for the SC model is 36,672 M Euro (see Table 8-2).

Table 8-2: Shapley Value Compared with Value Created without Cooperation

	Value created without cooperation in Euro	Shapley value in Euro	Changes in percentage of values in Euro
V(a)	7,326 M	15,005 M	205%
V(b)	3.504 M	10,556 M	301%
V(c)	3,909 M	11,110 M	284%
Total	**14,740 M**	**36,672 M**	**249%**

In Table 8-3, V(a) represents the value created by SC entity 1 based on the annual report of BMW, V(b) represents the value created by SC entity 2 based on the annual report of Continental, V(c) represents the value created by SC entity 3 based on the annual report of BASF. Compared to the sum of the value of 14,740 M Euro created without cooperation, cooperative GT allows for an additional value of 21,932 M Euro (36,672 M Euro minus 14,749 M Euro). The single results of each calculation step are listed in Table 8-3.

Table 8-3: Single Results of the Shapley Value Calculation

Permutations			No			Partial			Full
			V(a)	V(b)	V(c)	V(a,b)	V(a,c)	V(b,c)	V(a,b,c)
Initial			7,326,586,636	3,504,433,143	3,909,240,127	13,974,377,739	14,676,954,818	9,602,207,251	36,672,809,815
a	ab	abc	7,326,586,636	6,647,791,083	22,698,432,076	13,974,377,739	30,025,018,732	29,346,223,160	36,672,809,815
a	ac	abc	7,326,586,636	21,995,854,998	7,350,368,162	29,322,441,654	14,676,954,818	29,346,223,160	36,672,809,815
b	ba	abc	10,469,944,596	3,504,433,143	22,698,432,076	13,974,377,739	33,168,376,672	26,202,865,220	36,672,809,815
b	bc	abc	27,070,602,564	3,504,433,143	6,097,774,108	30,575,035,708	33,168,376,672	9,602,207,251	36,672,809,815
c	ac	abc	10,767,714,691	21,995,854,998	3,909,240,127	32,763,569,689	14,676,954,818	25,905,095,125	36,672,809,815
c	bc	abc	27,070,602,564	5,692,967,125	3,909,240,127	32,763,569,689	30,979,842,691	9,602,207,251	36,672,809,815
Shapley value			**15,005,339,621**	**10,556,889,082**	**11,110,581,113**				

SC entity 1 creates an additional value V(a) of 7,326 M Euro in case of non-cooperation. SC entity 2 creates an additional value V(b) of 3,504 M Euro in case of non-cooperation. SC entity 3 creates an additional value V(c) of 3,909 M Euro in case of non-cooperation. These figures are shown in Table 8-3 in line ‘Initial’ subsumed under Column No. In the next step, the value is calculated if two of the three SC entities collaborate. The results are subsumed in line Initial under Column Partial: V(a,b) = 13,974 M Euro, V(a,c) = 14.676 M Euro, and V(b,c) = 9,602 M Euro. For each combination, the created value is calculated. The Shapely value for each SC entity is calculated by summing up the value of all combinations in one column and then dividing the sum through the number of combinations. In the case of Shapley value of SC entity 1, the total of all combinations is 90,032 M Euro. This sum is divided by the number of combinations that is six so that the Shapley value of SC entity results in 15,005 M Euro (see Table 8-3). Table 8-4 shows the coalition benefit that occurs in case that the three SC entities of the SC model fully collaborate. For each SC entity, the coalition benefit results from the formula 'Shapley value minus Value created without cooperation'. The total coalition benefit is 21, 932 M Euro. The average coalition benefit in percentage is 60% compared to the value created through isolated activities by each SC entity.

Table 8-4: Coalition Benefit of the SC Model

Value of each SC entity	Coalition benefit in Euro	Coalition benefit in percentage
V(a)	7,678,752,965	51%
V(b)	7,052,455,938	67%
V(c)	7,201,340,986	65%
Total	**21,932,549,889**	**60%**

Kreutzer and Sirrenberg (2019, p. 52) name costs and negative effects of the transition to an AI-based company by approximately 9% separated into transition and implementation costs (5%) and negative externalities (4%). These figures are based on the AI use cases evaluated by Bughin et al. (2018). For the calculation of EVA, the transition and implementation costs are considered and loss of sales due to loss of domestic consumption because unemployed individuals consume. Loss of economic contribution because unemployed individuals do not produce economic input is considered with a 2.5% reduction of sales referring to Kreutzer and Sirrenberg (2019, p. 52). This consideration follows the principle of conservative assumptions.

The investments in new AI infrastructure, displaced workforce cost, hiring of new workers and continuous upgrade of skills are added to the total expenses (see). Table 8-5 depicts the impact of full range of cooperation on EVA of the SC model of the three SC entities with 20,185 M Euro and the EVA reduced by the transition and implementation costs/externalities with 17,773 M Euro.

Table 8-5: Full Range of Cooperation Impact on EVA of SC Model

EVA tree elements	**Initial EVA in Euro**	**EVA after full range cooperation in Euro**	**EVA tree with full range of cooperation reduced by transition and implementation costs/externalities in Euro**
Net profit	9,831 M	54,412 M	50,965 M
Taxes	3,067 M	16,323 M	15,289 M
NOPAT	*6,763 M*	*38,088 M*	*35,676 M*
Total assets	184,193 M	179,149 M	179,149 M
Cost of capital	18,407 M	17,902 M	17,902 M
EVA	**-11,643 M**	**20,185 M**	**17,773 M**

The testing of the theory with the EVA approach and cooperative GT principles is conducted with a few assumptions:

- Same weighting factor of the SC performance to allocate VC for each company.
- Individual strength and individual market power is not considered.
- Individual initial maturity degree is not considered.
- Tax on net profit = 30%.
- Static cost comparison, no cash flow periods respected. Thus, one-time cost for investments in AI-infrastructure compared to one time VC instead of dynamic VC across multiple years. Running costs are not considered.

8.2.4 Conclusion of the Validation

The coalition benefit of the positive scenario in the SC model for three companies is almost 22 bn Euros (see Table 8-4). Referring to the argumentation from Table 6-10 and Table 6-11 in Section 6.4.4 this additional amount compared to competing SC that are locked in a negative scenario can be applied by the SC entities to reinvest e.g. into research for innovative products and services, additional promotional activities, SC performance improvement initiatives, employee qualification programmes, or to increase the payment of dividends to shareholders (see Table 8-6). The application of the coalition benefit in the listed areas in Table 8-6 positively impacts the relative market shares of the SC entities and thus creates additional cash flow compared to competitors. A strong equity capital base makes it possible to bridge unstable economic periods such as business recessions in which competitors often file for insolvency due to lack of liquidity. The reduction of unit costs by applying efficiency-improving technologies from the factor market and low TC by successfully defending cyberattacks keeps the SC entities more flexible by applying different price models to pro-actively drive the behaviour of consumers regarding price competition or own margin improvement. A relatively high proportion of the coalition benefit can be invested in activities and measures to protect the knowledge of the common culture so that competitors cannot learn the root causes of why valuable resources contribute value to the SC. This effect is one key success factor for sustainable competitive advantages in the sense of J. Barney (1991) as argued in Section 7.4.4. Additionally, another proportion of the coalition benefit can be invested in high employee loyalty. Apart from permanent employee qualification, relatively high salaries compared to SC entities working in isolation in their SC significantly improve employee retention, keeping valuable knowledge in the common culture and does not migrate to the competing SC. The spiral of re-investing in measures that increase the tangible value, and the EVA amplifies the competitive advantages and leads to sustainable competitive advantages for multiple periods.

Table 8-6: Application of Coalition Benefit to Achieve Sustainable Competitive Advantages

No	Application of coalition benefit	Impact on sustainable competitive advantages
1	Research for innovative products and services that meet changing demand patterns.	Keeping or even increasing relative market shares and thus creating additional cash flow compared to competitors.
2	Additional shareholder dividend payment.	Strong equity capital base makes an SC strong in periods of weaknesses such as business recessions.
3	Permanently processing performance improvement initiatives.	Reducing unit cost and thus being more flexible by deciding on appropriate price models to start price competition or to increase margin.
4	Research for improved defence against cyberattacks.	Significantly reduced TC and no distraction from the core operating objectives compared to competitors.
5	Identification and implementation of emerging technologies.	Applying efficiency-improving technologies from the factor market improves cash flow that amplifies EVA to keep competing SC at distance.
6	Additional investment in knowledge protecting applications.	Competitors cannot learn the root-causes why valuable resources contribute value to the SC. This effect keeps the resource and the resource mix sustainably competitive.
7	Additional promotional activities and customer-relationship measurements.	Keeping or even increasing relative market shares and thus creating additional cash flow compared to competitors.
8	Investment in high employee loyalty such as permanent trainings, relatively high salaries, incentives, and employee events.	Employees with valuable knowledge stay with the SC entities and do not improve competing SC with their valuable knowledge.

8.3 Test the Proposition that Fully Implemented AI-enabled Supply Chain Collaboration Creates Substantial Additional Value

8.3.1 Target and Approach

In this Section, Proposition 3 is tested. A sensitivity analysis is used to show the extent to which the calculated value of a maximum of 43% of the full range of cooperation is achievable. The following sensitivities are reviewed:

- Impact by isolated activities by the entities of the SC model.
- Impact by full range of cooperation in an SC of good maturity.
- Impact by full range of cooperation in an SC of low maturity.

The sensitivity analysis is based on use cases from literature and from personal experience by the author of this thesis. A conservative approach is chosen so that the low end of the proposed impact by literature is considered. In Section 7.6, Proposition 3 was argued based on empirically proven studies from literature and from the results of one project of the author of this thesis. These results were combined with deductive reflections and corresponding theories so that assumptions were derived according to assignment of parameters of the identified values. The sensitivity analysis in this section applies the results of other use cases from literature and the result of one other project of the author of this thesis directly on the figures of the EVA tree from the SC model introduced in Section 8.2.2. Consciously, the parameters that are defined in Section 7.6.5 are not used with the sensitivity analysis since these conceptual assumptions should be tested.

8.3.2 Non-cooperation and Full Range of Cooperation with Good Maturity

Table 8-7 lists the results of the sensitivity analysis for the VC in case of non-cooperation of the SC entities and in case of full range of cooperation. The situation of full range of cooperation is characterised with a good maturity of forecast accuracy. A good maturity is defined with a forecast accuracy of 70%. B. Bowman (2020) informs that a forecast accuracy of 70% is sufficient to get by without loss of sales due to out-of-stock situations. B. Bowman (2020) states that forecast accuracy is generally in the range of 20% to 80% and describes 70% forecast accuracy as a typical industry benchmark, with a targeted safety stock of 30 days. Both KPIs are considered the initial situation of the SC model. In general, SC has the ability to alter SC two months out. Thus, the delivery time is supposed to be 60 days and a manufacturing lead time of 30 days (B. Bowman, 2020).

Table 8-7: Results of Sensitivity Analysis of Non-cooperation and Full Range of Cooperation with Good Maturity

Input Parameter	Initial Value in Euro	Situation of non-cooperation in the SC model		Situation of full range of cooperation with good SC maturity	
		Value of activities in Euro	Value in Euro	Value of activities in Euro	Value in Euro
Sales	208,004,400,000	6,240,132,000	214,244,532,000	14,561,043,450	222,565,443,450
COGS	163,101,400,00		163,101,400,00	-7,957,216,800	155,144,183,200
Gross Margin	*44,903,00,000*		*51,143,132,000*		*67,421,260,250*
Total Expenses	35,071,600,000		35,071,600,000		35,071,600,000
Net Profit	*9,831,400,000*		*16,071,600,000*		*32,349,660,250*
Taxes	3,067980,000		4,821,459,600		9,704,898,075
NOPAT	*6,763,420,000*		*11,250,072,400*		*22,644,762,175*
Inventory	21,911,400,000	-1,095,570,000	20,815,830,000	-8,764,560,000	13,146,840,000
Other current assets	64,957,300,000		64,957,300,000		64,957,300,000
Current assets	*86,868,700,000*		*85,773,130,000*		*78,104,140,000*
Fixed assets	97,324,500,000		97,324,500,000		97,324,500,000
Total assets	*184,193,200,000*		*183,097,630,000*		*175,428,640,000*
WACC	9,99%		9,99%		9,99%
Cost of capital	18,407,040,453		18,297,556,491		17,531,168,757
EVA	**-11,643,620,453**		**-7,047,484,091**		**5,113,593,418**

The calculation of the initial EVA value is explained in Section 8.2.2. The same formula applies to the EVA of the situation of non-cooperation and the situation of full range of cooperation with good maturity in Table 8-7. The value of activities is argued in the following.

<u>Increasing sales of 6.24 bn Euro in the situation of non-cooperation</u>:

Blackburn et al. (2015) have empirically proven that a forecast accuracy of 96% is possible with AI-enabled predictive analytics. Chui et al. (2018) have empirically found that a forecast accuracy improvement of 20% is translated into a revenue increase of 2 to 3 percent. Literature gives no information about an improvement of more than 20%. Thus, although 26% improvement is possible (current forecast = 70%), the assumed sales increase remains 3% for the SC model calculation. The use case of Blackburn et al. (2015) refers to one SC company.

Therefore, the results are assigned to the isolated activities. It is supposed that no coalition benefit is gained but that all three SC entities are able to achieve this result.

Inventory reduction of 1.1 bn Euro in the situation of non-cooperation:

An inventory reduction of 5% goes along with the forecast improvement of 20% (Blackburn et al., 2015; Chui et al., 2018). Again, a coalition benefit is not expected due to isolated improvement of forecast accuracy.

Increasing sales of 14.56 bn Euro in the situation of full range of cooperation:

Elia et al. (2020) argue that AI-enabled data mining based on big data increases sales of a SC of 5% to 10%. The conservative average amount of 7% is chosen to calculate the impact on the SC model. The common application and exchange of data and information contribute to the coalition benefit. It could be argued that the 14.5 bn Euro might be considered as the coalition benefit and that the amount of 6.2 bn Euro should be included in this calculation. However, Elia et al. (2020) inform about the potential benefit of applying big data and AI in SC management and keep it open if these improvements can be achieved isolated or only jointly by the SC entities. Thus, the conservative approach necessitates the decision to respect only one amount. Another contribution of 735,450 Euro comes from widespread collaboration with VMI, CRP based on shared and centralised forecasting informed by Metters et al. (1996). That kind of impact is not included in the other benefit potential and thus a valuable additional benefit.

COGS reduction of 7.95 bn Euro in the situation of full range of cooperation:

A personal use case implemented by the author of this study in 2017 resulted in a 50% reduction of SC planning costs through widely adopted and AI-enabled SC planning and forecasting. Schneeweiss and Zimmer (2003, p. 699) confirms this impact by empirically proving that reactive anticipation between supplier and producer reduces costs by 50% in the field of production planning and execution. SC planning in this case includes production, transportation, and warehouse planning. The share of logistics costs is calculated based on Keller (2020) that results COGS reduction of 1.2% and 1,957,216,800 Euro. Metters et al. (1996) inform about coalition benefit of 10% to 20% profit improvement through widespread collaboration with VMI, CRP based on shared and centralised forecasting. This impact is translated into COGS reduction by 3.7% in case of this SC model which contributes an improvement of 6 bn Euro. The personal use case of the author of this thesis and the use case by Metters et al. (1996) complement each other, justifying the addition of both benefits.

<u>Inventory reduction of 8.76 bn Euro in the situation of full range of cooperation</u>:

Collaboration and full visibility on all movements across all SC entities raise inventory turnover by 10%, thus cutting the average inventory (Nguyen et al., 2019). Schneeweiss and Zimmer (2003) emphasise this use case by stating that the reactive anticipation mechanism contributes to inventory cost reduction. The use case is translated into an inventory reduction of 15% and an inventory cost reduction of 3,286,710,000 Euro. Widespread collaboration with VMI, CRP supported by centralised and shared demand forecast data leads to inventory reduction of up to 25% (H. L. Lee et al., 1997), that results in inventory cost reduction of 5,477,850,000 Euro. Both use cases complement each other, justifying the addition of both benefits.

