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# Analytics and Business Survival—Critical Success Factors and the Demise of HP Bulmer Ltd.

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**Abstract**

This article examines the requirements for the successful deployment of business analytics in industry and uses this as a framework to provide a business intelligence perspective on the demise of a case study company, drinks manufacturer HP Bulmer Ltd., resulting in the collapse and takeover of the company in 2003. Based on a scoping literature review and a qualitative interpretivist approach, the article investigates the critical success factors for business analytics software projects and classifies these into five main organisational pillars that are required for successful analytics deployment. Then, using documents available in the public domain, the article examines the case study of HP Bulmer Ltd., which used analytics software in the 1990s and early 2000s as the company attempted to establish itself as a global drinks manufacturer. The article reports on how the company struggled to put the necessary pillars in place for successful use of their analytics systems, but having finally achieved this, then failed to take the necessary decisions to steer the company towards profitability as opposed to rapid growth in turnover. The article uses the case study to reflect on the key aspects of analytics technology deployment and the wider field of digitalisation and digital transformation, and points to the critical importance of political will to formulate and steer data-informed strategy. The research contributes to the development of theory regarding analytics deployment and will be of value to practitioners faced with the challenges of implementing analytics systems in industry.

**Keywords:** analytics; critical success factors; CSFs; five-pillars model; HP Bulmer Ltd.; lessons learnt; digitalisation



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## 1. Introduction

The deployment of analytics software has become a central concern for organisations seeking to improve decision making, enhance operational efficiency, and gain competitive advantage [1]. Over the past four decades, steady advances in information systems (ISs), enterprise software, and data management have driven the progression from basic transaction processing and reporting to sophisticated business analytics and artificial intelligence-enabled platforms, but despite substantial investment, some organisations fail to realise the anticipated benefits from analytics software initiatives. However, in their study of key issues in analytics implementation, Chen et al. [2], found that "little research effort has been devoted to understanding how to best convert analytics assets into positive business performance" [2] (p. 239), a perspective reiterated by Radyanto et al. [3], who point out that "despite the fact that big data analytics provides a number of advantages, little study has been done on how businesses may use it and get economic value from such technology” [3] (p. 343).

There are several overlapping categories of analytics. These include the early descriptive and reporting systems providing standard reports, dashboards, and key performance indicators (KPIs) derived from historical data [4]. Diagnostic analytics extended descriptive capabilities by enabling drill-down, querying, and ad hoc analysis to understand why certain outcomes occurred. Online analytical processing tools and data visualisation platforms fall into this category [5]. Predictive analytics employs statistical modelling, data mining, and machine learning techniques to forecast future outcomes [6], and often requires more advanced data infrastructure and analytical skills. Prescriptive analytics builds on predictive models to recommend actions, frequently using optimisation and simulation techniques [7]. Finally, some of the major software vendors have expanded the functionality of their core products, in which analytics is sometimes offered as enterprise analytics platforms linked to enterprise resource planning (ERP), customer relationship management (CRM), and supply chain systems [8].

Across the above categories, deployment challenges increase with analytical sophistication, data volume, and organisational scope. One area of research that has been pursued is the identification of critical success factors (CSFs) to support effective deployment and sustained value creation from analytics software [9]. The CSFs identified in the literature often cut across software types while varying in emphasis depending on analytical maturity [10,11]. One theme of particular significance for many companies is profitability analysis, notably by customer and by product. Van Raaij et al. [12] note “while most firms will know the customer revenues, many firms are unaware of all costs associated with customer relationships. In general, product costs will be known for each customer, but sales and marketing, service, and support costs are mostly treated as overheads” [12] (p. 573).

The dearth of profitability information in standard information systems (e.g., ledgers and financial management and marketing software packages) has led to the search for analytics systems that can produce such analysis, drawing on data from a range of sources, including the core information systems. Customer profitability analysis (CPA) is one such application, which can be defined as “the allocation of revenues and costs to customer segments or individual customers, such that the profitability of those segments and/or