8.3.3 Full Range of Cooperation with Good Maturity Compared to Full Range of Cooperation with Low Maturity

Table 8-8 compares the results of the sensitivity analysis of an SC with good maturity and an SC of low maturity of forecast accuracy. For this comparison, the low maturity is determined by a forecast accuracy of 50%. B. Bowman (2020) informs that a forecast accuracy of 50% implies safety stock of 45 days (+15 days compared to 70% forecast accuracy) or the potential of stock out. With the focus on forecast accuracy improvement in the SC model, the stock out aspect is argued and use cases are included in the sensitivity analysis that reduce forecast errors. The results of this sensitivity analysis are added to the calculated EVA tree positions of the situation of full range of cooperation with good maturity. The calculation of the additional value refers to the initial EVA tree positions of the SC model. On the one hand, the value created by the use cases in the situation are independent from the other use cases and complementary to the benefits of the situation of full range of cooperation with good SC maturity. On the other hand, the additional value can be achieved parallelly so that it is useful to refer to the initial figures of the EVA tree.

Table 8-8: Comparison of Results of Sensitivity Analysis of Full Range of Cooperation with Good Maturity and Low Maturity

Input Parameter	**Situation of full range of cooperation with good SC maturity in Euro**	**Situation of full range of cooperation with low SC maturity**	
		Value of activities in Euro	**Value in Euro**
Sales	222,565,443,450	2,120,318,200	224,685,761,650
COGS	155,144,183,200	-3,832,882,900	151,311,300,300
Gross Margin	*67,421,260,250*		*73,374,461,350*
Total Expenses	35,071,600,000	-1,402,864,000	33,668,736,000
Net Profit	*32,349,660,250*		*39,705,725,350*
Taxes	9,704,898,075		11,911,717,605
NOPAT	*22,644,762,175*		*27,794,007,745*
Inventory	13,146,840,000	-6,573,420,000	7,668,990,000
Other current assets	64,957,300,000		64,957,300,000
Current assets	*78,104,140,000*		*72,626,290,000*
Fixed assets	97,324,500,000		97,324,500,000
Total assets	*175,428,640,000*		*169,950,790,000*
WACC	9,99%		9,99%
Cost of capital	17,531,168,757		16,983,748,947
EVA	**5,113,593,418**		**10,810,258,798**

<u>Increasing sales of 2.12 bn Euro with full range of cooperation and low maturity</u>:

Based on the use cases and analysis of H. Bauer et al. (2017), Kurzlechner (2017), and Pohlen and Coleman (2005), the reduction of forecast errors leads to a sales increase of 2,120,318,200 Euro. It has been argued that the application of AI to avoid out of stock situations reduces lost sales of 65%. The share of lost sales in the SC model is supposed to be 2% (= 3,262,028,000 Euro) of the total sales.

<u>COGS reduction of 3.83 bn Euro with full range of cooperation and low maturity</u>:

H. Bauer et al. (2017), Kurzlechner (2017), and Pohlen and Coleman (2005) determine the impact on COGS by reduced forecast error to be 5% to 10% of the logistics costs. Logistics costs consist of transport and warehouse costs. Inventory costs are not included for the purposes of this calculation. Logistics costs have a share of 27% of the COGS (Keller, 2020). The conservative approach of 5% reduction is equal to 2,201,868,900 Euro. This impact mainly results from AI-enabled forecasting. Additionally, Metters et al. (1996) argue a coalition benefit of 10% of the profit by widespread application of SC planning instruments. The benefit of 10% is separated on sales, COGS, and total expenses. A conservative approach for COGS is an impact of 1% that results in a COGS reduction of 1,631,014,000 Euro.

<u>Total expenses reduction of 1.40 bn Euro with full range of cooperation and low maturity</u>:

H. Bauer et al. (2017), Kurzlechner (2017), and Pohlen and Coleman (2005) determine the impact on total expenses by reduced forecast error on 25% to 40% of the administration costs. Administration costs are supposed to be 10% of the total expenses. A conservative impact of 30% results in a reduction of total expenses of 3% which is equal to 1,052,148,000 Euro. Additionally, the coalition benefit by the use case of Metters et al. (1996) is calculated with a reduction of 1% of the total expenses equal to 350,716,000 Euro.

Inventory reduction of 5.48 bn Euro with full range of cooperation and low maturity:

H. Bauer et al. (2017), Kurzlechner (2017), and Pohlen and Coleman (2005) determine the impact on inventory reduction by reduced forecast errors on up to 50%. However, the amount of the forecast improvement has not been specified so that a conservative inventory reduction of 25% is calculated what results in reduced inventory cost of 5,477,850,000 Euro.

8.3.4 Conclusion of the Validation

The sensitivity analysis with the referred use cases shows that additional VC with different ranges of cooperation is possible. Table 8-9 lists the VC proposed in Proposition 3 compared to VC tested with the sensitivity analysis in this section.

Table 8-9: Comparison of Proposed VC and Tested VC

EVA tree elements	**Additional value with full range of cooperation in Euro**	**Additional value with full range of cooperation with low maturity in Euro**	**Delta of VC proposed and tested**
Sales	237,970,553,886	224.685.761.650	6%
COGS	148,253,464,051	151.311.300.300	-2%
Gross Margin	*89,717,089,835*	73.374.461.350	18%
Total Expenses	35,304,826,140	33.668.736.000	5%
Net Profit	*54,412,263,695*	39.705.725.350	27%
Taxes	16,323679,109	11.911.717.605	27%
NOPAT	*38,088,584,587*	27.794.007.745	27%
Inventory	19,821,709,782	7.668.990.000	61%
Other current assets	64,112,530,314	64.957.300.000	-1%
Current assets	*83,934,240,096*	72.626.290.000	13%
Fixed assets	95,214,991,463	97.324.500.000	-2%
Total assets	*179,149,231,558*	169.950.790.000	5%
WACC	9,99%	9,99%	0%
Cost of capital	17,902,979,874	16.983.748.947	5%
EVA	**20,185,604,713**	**10.810.258.798**	**46%**

In general, the additional VC through AI in the SC proposed in Section 7.6 is confirmed. However, the full potential of VC is not achieved with the considered use cases. As shown in Column ‘Delta of VC proposed and tested’, the proposed EVA is almost twice as high compared to the tested EVA (+46%). One reason for the lower value discovered through the sensitivity analysis is that only the direct potential and the benefit identified by the authors of the use cases is considered. No indirect impact on the EVA tree elements is respected to avoid any bias from individual decisions required from the author of this thesis. The direct impact on sales by AI-enabled forecasting and on COGS implies indirect impact on total expenses due to reduced administration costs in case of less out-of-stock situations so that TC are reduced as well as fixed assets such as the positive impact on the positive reputation of a brand of a company. The fact that mutual interdependencies between the direct impacts on sales, COGS, or inventory amplifies the positive impact on the VC in the SC is another indirect aspect that is not included in the sensitivity analysis but included in the Proposition 3 calculation. Another aspect is, that the low maturity of forecast accuracy of 50% limits the results of the worst scenario tested. The impact of an improvement of forecast accuracy higher than 40% is not tested. Table 8-9, Column 'Delta of VC proposed and tested' shows the deviation of each EVA tree element. It should be emphasised that the impact of AI-enabled SC descriptors in the sensitivity analysis on the VC through inventory reduction is 61% higher than calculated with the parameters of Proposition 3. However, the effect on the EVA is mitigated by the cost of capital so that only 5% deviation remains. The strong indirect impact from the significantly reduced inventory on warehouse costs is not fully respected in the sensitivity analysis. The higher NOPAT (+27%) is the stronger deviation between proposed and tested VC. The combination of 6% higher sales and 2% lower COGS amply the impact on the Gross margin, the taxes and thus on the NOPAT.

8.4 Discussion of Testing Other Propositions in the Theory

Proposition 1 needs to be tested regarding the argumentation that AI is only valuable if the SC performance creates a certain level of competitive advantages. Mikalef and Gupta (2021) have empirically tested the positive impact of AI on organisational performance. It has been argued that eight resources are necessary to establish the necessary AI capability. The referred resources by (Mikalef & Gupta, 2021) and the resource mix proposed in this study match to a high degree (see Table 8-10).

Table 8-10: Eight Resources Proposed by Empirical Testing Compared to Resource Mix Applied by this Study

No	Resource category	AI capabilities of resource by (Mikalef & Gupta, 2021)	Resource mix applied and argued in this study
1	Tangible	Data	Big data availability
2		Technology	Increasing computing and bandwidth, blockchain
3		Basic resources	Assets mainly represented by agents, organisational processes
4	Human	Technical skills	Adaptability of agents
5		Business skills	Application of common culture of the SC and decision-making skills related
6	Intangible	Inter-departmental	Inter-company
7		Organisational change capacity	Dynamic capabilities of the SC
8		Risk proclivity	Assumption that a significant number of human agents will be replaced by AI-enabled agents and that the positive scenario will be implemented.

The framework applied by Mikalef and Gupta (2021) is comparable to the CF in this study. Thus, the test results confirm that AI positively impacts SC performance. It is argued that knowledge created, acquired, and stored by AI applications is a key value driver of competitive advantages. Herden (2020) applies eight case studies in the field of SC management and logistics to prove that knowledge-based analytics contributes to competitive advantages. AI is applied in the field of analytics. The analytics capabilities of resources improve decision-making. Khan, Chaabane, and Dweiri (2019) apply a case study to prove the positive impact of knowledge-based decision-making on SC performance. These case studies provide a good indication that Proposition 1 is validated and that AI is a valuable resource.

Proposition 4 requires testing regarding the discussed paradigm shift from a demand-driven SC to a forecast-driven SC. The fact that improved forecast accuracy significantly improves value has been proven e.g., by Blackburn et al. (2015) and the testing of Proposition 3. However, a clear validation test that proves the proposed paradigm shift is not provided by available literature. There is the need for additional data collection and research on this proposition.

Proposition 5 needs a testing in regard to the optimisation of inter-company collaboration in future SC. A specific inter-company process organisation is recommended to improve VC based on process-orientation, decentral cooperation, and autonomous decision-making. Literature provides multiple case studies to which it is referred in Chapter 7 that confirm this proposition. Thus, a specific test was not performed due to time and resource constraints.

Proposition 6 needs a testing regarding the contribution of AI to SC equilibria. Amongst other literature Wang (2019) demonstrate analytically and numerically that a SC equilibrium creates value and Liu and Wang (2019) provide analytical results and use simulations to confirm additional value through a SC equilibrium. However, it is proposed by the author of this study to invest research in case studies validating the impact of AI on SC equilibria.

8.5 Summary

In Chapter 8 the findings from two propositions of the theory about the impact of AI on VC in the SC have been tested. The other four propositions were discussed and the reason why comprehensive testing is not processed was given. The test results show that the developed theory is valid and can be used for both theoretical and practical work.

Chapter 9 Conclusion and Further Work

9.1 Main Achievements

This section summarises the main achievements from this thesis according to the initially formulated research objectives.

Research Objective 1 serves to review, analyse, and evaluate the technologies for improving SC performance.

Literature review presents a concise view on the nature of the SC as a CAS and the associated challenges of developing performance improvements for sustainable competitive advantages. Technological developments through web-based real-time communication, steadily increasing bandwidth and increasing computational power, open up for data-driven and data-centric based inter-company cooperation along the entire SC. NLP, computer vision, and expert systems with prescriptive analytics capabilities have matured to the point that a SC is enabled to include more and more autonomous and self-learning processes on strategic, tactical and as well as operational level, so that AI-enabled applications contribute to an improvement of SC efficiency, agility and effectiveness. There is a significant growth of companies applying AI therefore a significant economic impact in the upcoming decade is expected. However, no CF is found which provides the foundation to explore the increasing impact of AI on inter-organisational decision-making, SC planning, or autonomous devices and their impact on establishing value creating SC equilibria. The literature review reveals that it is important and relevant to reassess and rethink, the still valid SC concepts of the 1990s and 2000s according to SC efficiency and responsiveness considering the challenges and the impact of new AI-enabled technologies and deduced concepts of autonomy and big data. These results support the importance of this thesis which explicitly employed to explore the impact of AI on VC in the SC.

Research Objective 2 serves to develop a CF with the purpose to explore, analyse, and evaluate the impact of AI on VC in the future SC.

Semi-structured expert interviews and a Delphi Study were conducted with 37 experts to collect and present data for further use with a CIB-analysis. The outcome of the first Poll of the Delphi Study is a CF composed of 13 descriptors with two variants each. These 13 descriptors are grouped to SC performance indicators, process and structure elements, and contextual factor “Technology”. With Delphi Study Poll 2, the participating experts define the relationships between the descriptor variants. Four consistent scenarios are found as outcomes of this CIB-analysis of which two are explored more thoroughly. These two scenarios represent two poles of future SC, a positive scenario with relatively high SC performance and a negative scenario with relatively low SC performance. The positive scenario differs mainly in the performance-critical characteristics decentralised coordination, widely adopted autonomous SC planning techniques, fully implemented use of autonomous driving and blockchain as a global process driver for the whole SC. Fully integrated and widely adopted use of AI in forecasting, process-orientation, and decision autonomy are variants which will be found in all future SC scenarios as value drivers. The descriptor variant speculation is seen by the participating experts as prevailing characteristic of future SC instead of postponement. This assessment opens potential for further considerations on possible paradigm shift from more demand-driven SC to reliable forecast-driven SC.

Research Objective 3 serves to build a theory on the findings from exploring the CF. Based on the findings from the CIB-analysis, 6 propositions about the CF are established which are explored with the target to establish a theory about the impact of AI on VC in the SC. With AI, the SC achieves competitive advantages through improving ordinary and as well as dynamic capabilities. The combination of knowledge creation and knowledge distribution with fully implemented and widely adopted AI-enabled forecasting and autonomous SC planning, is the only feasible future concept to leverage sufficient value through the inevitable data-centric approach across the SC. This permanent SC learning takes place to a large extent within and between AI applications and is represented by tacit knowledge in the common culture of the SC. AI creates value through protecting the common culture of the SC against competing SC. From the viewpoint of system theory, the future of CAS is non-random. Therefore, especially the self-learning ability of AI to detect the smallest but observable patterns in the behaviours of the factor and consumer markets or the daily operational business through permanently exploring big data, significantly improves future forecast accuracy in all relevant application areas. The SC strongly benefits through reduced bullwhip effect and access to first-mover knowledge pool which is limited for competing SC, so that the resource mix can be permanently adjusted to the needs of the turbulent environment. AI enables SC to faster find back to a controlled equilibrium from a state of disorder close to the edge of chaos, where unnecessary TC and process costs are produced. Although AI only indirectly contributes to emergence of new SC structures, value is created by strengthening the collective behaviour of human experts to permanently find new SC (quasi-) equilibria. The recommended future organisation structure allows for a high degree of controlled freedom for adaptive agents providing cross-company clusters at the interfaces of SC entities. Depending on the range of cooperation, the SC system composed with the CF is able to create additional value between17% and 43% with AI-enabled descriptors of the positive scenario.

Research Objective 4 serves to verify the proposed theory and the identified AI applications through case studies.

The concept of EVA is applied on a model of three SC entities to test the theory. The case study is fed by the figures from three freely accessible annual reports. Principles of cooperative GT are used to calculate the Shapley value to allocate the commonly created value of the SC entities. The findings from the CF serve to calculate the EVA for the three ranges of cooperation. It is proved that the widely adopted and commonly used AI-enabled descriptors from the positive scenario create an additional value of 36,672 M Euro in this case study compared to a total additional value of 14,740 M value of the non-cooperative alternative. This created value is constituted in an EVA of the cooperative scenario of 20,185 M Euro.

9.2 Contributions to the New Knowledge Generation

The literature review results indicate a growing importance of AI in the SC to ensure sustainable competitive advantages. This finding supports the significance of this research. The overall aim of this research is to analyse and evaluate the impact of AI on VC in the SC. The contributions of this thesis to the new knowledge generation are in both aspects of theoretical advancement and practical applications. The following contributions have been made associated to the theoretical advancements:

1. The thesis proposes a new framework to discover relationships between descriptors in the SC. Such a perspective of VC through AI in the area of SC was not present prior to this study. This CF allows academics to be able to evaluate impacts of AI in the SC, in a fact-based and competent manner. The CF of the thesis contributes with its system-theoretical

structure to build complementary research on it because it is self-contained and logically coherent. Researchers have the possibility to either substitute or supplement descriptors and/or variants or apply different analysis methods instead of the applied CIB-analysis.

2. The application of the CF discovers that sustainable competitive advantages can only be achieved if AI-enabled SC descriptors are widely and jointly adopted across the entire SC and if knowledge created by the SC is protected against substitutability. This finding opens new viewpoints for further academic research in the direction of VC through data-driven collaboration. Major issues with the evaluation of creating and allocating value in the SC are detected and discussed. These issues include the selection of appropriate methods to identify and adequately calculate tangible value which is commonly created by the SC entities. Available literature informing about improving forecast accuracy through AI and its positive impact on SC performance, do not distinguish if this additional value is solely created by one SC entity or if more value might be expected if all SC entities commonly apply AI applications to improve forecast accuracy. The discussed example of how AI reduces Bullwhip effect elucidates that there is value created by AI which can only be created with collaboration in the SC.
3. The thesis establishes a theory on the impact of AI on VC in future SC. This theory provides a system of six scientifically justified propositions that explain phenomena of the SC reality and the underlying laws. The majority of researchers are concerned with the mathematical aspects of AI algorithms and the improvement potential in certain areas of the SC. This theory sheds new light on the contribution of self-learning abilities of AI to the common culture of the SC and particularly on the protective mechanisms, that AI provides through tacit knowledge creation and allocation to contribute to sustainable

competitive advantages. Exploring this aspect of SC learning by extended RBV provides new opportunities for academics to link own research. The theory on the one hand confirms existing stances about future scenarios of the SC and on the other hand are confirmed by existing studies and surveys on the opinions of the participating experts. However, this theory takes also a complementary, slightly different stance to existing academic opinion. The conjecture is that AI allows for reliable forecast-driven SC and a substitution of postponement approaches. This conjecture is open to arguments by other researchers and wait for refutation or confirmation through deductive reasoning or inductive testing. These academic debates will enrich the academic body of knowledge.

The following contributions have been made for practical applications:

1. By applying the CF to real SC entities, the generated insights may influence decision processes about resource mix to improve ordinary and/or dynamic capabilities of the SC. Practitioners can apply the CF to derive logical dependencies also beyond the proposed descriptors and event pairs. This is a valuable contribution due to the complex nature of SC, where human experts from different SC entities interact in a CAS. The CF reveals that the recommended organisational structure of future inter-company cooperation may provide an initial starting point to initiate studies and projects to synchronise process-orientation, decentral coordination, and decision autonomy.
2. A further practical contribution of this thesis is the CIB-analysis, to discover, quantify and evaluate the impact of investments in AI on future SC performance. This method combined with the provided EVA model enables a company to calculate business cases on future VC and value allocation in the SC. The proposed method is a strong argument for companies to convince SC partners for value creating collaboration in the SC. The

analysis presents the benefits of creating and leveraging first-mover knowledge pools and therefore underpins the necessity to initiate measures to apply AI aiming to identify so far hidden patterns to significantly improve operational, tactical, and strategic decision-making in the SC.

3. The theory identifies and discusses the most relevant AI-related impact factors on the survival of future SC. The theory reveals that AI only indirectly impacts the emergence of new SC structures so that investments in the motivation and qualification of human experts must not be neglected. However, the theory emphasises the need to invest in a data-driven cooperation between human experts and AI applications in general and in a central SC-wide AI-enabled platform. The findings of the theory of this thesis underpin that it is crucial for sustainable competitive advantages to initiate as early as possible assessments about the maturity of the current SC. Depending on these results, the theory about the impact of AI on VC in the SC is recommended to support further decision-making by executives.

9.3 Limitations and Further Work

Despite the clear research methodology and various results that contribute new knowledge to the research community that is concerned with VC of AI in the SC, there are limitations that need to be addressed. These limitations exist due to the time and resource constraints of the researcher and are discussed as follows:

1. The primary research of this thesis is to collect, present and analyse data aims to combine academic expert knowledge and practitioners' experiences in the field of AI and SC management. The primary data for building the CF and for feeding the CIB-analysis are gathered through expert interviews and experts participating in a Delphi Study. It must be

highlighted that the CF results and the findings from the CIB-analysis are as good as the participating experts. Furthermore, expert knowledge of academics who have spent a large part of their career in higher education institutions depend on the body of AI and SC literature as long as empirical research is only limited possible. Practitioners shared years of experience with the SC of their own companies and their experience strongly depends on the maturity of their individual SC businesses. Therefore, it is possible that aspects, associations and challenges which are specifically relevant to other companies and SC are not sufficiently covered by the CF.

2. With the target to mitigate the limitations, the author of this study applies deductive reasoning based on the results of the primary research to enrich and enlarge the previous findings and to offer initial starting points for generalisation through a theory. However, these results are only as good as the capability of the author of this thesis.
3. All case studies, simulation models or theoretical thoughts from literature about impact of AI on EVA elements such as forecast accuracy on sales or inventory, make no clear distinction about the impact on one company or on common usage by more than one company. Mathematical models about the allocation of a shared value presume an input value but do not argue how this jointly generated value comes about. It is also not argued what impact factors make the difference between cooperative and non-cooperative behaviours. Therefore, the factor of 2,5 for fully cooperating in the SC is a vague assumption which needs to be tested by future research.
4. In a particular IA method, the CIB-analysis, is chosen to have the participating experts of the Delphi Study rate, the impact of the descriptor network. Despite of the advantages of this method, the disadvantage of evaluating even pairs of 13 descriptors each with two

variants is expected to take too much time. Therefore, each participant was sent only a limited number of event pairs. For that reason, each event pair is only rated by a lower number of experts. This disadvantage is mitigated by the sensitivity analysis of the Delphi Study Poll 3 but might contain hidden inaccuracies.

5. Since the beginning of this thesis, quantum computing technology has been evolved, suggesting an impact on AI and VC in the SC. Due to time restrictions it is not possible to take this parallel stream of technology into consideration. However, it might be that the explored SC phenomena result in slightly different future SC scenarios.
6. The testing of the theory is limited due to capacity reasons and time restrictions. Additional data are necessary to make qualitatively discussed Propositions 1, 4, 5, and 6 quantifiable by a suitable test procedure. These data cannot be derived from the available literature.

Based on these limitations, following further work is proposed that builds on this thesis:

1. Further research can be conducted on the impact of the positive scenario and widely adopted AI-enabled SC descriptors, with the aid of empirical studies to validate the generalisation of the theory.
2. Further research applying the CF and IA to explore the impact of quantum computing technology on the dynamic and ordinary capabilities of future SC scenarios, particularly from the background of uncovering hidden patterns in the markets.
3. More research to explore the hypothesis that future SC can be based on forecasting instead of demand-driven approach. To what extent is it possible to dispense with a decoupling point?

4. In the context of AI and its capability to contribute to emergence, feasibility, and value through direct impact on emergence in the SC by AI based on biometrics/biomimicry approaches can be investigated with further research.
5. Further research can be conducted to invest in increasing the network of the CF and precise the weighting factors for value drivers in the EVA concept by identifying and analysing more case studies.

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Appendix A. Evaluation of Scenario Techniques

No	**Requirements on scenario techniques for this thesis**	**Weighting**	**Genius forecasting**		**Trend extrapolation**		**SRI matrix**		**Probability trees**		**Horizon mission methodology**		**GBN matrix**		**Cross impact analysis**		**CIB-analysis**		**Trend impact analysis**	
1	Orientation according to future developments in the SC	2	1	2	2	4	2	4	3	6	2	4	3	6	2	4	2	4	3	6
2	Preparation of decisions in regard to technology evolution	3	1	3	3	9	2	6	3	9	2	6	3	9	2	6	3	9	3	9
3	Strategy development	2	1	2	2	4	3	6	2	4	1	2	3	6	2	4	2	4	3	6
4	Strategy verification	0	1	0	1	0	3	0	3	0	1	0	3	0	2	0	2	0	3	0
5	Early recognition of change opportunities	1	1	1	1	1	2	2	2	2	2	2	2	2	1	1	1	1	3	3
6	Find visionary scenarios independently from current trends	0	3	0	0	0	3	0	1	0	3	0	1	0	1	0	1	0	0	0
7	Quantified probability of occurence	1	0	0	3	3	1	1	3	3	1	1	1	1	3	3	2	2	3	3
8	Transparency on direct and indirect impact	3	1	3	1	3	0	0	2	6	1	3	1	3	2	6	3	9	3	9

9	Mass data-based evaluation	0	0	0	3	0	0	0	1	0	1	0	1	0	1	0	1	0	3	0
10	Expert-based evaluation (qualitative strategy)	3	3	9	1	3	3	9	3	9	3	9	3	9	3	9	3	9	1	3
11	Possibility to explore quantified results	3	0	0	3	9	1	3	1	3	1	3	1	3	3	9	3	9	3	9
12	Cover relatively high system complexity	3	2	6	0	0	2	6	1	3	2	6	1	3	3	9	3	9	3	9
13	Enable plausibility check of scenarios	2	1	2	1	2	1	2	2	4	1	2	2	4	3	6	3	6	3	6
14	Predict one expected future	0	3	0	3	0	0	0	2	0	3	0	2	0	1	0	1	0	1	0
15	Easily to apply	1	3	3	3	3	3	3	3	3	3	3	3	3	2	2	1	1	1	1
16	Provide what-if prediction	1	1	1	1	1	0	0	2	2	2	2	1	1	2	2	2	2	3	3
17	Strong methodological scaffolding	3	0	0	2	6	1	3	2	6	1	3	2	6	3	9	3	9	3	9
18	Consider multiple disciplines	3	1	3	1	3	2	6	2	6	3	9	3	9	3	9	3	9	3	9
19	Evalute more than one state per descriptor	3	1	3	1	3	1	3	1	3	1	3	1	3	2	6	3	9	3	9
20	Constitute the net impact of mutual impact	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	9	0	0
		Total		**38**		**54**		**54**		**69**		**58**		**68**		**85**		**101**		**94**

Appendix B. Delphi Study Poll 1 - Questionnaire

The original Surveys of each participant are available on request.

UNIVERSITY OF GLOUCESTERSHIRE

"Impact of artificial intelligence on supply chain efficiency - a transaction cost perspective on make-or-buy decisions" Delphi Study 2018

For doctoral research purposes, we conduct a Delphi study concerning the impact of artificial intelligence on supply chain efficiency. This first round of the Delphi study especially asks for your expertise in identifying applications of artificial intelligence in supply chains.

General Information

Company name:

Name:

What is your current job title?

Industry

Chemicals ○
Pharma ○
Consumer goods ○
Retail ○
Discrete manufacturing & automotive ○
Others (please state)

Definitions

Supply Chain

A supply chain is defined by the entire network of firms and activities involved in (1) designing a set of products or services and related processes, (2) acquiring and covering inputs into these products and services, (3) distributing and consuming these products or services, and (4) disposing of these products and services (Melnyk et al., 2009).

	Strongly agree	Agree	Neutral	Disagree	Strongly disagree
Do you agree with this definition?	○	○	○	○	○

What changes would you make? (Leave blank if none)

Artificial intelligence (AI)

AI is the study and design of intelligent agents, where an intelligent agent is a system that perceives its environment and takes actions that maximize its chances of success in a particular task. Some key attributes of an "intelligent" machine include inference, reasoning, learning from experience, planning, pattern recognition and epistemology. It is developed in general for specific application domains such as expert systems (Baque, 2014). AI is the machines ability to keep improving its performance without humans having to explain exactly how to accomplish all the tasks it's given (Brynjolfsson & MacAfee, 2017)

	Strongly agree	Agree	Neutral	Disagree	Strongly disagree
Do you agree with this definition?	○	○	○	○	○

What changes would you make? (Leave blank if none)

Trends

	Very Important	Important	Moderately Important	Slightly Important	Not Important
Please rate the importance of artificial intelligence for future supply chains.	○	○	○	○	○

Please indicate how artificial intelligence will improve supply	Extremely unlikely	unlikely	Neutral	likely	Extremely likely
Lower supply chain cost	○	○	○	○	○
Higher service	○	○	○	○	○
Lower activity time (e.g. lower cycle time)	○	○	○	○	○
Higher flexibility and responsiveness	○	○	○	○	○
Others, please state					

Consider the key supply chain processes. Please indicate the probability for the future use of artificial intelligence.	Not probable	Somewhat improbable	Neutral	Somewhat probable	Very probable
Plan – Processes that balance aggregate demand and supply to develop a course of action which best meets sourcing, production, and delivery requirements	○	○	○	○	○
Source – Processes that procure goods and services to meet planned or actual demand.	○	○	○	○	○
Make – Processes that transform product to a finished state to meet planned or actual demand.	○	○	○	○	○
Deliver – Processes that provide finished goods and services to meet planned or actual demand, typically including order management, transportation management, and distribution management.	○	○	○	○	○

Applications of Artificial Intelligence in Supply Chains

What do you consider to be the most important applications of artificial intelligence in supply chains? Please name and briefly describe up to five applications or use cases.

Application of artificial intelligence #1	
Application of artificial intelligence #2	
Application of artificial intelligence #3	
Application of artificial intelligence #4	
Application of artificial intelligence #5	

Appendix C. DELPHI STUDY POLL 1 - EVALUATION OF RAW DATA UC/APP

P-I D	#	Use Case / Application	SCOR Process Level 1				Performance Indicator			
			Plan	Sou-rce	Ma-ke	Deli-ver	Lower SC Cost	Higher Service	Lower Activity Time	Higher Flexibility & Responsiv-eness
04	1	"Strategic design"" of supply chains, by systems evaluating bigger amount of data e.g. - finding alternative supply sources - scenario simulation of complex supply network decisions etc.	x				x	x	x	x
08	2	Improved view on customers (relation of all information about customers and inference of decisions, e.g. regarding marketing)	x				x			x
01	3	Forecasting of demand and sales using machine learning (ML) algorithms. ML helps to combine big data such as customer recommendations or click data with traditional time series analysis.	x				x			x
09	4	Decision support for forecasting A items	x				x			x
10	5	Forecasting of near future on demand, supplier reactions, ... as machine defects	x					x	x	
02	6	Autonomous trucks				x	x			
06	7	Autonomous production			x		x			
06	8	Autonomous networks	x	x	x	x	x	x	x	x
17	9	Autonomous driving				x	x			
10	10	Support of operative logistics decisions		x	x	x	x		x	
15	11	Planning advisors: Increase productivity in planning by alerting and advising planners (e.g. demand or supply planner) on urgent or high-impact decisions. System should automatically take low-impact decisions based on available data.	x				x		x	
01	12	Customer or product segmentation using ML. Establish link to SCM planning systems for more precise targeting of customer or product groups.	x				x		x	?

01	13	Using status reports and control information from machines / equipment to predict maintenance and repair needs (based on appropriate ML algorithms).	x				x	x		
01	14	Using (ML) algorithms to predict customer behavior, especially shopping baskets (co-buying). Establish link to SCM planning systems.	x				x			x
09	15	Intelligent interfaces to capture order entry information and digitize it. --> Finally living up to expectation of B2B EDI between companies				x	x		x	
01	16	Formalize existing procedure and planning approaches in operational logistics planning and scheduling using ML and deep learning. Might be linked to blockchain technology	x	x	x	x	x		x	
02	17	Demand prediction	x				x			
02	18	Smart robots			x		x			
03	19	Information Sharing	x	x	x	x	x		x	x
03	20	Time Scheduling	x	x	x	x	x		x	
03	21	Logistics optimisation		x	x	x	x	x	x	x
03	22	Joint collaboration planning	x				x		x	x
03	23	Resource sharing			x		x			
04	24	Better evaluation of interdependencies between different internal and external factors in order to assess supply chains and use learnings for future planning of activities, such as (""Supply Chain Planning"") - better forecasting of required demand - better forecasting of required lead-times and activities - etc	x				x	x	x	x
04	25	Identifying more complex patterns and interdependencies in order to earlier warn of arising issues e.g. (""Supply Chain Monitoring"") - detection of unormal behavior patterns - maintenance of machines - detection of fraud in finance bookings, ordering etc.		x	x	x	x		x	
04	26	Learning of typical, repetitive, but more complex behaviors such as e.g. (""Supply Chain Execution"") - problem solving in case of delays etc. - problem solving in case of issues etc.		x	x	x	x		x	

04	27	Support in ""human interaction"" in the supply chain, e.g. - order taking - customer service calls		x	x	x	x	x	x	
05	28	It starts always at stages with high uncertainty and many data, thus most of the time from the customer perspective, (marketing -> profiling -> shaping)			x	x	x			?
05	29	Pricing to customer / to supplier (typically only 2 concerns are relevant for most of the business decisions) Which product offers most value to my customer, which price will he pay.		x		x	x	?		
05	30	All type of machine to human interfaces	x		x	x	x		x	
05	31	Personal avatars to organize / control / prioritize life		x	x	x		x		?
05	32	Support of every decision where more than 3 factors have to be considered	x	x	x	x	x		x	
06	33	Predictive maintenance	x		?		x			
06	34	Quality and output optimization	x		x	x	x			?
07	35	Inventory optimization		?	x	x	x			x
07	36	Warehouse management			?	x	x	x	x	
07	37	Distribution				x	x	x	x	x
07	38	Transportation planning	?			x	x	x	x	
07	39	Management of inhouse logistics and material-flows			x	x	x		x	
07	40	Planning and disposition of goods supply	x	x			x			x
07	41	Production planning and goods supply for production	x		x		x		x	?
08	42	Improved Demand Planning (building / accessing the required data bases to be able to apply machine learning algorithms in manifold areas being related to demand forecasting)	x				x			x
08	43	Predictive Maintenance: improving efficiency and effectiveness of production lines, reducing down times			x		x		x	
08	44	Prediction of Supply uncertainties and usage in related planning activities	x				x		x	x
09	45	Continuous monitoring of inbound and outbound shipments taking into account multiple parameters from supply chain partners, but also external like vessel schedules, weather, etc.		x		x	x		x	

09	46	Continuous planning parameter optimization to minimize total cost	x				x			
11	47	Manufacturing processes in high-tech industries such as computer, telecommunication devices, cellphones & automotive production industries	?		x		x		x	?
11	48	Service and self-service industries such as hospitals and banks					x		x	
11	49	Call centers and speech recognition systems of call centers				x	x			
11	50	Supervised and semi-supervised training simulators or training support simulators				x	x			
11	51	Military training, police forces and related applications can use AI to reduce the loss of lives in danger situations			x			x		
12	52	Autonomous Supply: Autonomously decided uninterrupted provision of supplies with minimum costs from numerous candidate suppliers by taking unforeseen events into consideration and respond immediately		x			x		x	
12	53	SC visibility: With the IoT, high visibility of materials, WIP and finished products and precise forecasting in supply chain	x		x		x		x	?
12	54	Transportation and Distribution: Optimized and autonomous large-scale transportation and item based delivery				x	x			
13	55	Demand Planning/ Forecasting	x				x		x	x
13	56	Procurement of routine items		x			x			
13	57	Driverless Transportation for long haul				x	x			
14	58	Predictive Analytics / Data Modeling Predictive analytics and data modeling are helping with development of algorithms that maximize demand forecasting, inventory balancing & route optimization. For example, if the AI predicts consumer demand for a new product, then the manufacturer will be able to ramp up production with reasonable certainty. Logistics Service Provider will know in advance volume, date, peak seasons - Strong impact on usage of economies of scale / better procurement / better planning	x				x		x	x

14	59	Machine-Learning: Newly popularized term in the SC world, closely linked to Big Data Trend Concept of computer learning to make sense of patterns from data analysis without necessarily being programmed to do so. Focus on algorithm instead of data. Logistics and SC problems are especially emendable to solving through machine learning, particulary as the size of data sets grow. Network Optimization, demand forecasting and supply planning are all problems that can use large data sets to reduce risks in SC	x			x	x		x	
14	60	Autonomous shipping Already started in the automotive industry (e.g. Tesla); first trucks in the logistics industry are also equipped with such a kind of technology; Drones - Last Mile delivery Cargo vessels sometimes run sections of long voyages on autopilot, making fully autonomous vessels a logical next steps. - Rolls- Royce 2020 Prediction In addition to cutting costs (e.g. up to 44% of ship's running costs are in the crew), autonomous vessels will have the possibility to reduce need for human interaction and human error				x	x			
15	61	Demand forecasting: Improvement of customer demand forecasts along complete product life cycle by resolving complex interdependencies between company internal data (historic sales data of same and other products, master data, campaigns & promotions, pricing etc.) as well as external data (POS/customer data, social media data, weather, etc.).	x				x		x	x
15	62	Ensure reliable delivery dates along supply chain: Using shared supply chain information (inventories, processing times, ...) as well as external data (weather, traffic, accidents, …) to reliably predict delivery dates to customer as well as pro-actively notify supply chain planners in case of supply chain disruptions.				x	x	?	x	

15	63	Fault detection in operations: Automatic fault detection on processes in operations by analyzing diverse inputs (e.g. video, audio and sensor data like weight, temperature in combination with (inaccurate) master data) Example for ""Deliver"": Detect packing errors (wrong product in package), detect shipping errors (wrong pallet in container)			x	x	x		x	
15	64	Ad-hoc routing of shipments: Choose carrier/routing for each shipment in real-time depending on cost and time of each delivery option				x	x			
16	65	Strategic, Tactical and Operational Supply Chain Planning - In comparison to humans AI is able to handle a much more higher number of influencing factors on decisions made during planning activities allowing to design optimal supply chains in terms of material, information and funds flow	x	x	x	x	x		x	?
16	66	Risk Management - Evaluation of risks on a higher detail level and with a higher event prediction rate	x				x		x	
16	67	Data Handling - AI is better in sampling, cleansing, processing, and storing the data that have the biggest value for supply chains	x	x	x	x	x		x	?
16	68	Assisting - AI could complement humans' decisions in operations	x	x	x	x	x		x	?
17	69	Demand forecast	x				x		x	x
17	70	Warehousing			x	x	x		x	
17	71	Network planning	x				x	x		x
17	72	Route planning	x			x	x	x	x	
Total			**37**	**19**	**31**	**39**	**69**	**18**	**43**	**30**

P-ID: Participant-Identification

Appendix D. DELPHI STUDY POLL 1 - UC/APP CATEGORIES / RESULTING DESCRIPTOR MATRIX

Descriptors		Structure and process elements of SCM				AI relevant use cases						SC performance indicators		
UC/APP Categories		Type of interorganisa-tional specialisation	Dimensions of process design	Network material flow	Type of coordination	Interorganisa-tional decision delegation	Use of AI in forecasting	Use of autonomous SC planning techniques	Use of autonomous driving	Use of emerging technology blockchain	Use of AI to attack SC system architecture	SC efficiency	Transaction cost in the SC	SC responsiveness
C1	Forecasting						x	x						
C2	Collaboration	x			x	x				x		x		
C3	Movement			x					x					
C4	Monitoring					x								
C5	Scheduling		x									x		x
C6	Communication				x								x	
C7	Consumer Centricity		x					x				x	x	x
C8	Supply Network Design										x			
C9	General Statement													
Total		**1**	**2**	**1**	**2**	**2**	**1**	**2**	**1**	**1**	**1**	**3**	**2**	**2**

Appendix E. DELPHI STUDY POLL 2 - QUESTIONNAIRE

A - Questionnaire Guideline

The original Surveys of each participant are available on request.

Contact and response

We'd like to ask you to use the MSExcel spreadsheet for your answers. If you prefer a print out and handwritten answers, we would appreciate to have your document scanned and attached in an email.

[redacted]

Please, send the responses back by Thursday, **June 28th, 2018** at the latest

Review Delphi study poll 1 and purpose of poll 2

With the first questionnaire, we asked you to name the most important applications of artificial intelligence (AI) in supply chains.
AI applications impact structure, process and performance elements of supply chains either directly or indirectly.
The resulting AI applications are the scaffold of the generic framework for our research with the target to develop scenarios for future behaviour in supply chains.

Now with this second poll, we want you to evaluate the potential impact of the AI applications on these supply chain inherent elements.
Therefore, we apply a specific scenario technique, cross-impact balance analysis (CIB analysis).

General explanation of the cross-impact balance analysis (CIB analysis)

We conduct a CIB-analysis which feeds our system-theoretical approach methodically. The system to be evaluated is a supply chain (SC).
This system is described by multiple influencing factors (descriptors). Each descriptor in our SC model consists of two states (two variants).
The descriptor variants have mutual interrelations. These mutual interrelations are evaluated by the below Likert scale.

Rating	Explanation
-3	strongly restricting influence
-2	Restricting influence
-1	Weakly restricting influence
0	No influence
1	Weakly promoting influence
2	Promoting influence
3	Strongly promoting influence

Two descriptors form a four-field matrix. Always the descriptor in a row influences the descriptor in a column!

Template	Descriptor B	
Descriptor A	Variant B1	Variant B2
Variant A1	impacts	
Variant A2		

- Always read from left to right
- Row always impacts column
- Variant A1 of descriptor A impacts Variant B1 of descriptor B

Example	Interorganisational decision delegation	
Use AI in forecasting	More autonomy	Less autonomy
Commonly spread and fully integrated	1 3	2 -3
Isolated with individual data bases	3 -1	4 0

1 Commonly spread and fully integrated usage of AI in forecasting **strongly promotes (3)** more autonomy of interorganizational decision delegation

2 Commonly spread and fully integrated usage of AI in forecasting **strongly restricts (-3)** less autonomy of interorganizational decision delegation

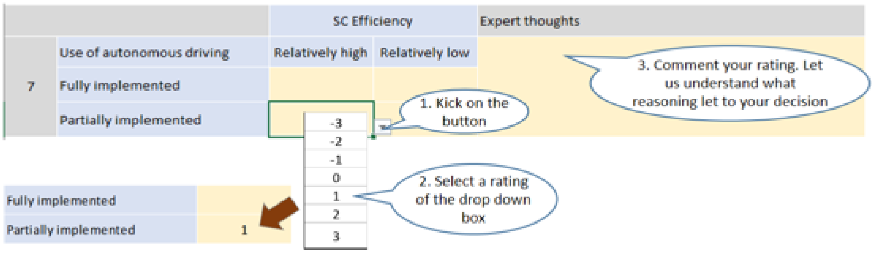
3 Isolated AI in forecasting with individual databases **weakly restricts (-1)** more autonomy of interorganizational decision delegation

4 Isolated AI in forecasting with individual databases **does not affect (0)** less autonomy interorganizational decision delegation

How to fill out part 1 of the questionnaire

With part 1 of the questionnaire, we kindly ask you to actively evaluate the interrelation between the listed descriptors.
These descriptors are the key elements of the framework.

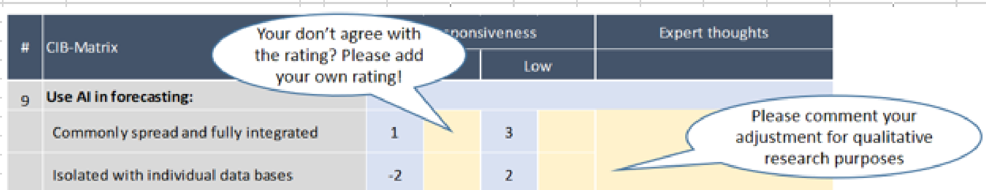
Please see tab "Descriptor_description" for short explanation of each of the descriptors.



We are conducting a qualitative research. It is essentially vital for our methodology to know your thoughts - let us participate in your reasoning with the final step 3!

How to fill out part 2 of the questionnaire

With part 2 of the questionnaire, we kindly ask you to review the pre-evaluation of the interrelation between the listed descriptors.
The CIB-matrix consists of 13 active key descriptors with mutual interrelations. Each of the descriptors has two variants.
Hence, the CIB-Matrix consists of more than 500 interrelations to be evaluated. Therefore, we splitted the complete CIB-Matrix, so that the effort for each expert will be feasible.



We are conducting a qualitative research. It is essentially vital for our methodology to know your thoughts - let us participate in your reasoning.

Additional information for comprehensive understanding - not necessary to fill out the questionnaire

For more information about CIB-analysis please refer to
Weimer-Jehle, W. (2006). Cross-impact balances: A system-theoretical approach to cross-impact analysis.
Technological Forecasting and Social Change, 73(4), 334-361

4 Key descriptors of questionnaire part 1

Block A: AI in forecasting

		SC Efficiency		Expert thoughts
1	Use AI in forecasting	Relatively high	Relatively low	
	Commonly spread and fully integrated			
	Isolated with individual data bases			

		Transaction Cost in the SC		Expert thoughts
2	Use AI in forecasting	Increasing	Decreasing	
	Commonly spread and fully integrated			
	Isolated with individual data bases			

Block B: Autonomous planning

		SC Efficiency		Expert thoughts
3	Use of autonomous SC planning techniques	Relatively high	Relatively low	
	Commonly spread			
	Not widely spread			

		Transaction cost in the SC		Expert thoughts
4	Use of autonomous SC planning techniques	Increasing	Decreasing	
	Commonly spread			
	Not widely spread			

Block C: Use emerging technology blockchain

		SC Efficiency		Expert thoughts
5	Use emerging technology blockchain	Relatively high	Relatively low	
	Global process driver for the whole SC			
	Only used as data memory			

		Transaction cost in the SC		Expert thoughts
6	Use emerging technology blockchain	Increasing	Decreasing	
	Global process driver for the whole SC			
	Only used as data memory			

Block D: Autonomous Driving

		SC Efficiency		Expert thoughts
7	Use of autonomous driving	Relatively high	Relatively low	
	Fully implemented			
	Partially implemented			

		Transaction cost in the SC		Expert thoughts
8	Use of autonomous driving	Increasing	Decreasing	
	Fully implemented			
	Partially implemented	1		

Complete CIB-Matrix of questionnaire part 2

Please see tab "complete CIB-Matrix"

B - Questionnaire Part 1

The original Surveys of each participant are available on request.

UNIVERSITY OF GLOUCESTERSHIRE

"Impact of artificial intelligence on supply chain efficiency - a transaction cost perspective on make-or-buy decisions" Delphi Study 2018

For doctoral research purposes, we conduct a Delphi study concerning the impact of artificial intelligence on supply chain efficiency. This second round of the Delphi study especially asks for your expertise in evaluating cross-impacts between influencing factors.

Part 1 Name

The CIB-matrix consists of 4 active key descriptors (rows) impacting 2 passive descriptors (columns). Always 2 descriptors out of 4 are assigned to each experts.
Please actively rate the strength of influence of the descriptor variants in each row. Please comment your rating decision to support our qualitative research approach.
Only the yellow-coloured fields are to be maintained. Please see tab "Descriptor_description" for short explanation of each of the descriptors.
For further guidance see tab "Guideline (how to fill out part 1 of the questionnaire)".

Block A: AI in forecasting

		SC Efficiency		Expert thoughts
1	Use AI in forecasting	Relatively high	Relatively low	
	Commonly spread and fully integrated			
	Isolated with individual data bases			

		Transaction Cost in the SC		Expert thoughts
2	Use AI in forecasting	Increasing	Decreasing	
	Commonly spread and fully integrated			
	Isolated with individual data bases			

Block B: Autonomous planning

		SC Efficiency		Expert thoughts
3	Use of autonomous SC planning techniques	Relatively high	Relatively low	
	Commonly spread			
	Not widely spread			

		Transaction cost in the SC		Expert thoughts
4	Use of autonomous SC planning techniques	Increasing	Decreasing	
	Commonly spread			
	Not widely spread			

II
Block C: Use emerging technology blockchain

		SC Efficiency		Expert thoughts
5	Use emerging technology blockchain	Relatively high	Relatively low	
	Global process driver for the whole SC			
	Only used as data memory			

		Transaction cost in the SC		Expert thoughts
6	Use emerging technology blockchain	Increasing	Decreasing	
	Global process driver for the whole SC			
	Only used as data memory			

Block D: Autonomous Driving

		SC Efficiency		Expert thoughts
7	Use of autonomous driving	Relatively high	Relatively low	
	Fully implemented			
	Partially implemented			

		Transaction cost in the SC		Expert thoughts
8	Use of autonomous driving	Increasing	Decreasing	
	Fully implemented			
	Partially implemented			

C - Questionnaire Part 2

UNIVERSITY OF GLOUCESTERSHIRE
at Cheltenham and Gloucester

"Impact of artificial intelligence on supply chain efficiency - a transaction cost perspective on make-or-buy decisions" Delphi Study 2018

For doctoral research purposes, we conduct a Delphi study concerning the impact of artificial intelligence on supply chain efficiency. This second round of the Delphi study especially asks for your expertise in evaluating cross-impacts between influencing factors.

Part 2 Name

The CIB-matrix consists of 13 active key descriptors with mutual interrelations. Each of the descriptors has two variants. Only selected active descriptors are assigned to each expert.
Please review the rating. If you do not agree with the pre-evaluation, please adjust and comment the reason for your adjustment.
Only the yellow-coloured fields are to be maintained. Please see tab "Descriptor_description" for short explanation of each of the descriptors.
If you are interested in the complete CIB-Matrix please see tab "Complete CIB-Matrix".
For further guidance see tab "Guideline (how to fill out part 2 of the questionnaire)".

#	CIB-Matrix	Responsiveness: High	Responsiveness: Low	Expert thoughts	Efficiency: High	Efficiency: Low	Expert thoughts	Transaction cost: Increasing	Transaction cost: Decreasing	Expert thoughts	Dec delegation: More autonomy	Dec delegation: Less autonomy	Expert thoughts
1	**SC responsiveness:**												
	Relatively high				0	0		-2	0		0	0	
	Relatively low				0	0		2	-2		0	0	
2	**SC efficiency:**												
	Relatively high	0	0					-2	0		0	0	
	Relatively low	0	0					2	-2		0	0	
3	**Transaction costs in the SC:**												
	Increasing	0	0		-3	-1					0	0	
	Decreasing	0	0		1	2					0	0	
4	**Interorganisational decision delegation:**												
	More autonomy	1	-2		-3	2		-1	1				
	Less autonomy	-2	2		2	-2		1	-1				
5	**Type of interorganisational specialisation:**												
	Process orientation	1	2		1	2		-1	1		2	-2	
	Functional orientation	-2	-1		-2	-1		1	-1		-2	2	
6	**Type of coordination:**												
	Centralised by one focal company	1	2		0	2		-1	1		-2	2	
	Equally decentralised by SC partners	-1	-2		0	-2		1	-1		2	-2	
7	**Dimensions of process design:**												
	Postponement	0	3		0	0		-1	1		0	0	
	Speculation	1	2		0	0		2	-2		0	0	
8	**Network material flow:**												
	Centralised network (Hub-and-spoke)	-3	-1		1	3		0	0		0	0	
	Decentralised network (Grid system)	3	1		-3	-1		0	0		0	0	
9	**Use AI in forecasting:**												
	[illegible]	[illegible]	[illegible]		[illegible]	[illegible]		[illegible]	[illegible]		[illegible]	[illegible]	

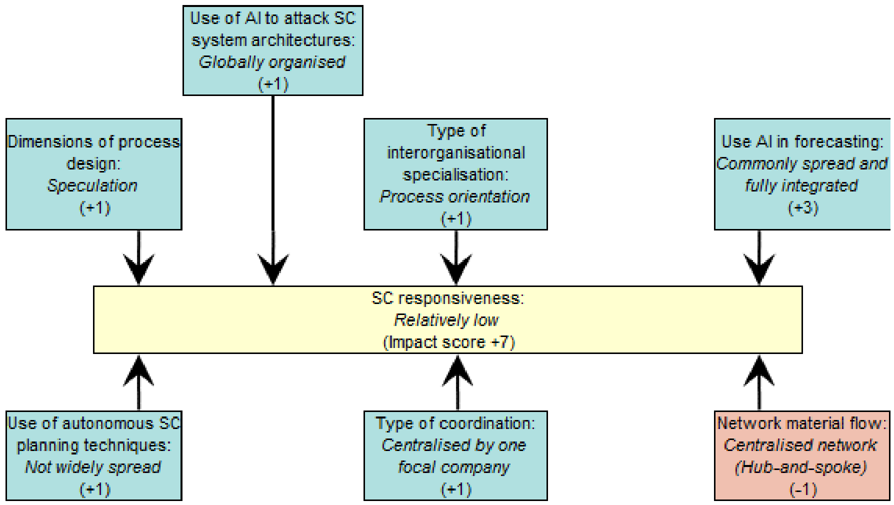
Appendix F. Delphi Study Poll 2 - Impact Balances of Consistent Scenario

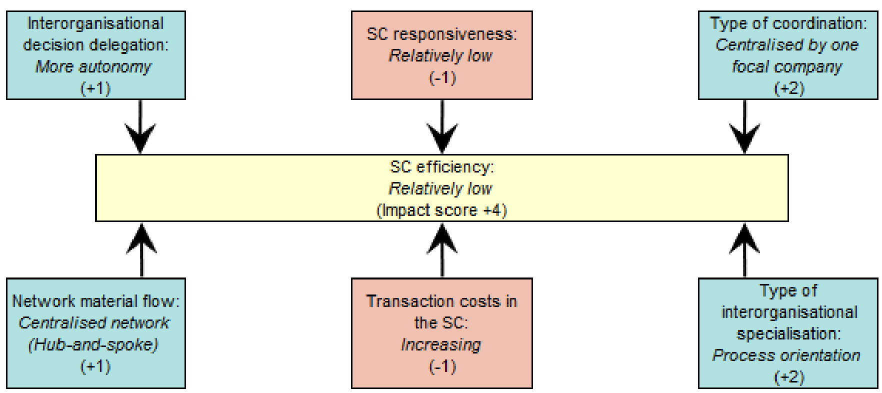
	Responsiveness		Efficiency		Transaction cost		Dec delegation	
	High	Low	High	Low	Increasing	Decreasing	More autonomoy	Less autonomy
SC responsiveness								
Relatively high			-2	1	-1	1	0	0
Relatively low			1	-1	2	-2	0	0
SC efficiency								
Relatively high	0	-1			-2	1	-1	1
Relatively low	-1	0			2	-2	1	-1
Transaction costs in the SC								
Increasing	0	0	-3	-1			0	0
Decreasing	0	0	1	2			0	1
Interorganisational decision delegation								
More autonomy	2	0	0	1	0	1		
Less autonomy	-2	1	2	-1	0	-1		
Type of interorganisational specialisation								
Process orientation	1	1	1	2	-1	1	2	-2
Functional orientation	-2	-2	-2	-1	1	-1	-2	2
Type of coordination								
Centralised by one focal company	1	1	0	2	-1	1	-2	1
Equally decentralised by SC partners	-1	0	0	-2	1	-1	2	-2
Dimensions of process design								
Postponement	0	2	1	1	0	1	0	0
Speculation	1	1	0	0	2	-2	0	0
Network material flow								
Centralised network (Hub-and-spoke)	-1	-1	1	1	0	0	0	0
Decentralised network (Grid system)	3	0	-2	-1	0	0	0	0
Use AI in forecasting								
Commonly spread and fully integrated	1	3	1	0	-2	2	3	-3
Isolated with individual data bases	-1	2	0	0	0	0	0	0
Use of autonomous SC planning techniques								
Commonly spread	2	2	2	0	0	2	3	-2
Not widely spread	0	1	0	0	0	0	1	-1
Use of autonomous driving								
Fully implemented	1	0	2	0	0	0	-1	1
Partially implemented	0	0	1	0	0	0	-1	1
Use of emerging technology blockchain								
Global process driver for the whole SC	2	0	2	0	-2	2	0	0
Only used as data memory	0	0	0	0	0	0	0	0
Use of AI to attack SC system architectures								
Regionally organised	-1	0	-1	0	1	-1	0	0
Globally organised	-2	1	-2	0	2	-1	0	0
		v		v	v		v	
Balance:	2	7	0	4	4	-2	4	-5

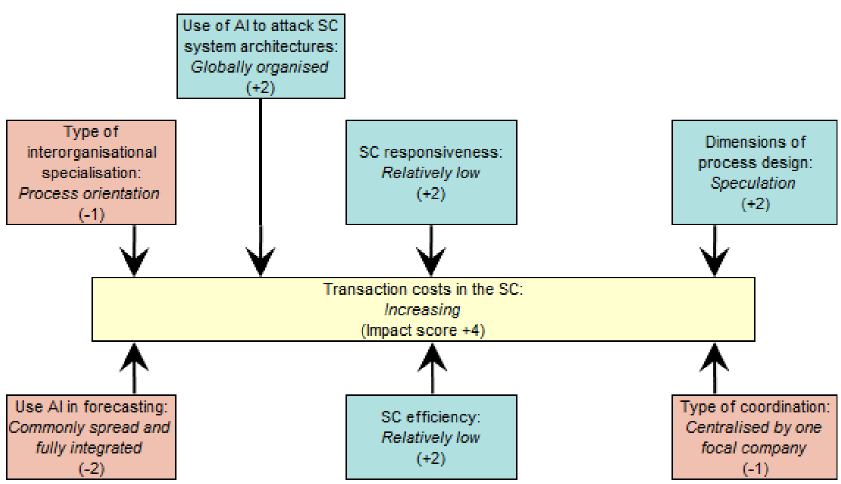
	Specialisation		Coordination		Process design		Net MatFlow		Forecasting	
	Process	Function	Focal	Equally	Postpone	Speculate	Central	Decentral	Integrated	Isolated
SC responsiveness										
Relatively high	0	-1	0	0	1	0	-3	1	1	0
Relatively low	1	-2	2	-2	1	1	-1	2	0	0
SC efficiency										
Relatively high	-1	-1	0	0	0	0	1	-2	1	0
Relatively low	1	-2	2	-2	0	0	2	-1	-1	0
Transaction costs in the SC										
Increasing	0	0	1	-1	1	1	0	0	1	0
Decreasing	0	0	0	0	0	0	0	0	0	0
Interorganisational decision delegation										
More autonomy	1	-1	-2	3	0	0	0	0	-1	1
Less autonomy	-2	2	3	-3	0	0	0	0	1	-1
Type of interorganisational specialisation										
Process orientation			-1	2	0	0	0	0	0	0
Functional orientation			1	0	0	0	0	0	0	0
Type of coordination										
Centralised by one focal company	2	-1			0	0	0	0	1	1
Equally decentralised by SC partners	-1	1			0	0	0	1	0	0
Dimensions of process design										
Postponement	0	0	1	0			1	-1	0	0
Speculation	0	0	0	0			0	0	2	0
Network material flow										
Centralised network (Hub-and-spoke)	0	0	0	0	0	0			0	0
Decentralised network (Grid system)	0	0	0	0	0	0			0	0
Use AI in forecasting										
Commonly spread and fully integrated	1	-1	-1	1	1	3	2	-2		
Isolated with individual data bases	-1	1	0	0	0	1	-1	2		
Use of autonomous SC planning techniques										
Commonly spread	3	-3	-2	3	-1	0	1	1	2	-1
Not widely spread	-1	1	2	-2	0	0	0	0	1	0
Use of autonomous driving										
Fully implemented	0	0	-1	1	0	0	-2	3	1	0
Partially implemented	0	0	0	0	0	0	0	0	0	0
Use of emerging technology blockchain										
Global process driver for the whole SC	1	0	0	1	0	0	0	0	1	-1
Only used as data memory	0	0	0	0	0	0	0	0	0	0
Use of AI to attack SC system architectures										
Regionally organised	0	0	0	0	0	0	0	0	0	0
Globally organised	0	0	1	-1	0	0	0	0	0	0
	v		v			v	v		v	
Balance:	5	-6	4	-2	3	5	3	-1	3	2

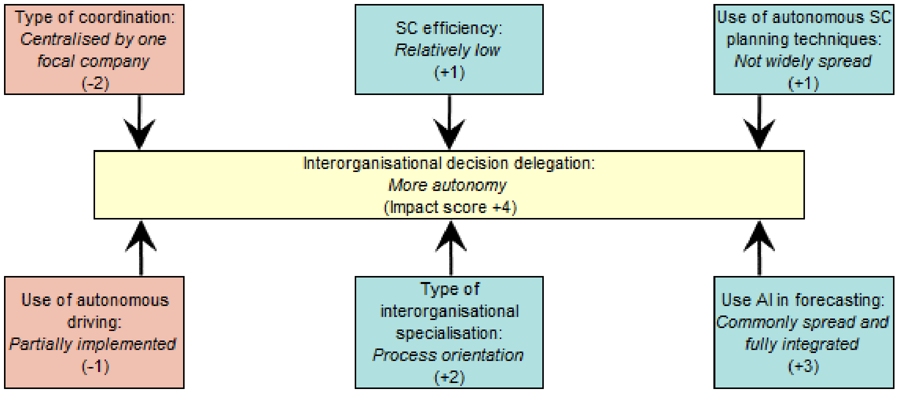
	Aut planning		Aut driving		Blockchain		AttackSC	
	Spread	Not widely	Fully	Partially	Process driver	Data memory	Regionally	Globally
SC responsiveness								
Relatively high	1	0	0	0	0	0	0	-1
Relatively low	0	3	0	0	0	0	0	1
SC efficiency								
Relatively high	0	0	0	0	0	0	0	1
Relatively low	0	2	1	0	0	0	0	0
Transaction costs in the SC								
Increasing	0	0	0	0	1	1	0	0
Decreasing	0	0	1	1	0	0	0	0
Interorganisational decision delegation								
More autonomy	0	2	1	0	0	0	0	-1
Less autonomy	1	0	-1	-1	0	0	1	0
Type of interorganisational specialisation								
Process orientation	2	0	0	0	0	0	0	0
Functional orientation	-2	0	0	0	0	0	0	0
Type of coordination								
Centralised by one focal company	0	2	0	1	0	1	0	1
Equally decentralised by SC partners	0	-2	0	-1	0	0	-1	-1
Dimensions of process design								
Postponement	0	0	0	0	0	0	0	0
Speculation	0	0	1	0	0	0	0	0
Network material flow								
Centralised network (Hub-and-spoke)	0	0	0	0	0	0	0	0
Decentralised network (Grid system)	0	0	0	0	0	0	0	0
Use AI in forecasting								
Commonly spread and fully integrated	1	3	0	0	0	0	1	1
Isolated with individual data bases	-3	-1	0	0	0	0	0	0
Use of autonomous SC planning techniques								
Commonly spread			1	1	1	2	2	3
Not widely spread			-1	-1	0	0	1	2
Use of autonomous driving								
Fully implemented	1	1			1	0	2	3
Partially implemented	0	0			0	0	1	2
Use of emerging technology blockchain								
Global process driver for the whole SC	1	0	1	1			1	0
Only used as data memory	0	0	0	0			-1	-1
Use of AI to attack SC system architectures								
Regionally organised	-1	0	-1	0	0	0		
Globally organised	-2	1	-2	0	1	0		
		v		v		v		v
Balance:	1	13	0	0	2	2	2	5

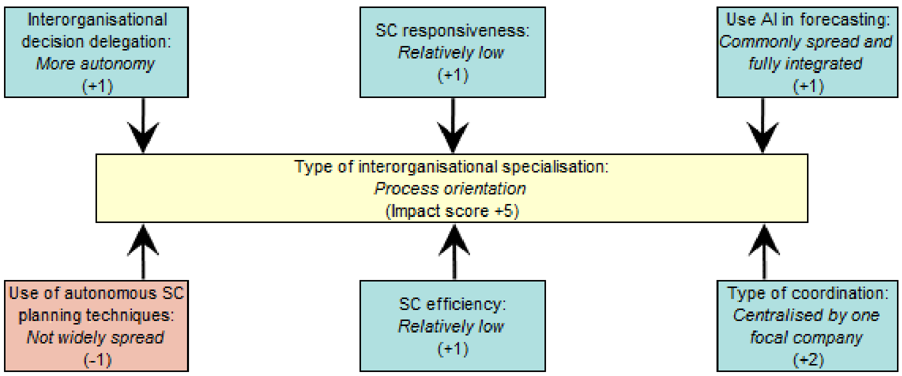
Appendix G. ScenarioWizard - Impact Balances of Negative Scenario (SF2M2)

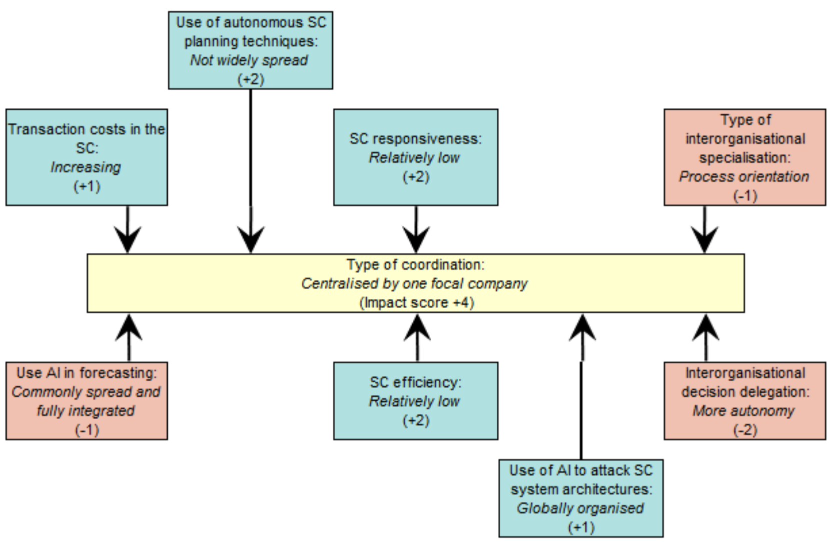


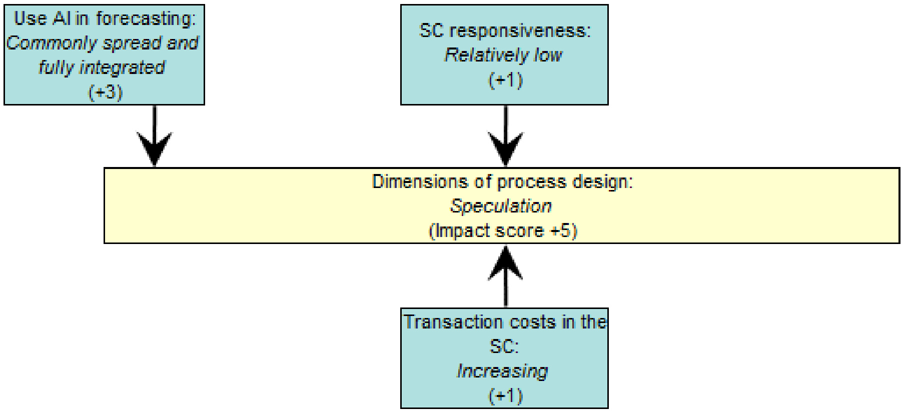


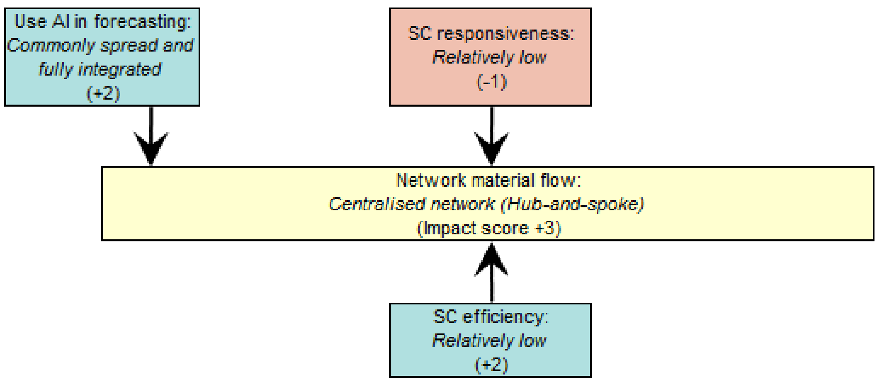


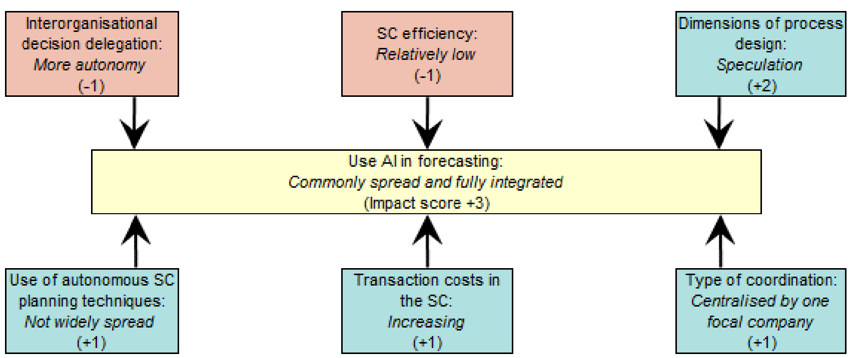

Type of coordination: Centralised by one focal company (-2)
SC efficiency: Relatively low (+1)
Use of autonomous SC planning techniques: Not widely spread (+1)
Interorganisational decision delegation: More autonomy (Impact score +4)
Use of autonomous driving: Partially implemented (-1)
Type of interorganisational specialisation: Process orientation (+2)
Use AI in forecasting: Commonly spread and fully integrated (+3)

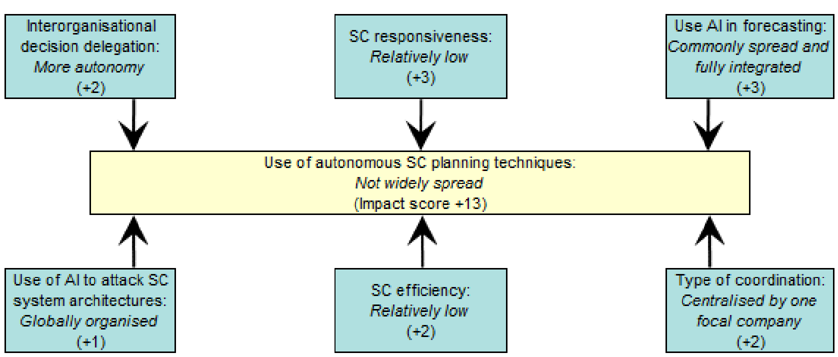

Interorganisational decision delegation: More autonomy (+1)
SC responsiveness: Relatively low (+1)
Use AI in forecasting: Commonly spread and fully integrated (+1)
Type of interorganisational specialisation: Process orientation (Impact score +5)
Use of autonomous SC planning techniques: Not widely spread (-1)
SC efficiency: Relatively low (+1)
Type of coordination: Centralised by one focal company (+2)

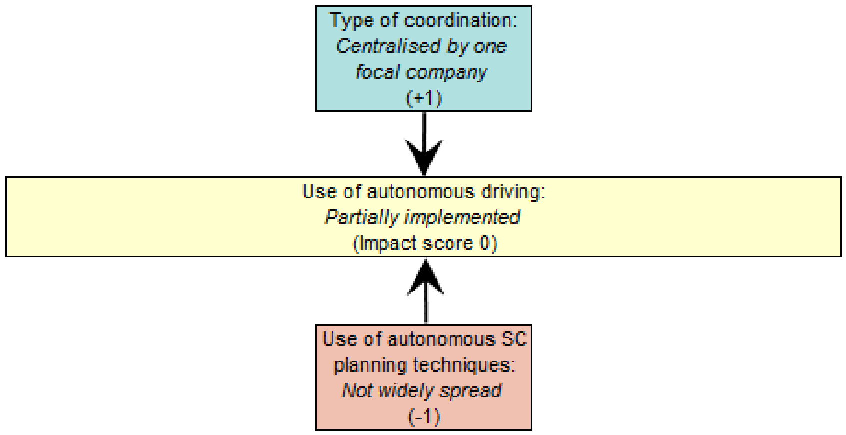

Use of autonomous SC planning techniques: Not widely spread (+2)
Transaction costs in the SC: Increasing (+1)
SC responsiveness: Relatively low (+2)
Type of interorganisational specialisation: Process orientation (-1)
Type of coordination: Centralised by one focal company (Impact score +4)
Use AI in forecasting: Commonly spread and fully integrated (-1)
SC efficiency: Relatively low (+2)
Interorganisational decision delegation: More autonomy (-2)
Use of AI to attack SC system architectures: Globally organised (+1)

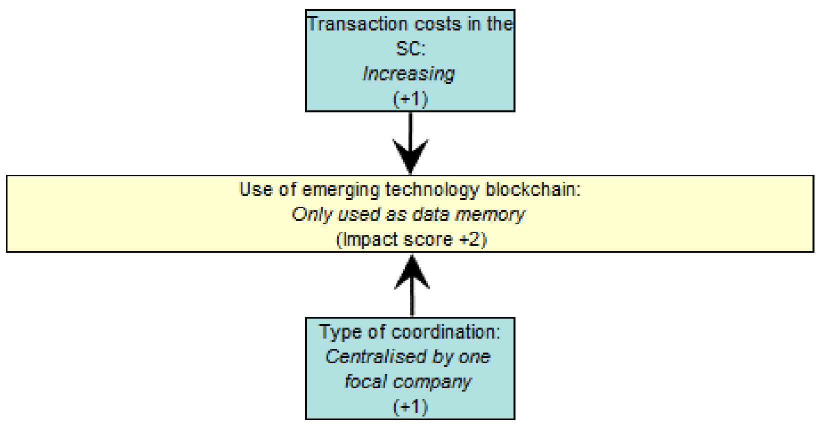

Use AI in forecasting:
Commonly spread and fully integrated
(+3)
SC responsiveness:
Relatively low
(+1)
Dimensions of process design:
Speculation
(Impact score +5)
Transaction costs in the SC:
Increasing
(+1)

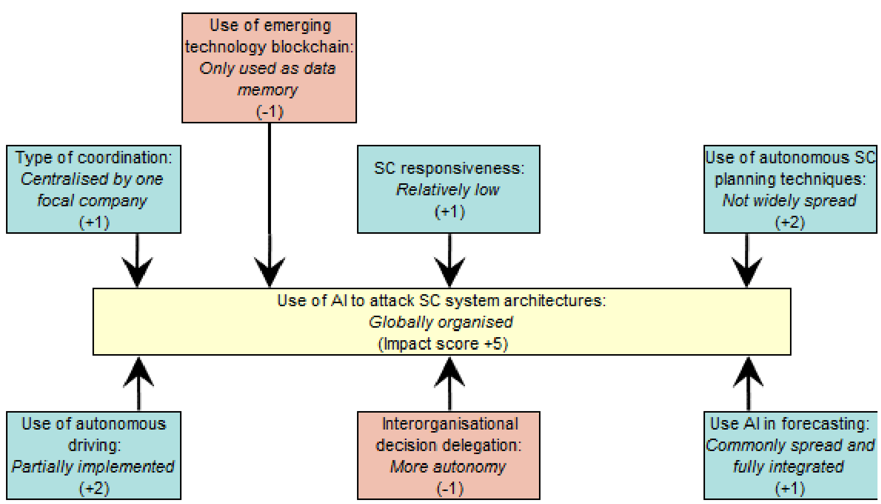

Use AI in forecasting:
Commonly spread and fully integrated
(+2)
SC responsiveness:
Relatively low
(-1)
Network material flow:
Centralised network (Hub-and-spoke)
(Impact score +3)
SC efficiency:
Relatively low
(+2)


Interorganisational decision delegation:
More autonomy
(-1)
SC efficiency:
Relatively low
(-1)
Dimensions of process design:
Speculation
(+2)
Use AI in forecasting:
Commonly spread and fully integrated
(Impact score +3)
Use of autonomous SC planning techniques:
Not widely spread
(+1)
Transaction costs in the SC:
Increasing
(+1)
Type of coordination:
Centralised by one focal company
(+1)

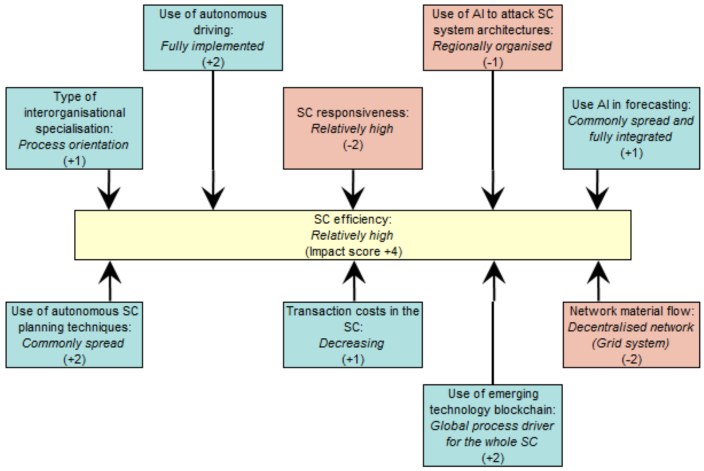

Interorganisational decision delegation:
More autonomy
(+2)
SC responsiveness:
Relatively low
(+3)
Use AI in forecasting:
Commonly spread and fully integrated
(+3)
Use of autonomous SC planning techniques:
Not widely spread
(Impact score +13)
Use of AI to attack SC system architectures:
Globally organised
(+1)
SC efficiency:
Relatively low
(+2)
Type of coordination:
Centralised by one focal company
(+2)

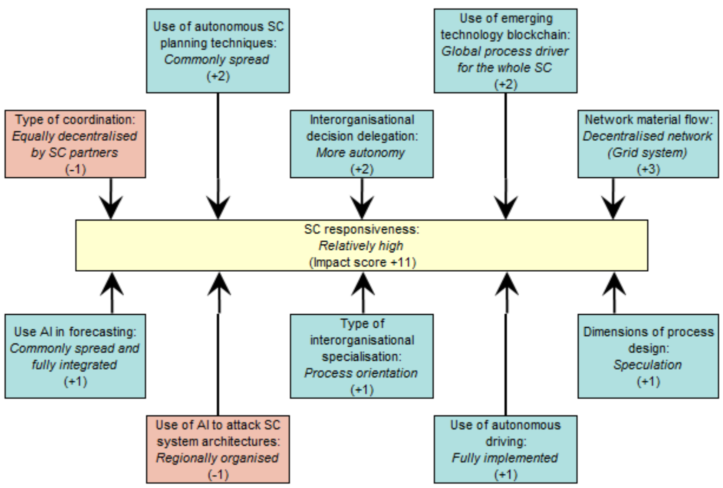

Type of coordination:
Centralised by one focal company
(+1)
Use of autonomous driving:
Partially implemented
(Impact score 0)
Use of autonomous SC planning techniques:
Not widely spread
(-1)

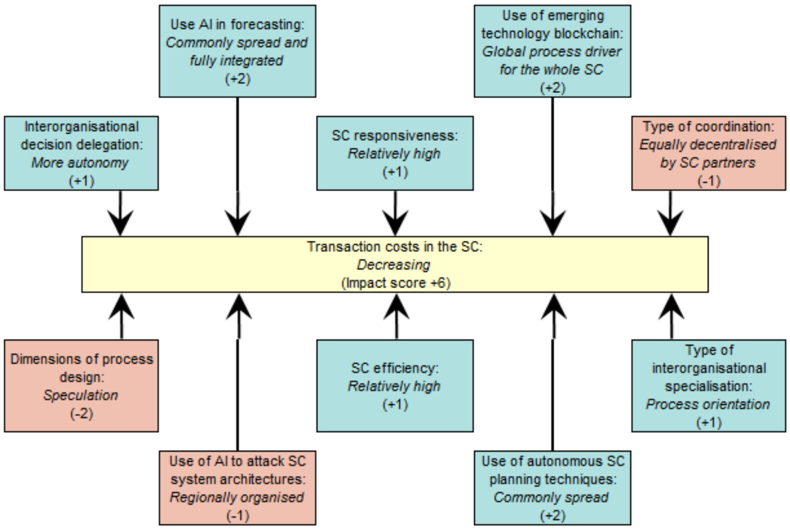

Transaction costs in the SC:
Increasing
(+1)
Use of emerging technology blockchain:
Only used as data memory
(Impact score +2)
Type of coordination:
Centralised by one focal company
(+1)

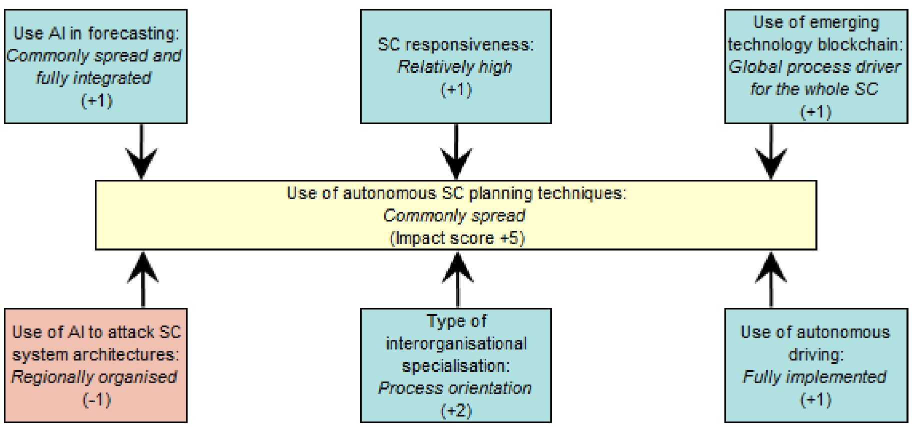

Use of emerging technology blockchain:
Only used as data memory
(-1)
Type of coordination:
Centralised by one focal company
(+1)
SC responsiveness:
Relatively low
(+1)
Use of autonomous SC planning techniques:
Not widely spread
(+2)
Use of AI to attack SC system architectures:
Globally organised
(Impact score +5)
Use of autonomous driving:
Partially implemented
(+2)
Interorganisational decision delegation:
More autonomy
(-1)
Use AI in forecasting:
Commonly spread and fully integrated
(+1)

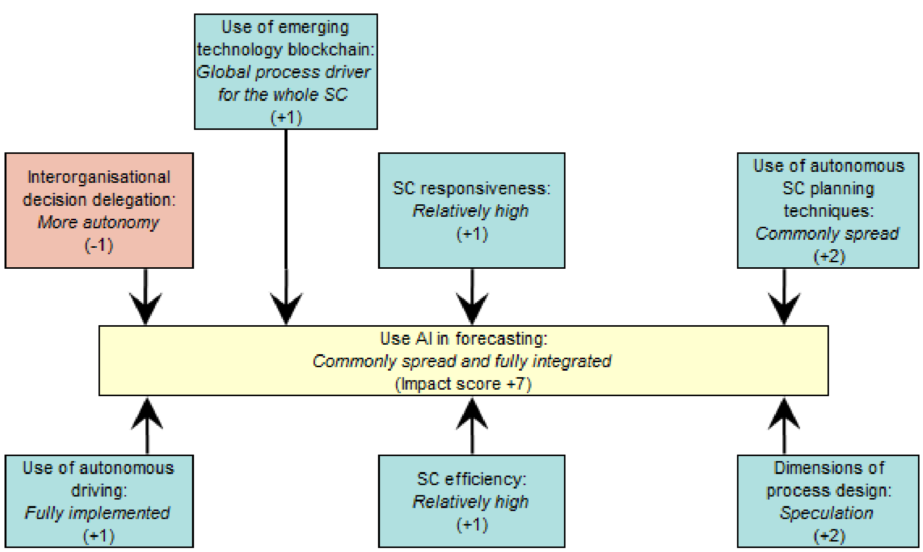
Appendix H. ScenarioWizard - Impact Balance of Positive Scenario (SF1M1)

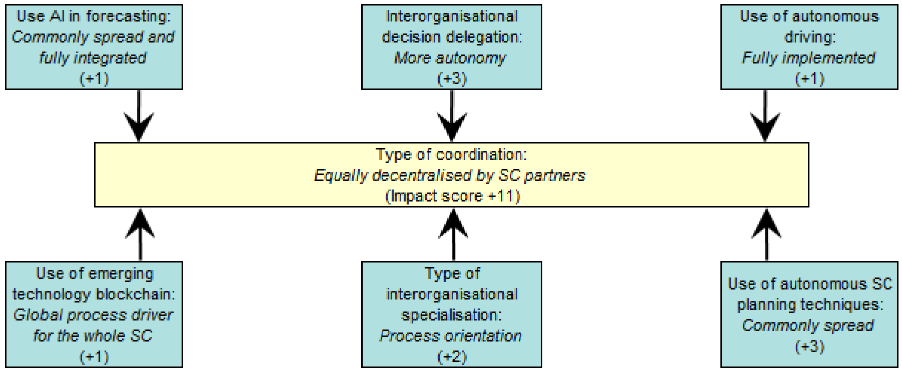


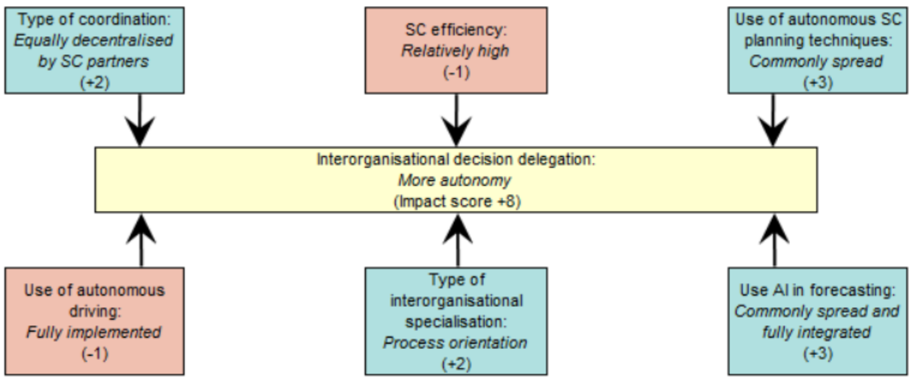


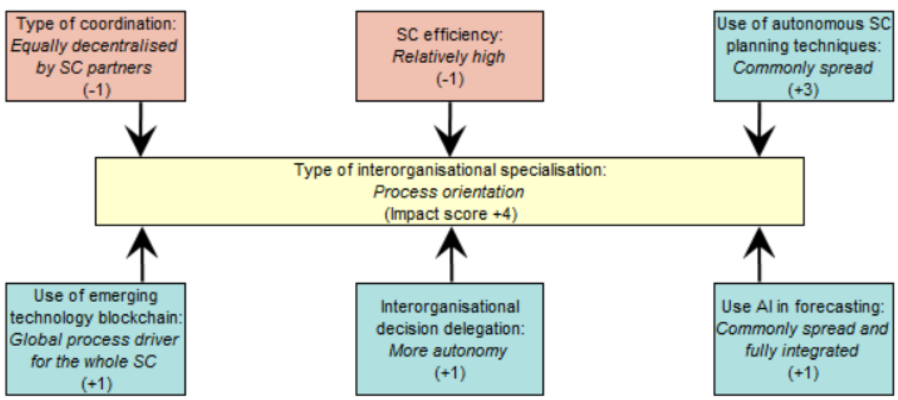

Use AI in forecasting: Commonly spread and fully integrated (+2)
Use of emerging technology blockchain: Global process driver for the whole SC (+2)
Interorganisational decision delegation: More autonomy (+1)
SC responsiveness: Relatively high (+1)
Type of coordination: Equally decentralised by SC partners (-1)
Transaction costs in the SC: Decreasing (Impact score +6)
Dimensions of process design: Speculation (-2)
SC efficiency: Relatively high (+1)
Type of interorganisational specialisation: Process orientation (+1)
Use of AI to attack SC system architectures: Regionally organised (-1)
Use of autonomous SC planning techniques: Commonly spread (+2)

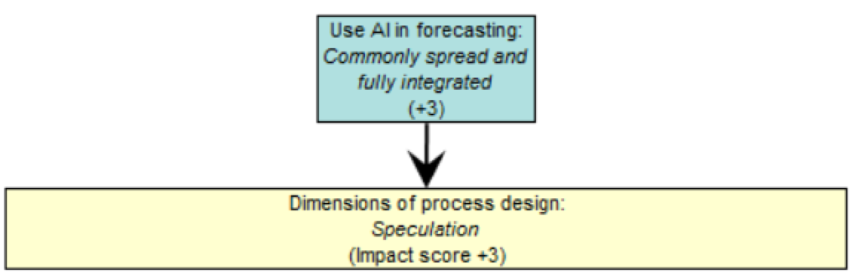

Use AI in forecasting: Commonly spread and fully integrated (+1)
SC responsiveness: Relatively high (+1)
Use of emerging technology blockchain: Global process driver for the whole SC (+1)
Use of autonomous SC planning techniques: Commonly spread (Impact score +5)
Use of AI to attack SC system architectures: Regionally organised (-1)
Type of interorganisational specialisation: Process orientation (+2)
Use of autonomous driving: Fully implemented (+1)

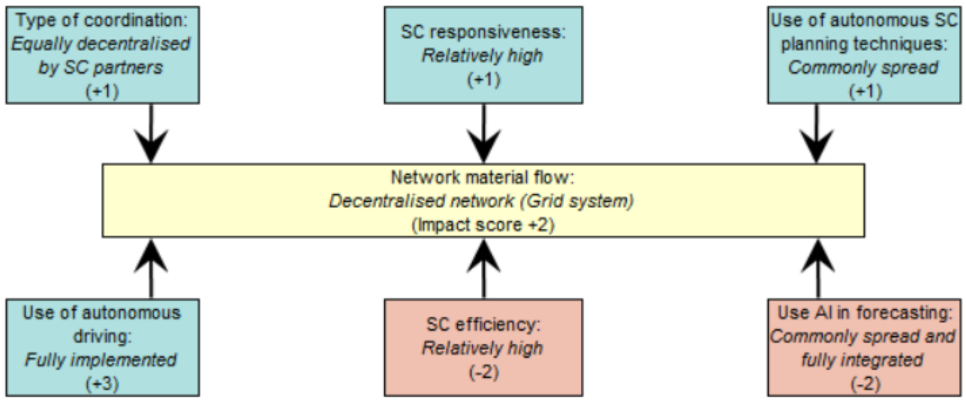

Use of emerging technology blockchain: Global process driver for the whole SC (+1)
Interorganisational decision delegation: More autonomy (-1)
SC responsiveness: Relatively high (+1)
Use of autonomous SC planning techniques: Commonly spread (+2)
Use AI in forecasting: Commonly spread and fully integrated (Impact score +7)
Use of autonomous driving: Fully implemented (+1)
SC efficiency: Relatively high (+1)
Dimensions of process design: Speculation (+2)


Use AI in forecasting: Commonly spread and fully integrated (+1)
Interorganisational decision delegation: More autonomy (+3)
Use of autonomous driving: Fully implemented (+1)
Type of coordination: Equally decentralised by SC partners (Impact score +11)
Use of emerging technology blockchain: Global process driver for the whole SC (+1)
Type of interorganisational specialisation: Process orientation (+2)
Use of autonomous SC planning techniques: Commonly spread (+3)

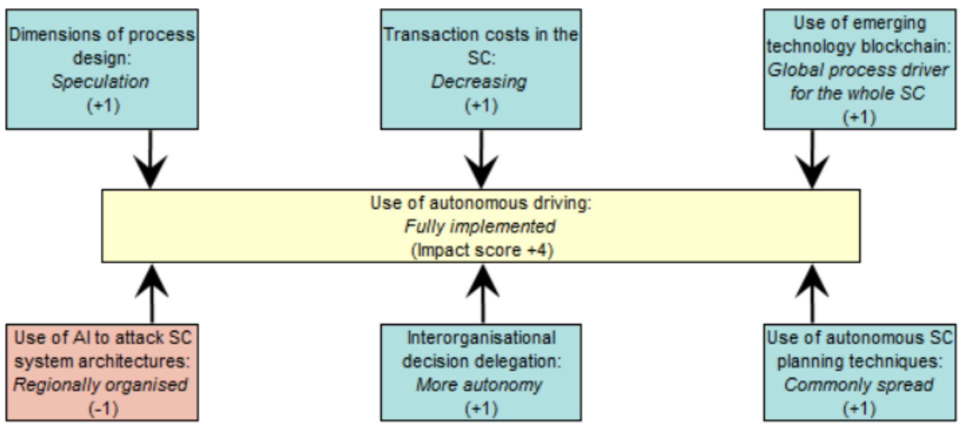

Type of coordination: Equally decentralised by SC partners (+2)
SC efficiency: Relatively high (-1)
Use of autonomous SC planning techniques: Commonly spread (+3)
Interorganisational decision delegation: More autonomy (Impact score +8)
Use of autonomous driving: Fully implemented (-1)
Type of interorganisational specialisation: Process orientation (+2)
Use AI in forecasting: Commonly spread and fully integrated (+3)


Type of coordination: Equally decentralised by SC partners (-1)
SC efficiency: Relatively high (-1)
Use of autonomous SC planning techniques: Commonly spread (+3)
Type of interorganisational specialisation: Process orientation (Impact score +4)
Use of emerging technology blockchain: Global process driver for the whole SC (+1)
Interorganisational decision delegation: More autonomy (+1)
Use AI in forecasting: Commonly spread and fully integrated (+1)

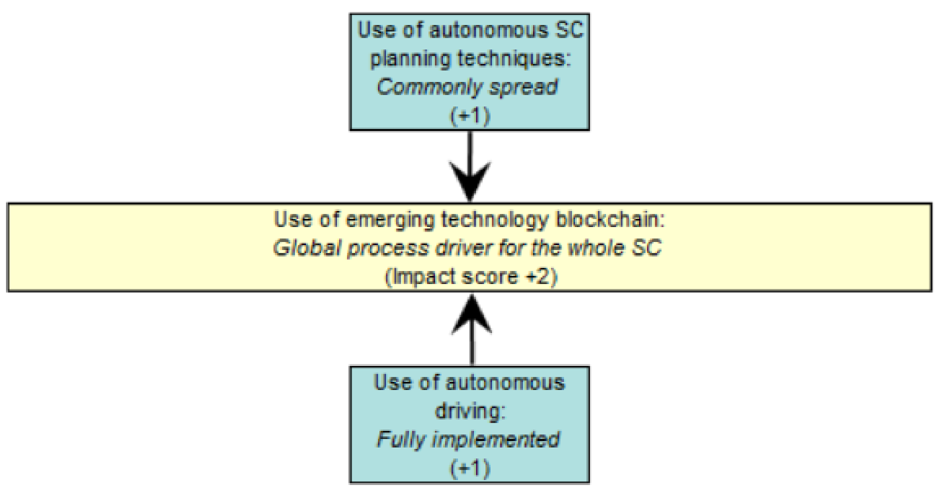

Use AI in forecasting: Commonly spread and fully integrated (+3)
Dimensions of process design: Speculation (Impact score +3)



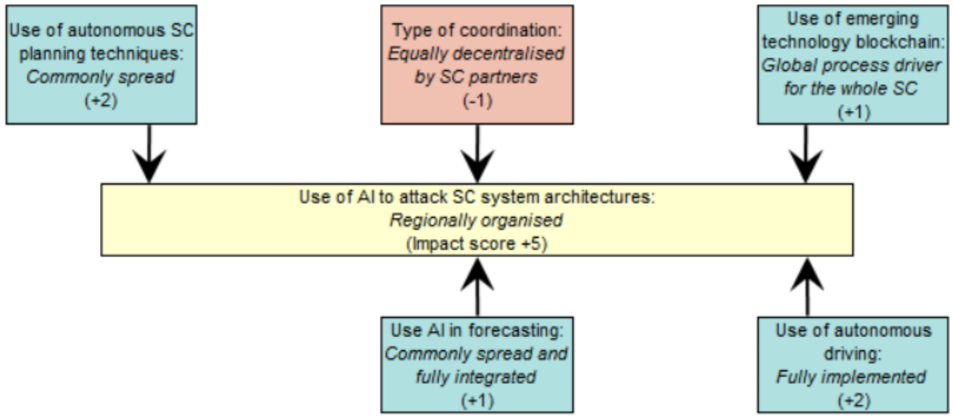
Type of coordination:
Equally decentralised by SC partners
(+1)
SC responsiveness:
Relatively high
(+1)
Use of autonomous SC planning techniques:
Commonly spread
(+1)
Network material flow:
Decentralised network (Grid system)
(Impact score +2)
Use of autonomous driving:
Fully implemented
(+3)
SC efficiency:
Relatively high
(-2)
Use AI in forecasting:
Commonly spread and fully integrated
(-2)



Dimensions of process design:
Speculation
(+1)
Transaction costs in the SC:
Decreasing
(+1)
Use of emerging technology blockchain:
Global process driver for the whole SC
(+1)
Use of autonomous driving:
Fully implemented
(Impact score +4)
Use of AI to attack SC system architectures:
Regionally organised
(-1)
Interorganisational decision delegation:
More autonomy
(+1)
Use of autonomous SC planning techniques:
Commonly spread
(+1)



Use of autonomous SC planning techniques:
Commonly spread
(+1)
Use of emerging technology blockchain:
Global process driver for the whole SC
(Impact score +2)
Use of autonomous driving:
Fully implemented
(+1)


Use of autonomous SC planning techniques: *Commonly spread* (+2)
Type of coordination: *Equally decentralised by SC partners* (-1)
Use of emerging technology blockchain: *Global process driver for the whole SC* (+1)
Use of AI to attack SC system architectures: *Regionally organised* (Impact score +5)
Use AI in forecasting: *Commonly spread and fully integrated* (+1)
Use of autonomous driving: *Fully implemented* (+2)

Appendix I. ScenarioWizard – Low AI Support Embedded in Scenario with Positive Impact on SC

	Responsiveness High	Responsiveness Low	Efficiency High	Efficiency Low	Transaction cost Increasing	Transaction cost Decreasing	Dec delegation More autonomoy	Dec delegation Less autonomy	Specialisation Process	Specialisation Function	Coordination Focal	Coordination Equally	Process design Postpone	Process design Speculate	Net MatFlow Central	Net MatFlow Decentral	Forecasting Integrated	Forecasting Isolated	Aut planning Spread	Aut planning Not widely	Aut driving Fully	Aut driving Partially	Blockchain Process driver	Blockchain Data memory	AttackSC Regionally	AttackSC Globally
SC responsiveness																										
Relatively high			-2	1	-1	1	0	0	0	-1	0	0	1	0	-3	1	1	0	1	0	0	0	0	0	0	-1
Relatively low			1	-1	2	-2	0	0	1	-2	2	-2	1	1	-1	2	0	0	0	3	0	0	0	0	0	1
SC efficiency																										
Relatively high	0	-1			-2	1	-1	1	-1	-1	0	0	0	0	1	-2	1	0	0	0	0	0	0	0	0	1
Relatively low	-1	0			2	-2	1	-1	1	-2	2	-2	0	0	2	-1	-1	0	0	2	1	0	0	0	0	0
Transaction costs in the SC																										
Increasing	0	0	-3	-1			0	0	0	0	1	-1	1	1	0	0	1	0	0	0	0	0	1	1	0	0
Decreasing	0	0	1	2			0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0
Interorganisational decision delegation																										
More autonomy	2	0	0	1	0	1			1	-1	-2	3	0	0	0	0	-1	1	0	2	1	0	0	0	0	-1
Less autonomy	-2	1	2	-1	0	-1			-2	2	3	-3	0	0	0	0	1	-1	1	0	-1	-1	0	0	1	0
Type of interorganisational specialisation																										
Process orientation	1	1	1	2	-1	1	2	-2			-1	2	0	0	0	0	0	0	2	0	0	0	0	0	0	0
Functional orientation	-2	-2	-2	-1	1	-1	-2	2			1	0	0	0	0	0	0	0	-2	0	0	0	0	0	0	0
Type of coordination																										
Centralised by one focal company	1	1	0	2	-1	1	-2	1	2	-1			0	0	0	0	1	1	0	2	0	1	0	1	0	1
Equally decentralised by SC partners	-1	0	0	-2	1	-1	2	-2	-1	1			0	0	0	1	0	0	0	-2	0	-1	0	0	-1	-1
Dimensions of process design																										
Postponement	0	2	1	1	0	1	0	0	0	0	1	0			1	-1	0	0	0	0	0	0	0	0	0	0
Speculation	1	1	0	0	2	-2	0	0	0	0	0	0			0	0	2	0	0	0	1	0	0	0	0	0
Network material flow																										
Centralised network (Hub-and-spoke)	-1	-1	1	1	0	0	0	0	0	0	0	0	0	0			0	0	0	0	0	0	0	0	0	0
Decentralised network (Grid system)	3	0	-2	-1	0	0	0	0	0	0	0	0	0	0			0	0	0	0	0	0	0	0	0	0
Use AI in forecasting																										
Commonly spread and fully integrated	1	3	1	0	-2	2	3	-3	1	-1	-1	1	1	3	2	-2			1	3	0	0	0	0	1	1
Isolated with individual data bases	-1	2	0	0	0	0	0	0	-1	1	0	0	0	1	-1	2			-3	-1	0	0	0	0	0	0
Use of autonomous SC planning techniques																										
Commonly spread	2	2	2	0	0	2	3	-2	3	-3	-2	3	-1	0	1	1	2	-1			1	1	1	2	2	3
Not widely spread	0	1	0	0	0	0	1	-1	-1	1	2	-2	0	0	0	0	1	0			-1	-1	0	0	1	2
Use of autonomous driving																										
Fully implemented	1	0	2	0	0	0	-1	1	0	0	-1	1	0	0	-2	3	1	0	1	1			1	0	2	3
Partially implemented	0	0	1	0	0	0	-1	1	0	0	0	0	0	0	0	0	0	0	0	0			0	0	1	2
Use of emerging technology blockchain																										
Global process driver for the whole SC	2	0	2	0	-2	2	0	0	1	0	0	1	0	0	0	0	1	-1	1	0	1	1			1	0
Only used as data memory	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0			-1	-1
Use of AI to attack SC system architectures																										
Regionally organised	-1	0	-1	0	1	-1	0	0	0	0	0	0	0	0	0	0	0	0	-1	0	-1	0	0	0		
Globally organised	-2	1	-2	0	2	-1	0	0	0	0	1	-1	0	0	0	0	0	0	-2	1	-2	0	1	0		
		v		v	v		v		v			v		v		v		v		v		v		v	v	
Balance:	3	5	-3	-2	7	-6	5	-5	0	-2	4	-2	2	3	0	4	2	1	-2	4	1	-2	1	1	0	2

Adjusted scenario

	Responsiveness High	Responsiveness Low	Efficiency High	Efficiency Low	Transaction cost Increasing	Transaction cost Decreasing	Dec delegation More autonomoy	Dec delegation Less autonomy	Specialisation Process	Specialisation Function	Coordination Focal	Coordination Equally	Process design Postpone	Process design Speculate	Net MatFlow Central	Net MatFlow Decentral	Forecasting Integrated	Forecasting Isolated	Aut planning Spread	Aut planning Not widely	Aut driving Fully	Aut driving Partially	Blockchain Process driver	Blockchain Data memory	AttackSC Regionally	AttackSC Globally
SC responsiveness																										
Relatively high			-2	1	-1	1	0	0	0	-1	0	0	1	0	-3	1	1	0	1	0	0	0	0	0	0	-1
Relatively low			1	-1	2	-2	0	0	1	-2	2	-2	1	1	-1	2	0	0	0	3	0	0	0	0	0	1
SC efficiency																										
Relatively high	0	-1			-2	1	-1	1	-1	-1	0	0	0	0	1	-2	1	0	0	0	0	0	0	0	0	1
Relatively low	-1	0			2	-2	1	-1	1	-2	2	-2	0	0	2	-1	-1	0	0	2	1	0	0	0	0	0
Transaction costs in the SC																										
Increasing	0	0	-3	-1			0	0	0	0	1	-1	1	1	0	0	1	0	0	0	0	0	1	1	0	0
Decreasing	0	0	1	2			0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0
Interorganisational decision delegation																										
More autonomy	2	0	0	1	0	1			1	-1	-2	3	0	0	0	0	-1	1	0	2	1	0	0	0	0	-1
Less autonomy	-2	1	2	-1	0	-1			-2	2	3	-3	0	0	0	0	1	-1	1	0	-1	-1	0	0	1	0
Type of interorganisational specialisation																										
Process orientation	1	1	1	2	-1	1	2	-2			-1	2	0	0	0	0	0	0	2	0	0	0	0	0	0	0
Functional orientation	-2	-2	-2	-1	1	-1	-2	2			1	0	0	0	0	0	0	0	-2	0	0	0	0	0	0	0
Type of coordination																										
Centralised by one focal company	1	1	0	2	-1	1	-2	1	2	-1			0	0	0	0	1	1	0	2	0	1	0	1	0	1
Equally decentralised by SC partners	-1	0	0	-2	1	-1	2	-2	-1	1			0	0	0	1	0	0	0	-2	0	-1	0	0	-1	-1
Dimensions of process design																										
Postponement	0	2	1	1	0	1	0	0	0	0	1	0			1	-1	0	0	0	0	0	0	0	0	0	0
Speculation	1	1	0	0	2	-2	0	0	0	0	0	0			0	0	2	0	0	0	1	0	0	0	0	0
Network material flow																										
Centralised network (Hub-and-spoke)	-1	-1	1	1	0	0	0	0	0	0	0	0	0	0			0	0	0	0	0	0	0	0	0	0
Decentralised network (Grid system)	3	0	-2	-1	0	0	0	0	0	0	0	0	0	0			0	0	0	0	0	0	0	0	0	0
Use AI in forecasting																										
Commonly spread and fully integrated	1	3	1	0	-2	2	3	-3	1	-1	-1	1	1	3	2	-2			1	3	0	0	0	0	1	1
Isolated with individual data bases	-1	2	0	0	0	0	0	0	-1	1	0	0	0	1	-1	2			-3	-1	0	0	0	0	0	0
Use of autonomous SC planning techniques																										
Commonly spread	2	2	2	0	0	2	3	-2	3	-3	-2	3	-1	0	1	1	2	-1			1	1	1	2	2	3
Not widely spread	0	1	0	0	0	0	1	-1	-1	1	2	-2	0	0	0	0	1	0			-1	-1	0	0	1	2
Use of autonomous driving																										
Fully implemented	1	0	2	0	0	0	-1	1	0	0	-1	1	0	0	-2	3	1	0	1	1			1	0	2	3
Partially implemented	0	0	1	0	0	0	-1	1	0	0	0	0	0	0	0	0	0	0	0	0			0	0	1	2
Use of emerging technology blockchain																										
Global process driver for the whole SC	2	0	2	0	-2	2	0	0	1	0	0	1	0	0	0	0	1	-1	1	0	1	1			1	0
Only used as data memory	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0			-1	-1
Use of AI to attack SC system architectures																										
Regionally organised	-1	0	-1	0	1	-1	0	0	0	0	0	0	0	0	0	0	0	0	-1	0	-1	0	0	0		
Globally organised	-2	1	-2	0	2	-1	0	0	0	0	1	-1	0	0	0	0	0	0	-2	1	-2	0	1	0		
	v		v			v	v		v			v		v		v	v		v		v		v		v	
Balance:	11	6	4	3	-4	6	8	-6	4	-6	-7	11	1	3	-1	2	7	-1	5	4	4	2	2	2	5	5

initial positive scenario

Appendix J. Initial EVA and Additional Values Created through the Range of Cooperations in the SC Model Based on Annual reports 2019

Initial EVA of each SC entity

Input Parameter	Value per EVA-tree position in Euro		
	BMW	**Continental**	**BASF**
Sales	104,210,000,000	44,478,400,000	59,316,000,000
COGS	86,147,000.000	33,893,400,000	43,061,000,000
Gross Margin	*18,063,000,000*	*10,585,000,000*	*16,255,000,000*
Total Expenses	10,945,000,000	11,173,600,000	12,953,000,000
Net Profit	*7,118,000,000*	*-588,600,000*	*3,302,000,000*
Taxes	2,135,400,000	176,580,000	756,000,000
NOPAT	*4,982,600,000*	*-765,180,000*	*2,546,000,000*
Inventory	5,994,000,000	4,694,400,000	11,223,000,000
Other current assets	32,041,000,000	13,149,300,000	19,767.000.000
Current assets	*38,035,000,000*	*17,843,700,000*	*30,990,000,000*
Fixed assets	16,640,000,000	24,724,500,000	55,960,000,000
Total assets	*54,675,000,000*	*42,568,200,000*	*86,950,000,000*
WACC	12.0%	10.0%	7.98%
Cost of capital	*6,561,000,000*	*4,256,820,000*	*6,938,610,000*
Initial EVA	**-1,578,400,000**	**-5,022,000,000**	**-4,92,610,000**

SC Entity 1 (Annual Report BMW)

Input Parameter	Additional value non-cooperation in Euro	Additional value partial cooperation in Euro	Additional value full cooperation in Euro
Sales	7,047,305,460	9,161,497,098	17,618,263,650
COGS	-3,136,956,858	-4,078,043,915	-7,842,392,145
Gross Margin	*10,184,262,318*	*13,239,541,013*	*25,460,655,795*
Total Expenses	-189,786,300	-246,722,190	-474,465,750
Net Profit	*10,374,048,618*	*13,486,263,203*	*25,935,121,545*
Taxes	3,112,214,585	4,045,878,961	7,780,536,464
NOPAT	*7,261,834,033*	*9,440,384,242*	*18,154,585,082*
Inventory	-228,659,112	-297,256,846	-571,647,780
Other current assets	-166,677,282	-216,680,467	-416,693,205

Current assets	*-395,336,394*	*-513,937,312*	*-988,340,985*
Fixed assets	-144,268,800	-187,549,440	-360,672,000
Total assets	*-539,605,194*	*-701,486,752*	*-1,349,012,985*
WACC	12.0%	12.0%	12.0%
Cost of capital	*-64,752,623*	*-84,178,410*	*-161,881,558*
Additional value created	**7,326,586,656**	**9,524,562,653**	**18,316,466,640**

SC Entity 2 (Annual Report Continental)

Input Parameter	Additional value non-cooperation in Euro	Additional value partial cooperation in Euro	Additional value full cooperation in Euro
Sales	3,007,896,278	3,910,265,162	7,519,740,696
COGS	-1,234,194,268	-1,604,452,548	-3,085,485,669
Gross Margin	*4,242,090,546*	*5,514,717,710*	*10,605,226,365*
Total Expenses	-193,750,224	-251,875,291	-484,375,560
Net Profit	*4,435,840,770*	*5,766,593,001*	*11,089,601,925*
Taxes	1,330,752,231	1,729,977,900	3,326,880,578
NOPAT	*3,105,088,539*	*4,036,615,101*	*7,762,721,348*
Inventory	-179,081,971	-232,806,563	-447,704,928
Other current assets	-68,402,659	-88,923,456	-171,006,647
Current assets	*-247,484,630*	*-321,730,019*	*-618,711,575*
Fixed assets	-214,361,415	-278,669,840	-535,903,538
Total assets	*-461,846,045*	*-600,399,858*	*-1,154,615,112*
WACC	10.0%	10.0%	10.0%
Cost of capital	*-46,184,604*	*-60,039,986*	*-115,461,511*
Additional value created	**3,151,273,143**	**4,096,655,087**	**7,878,182,859**

SC Entity 3 (Annual Report BASF)

Input Parameter	Additional value non-cooperation in Euro	Additional value partial cooperation in Euro	Additional value full cooperation in Euro
Sales	4,011,303,816	5,214,694,961	10,028,259,540
COGS	-1,568,023,254	-2,038,430,230	-3,920,058,135
Gross Margin	*5,579,327,070*	*7,253,125,191*	*13,948,317,675*
Total Expenses	-224,605,020	-291,986,526	-561,512,550
Net Profit	*5,803,932,090*	*7,545,11,717*	*14,509,830,225*
Taxes	1,741,179,627	2,263,533,515	4,352,949,068
NOPAT	*4,062,752,463*	*5,281,578,202*	*10,156.881,158*
Inventory	-428,135,004	-556,575,505	-1,070,337,510
Other current assets	-102,827,934	-133,676,314	-257,069,835

Current assets	*-530,962,938*	*-690,251,819*	*-1,327,407,345*
Fixed assets	-485,173,200	-630,725,160	-1,212,933,000
Total assets	*-1,016,136,138*	*-1,320,976,979*	*-2,540,340,345*
WACC	8.0%	8.0%	8.0%
Cost of capital	*-81,087,664*	*-105,413,963*	*-202,719,160*
Additional value created	**4,143,840,127**	**5,386,992,165**	**10,359,600,317**

Appendix K. Impact of AI-Enabled Descriptors on SC Performance Indicators

Performance indicators / AI-enabled descriptors	SC responsiveness		SC efficiency		TC		Total	
	H	L	H	L	INC	DEC	Positive	Negative
Forecasting Isolated	-1	+2	0	0	0	0	-1	-2
Forecasting widely adopted	+1	+3	+1	0	-1	+1	+3	-1
Isolated Autonomous SC	0	+1	0	+1	0	0	0	+2
Widely adopted autonomous SC	+2	+2	+2	+2	-2	+2	+8	0
Auton. Driving fully implemented	+1	0	+2	0	0	0	+3	0
Auton. Driving partially implemented	0	0	+1	0	0	0	+1	0
Blockchain global process	+2	0	+2	0	-2	+2	+5	-2
Blockchain data memory	0	0	+1	0	0	0	0	0
Total							21	-7
Total difference between positive impacts and negative impacts							**28**	

Dark green: positive impact which amplifies the positive SC performance

Light green: impact on performance

Red: not valid ratings for the quantification of the total value. Due to the statements of the participating experts, these ratings have to be interpreted in the sense that the experts suppose that the descriptor turns around the low performance to higher performance. In case e.g. of widely adopted autonomous SC planning, the experts expected that the low performance is restricted by the descriptor variant. The supposed rating is not considered. Therefore, the total difference between positive and negative impact is adjusted (cleaned) from this influence.

i Original Equipment Manufacturer

[ii] The original interviews are available on request

iii CPFR: Collaborative Planning, Forecasting, and Replenishment

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v Wilson (2018) exemplarily inform that AI will contribute to increase 75,000 new jobs to administer European Union's new General Data Protection Regulation (GDPR) requirements.

vi Logistics cost: Warehouse cost, transport costs, handling cost, picking costs, cost of logistics planning and coordination(Krieger, 2018)

[vii] VD = Value Driver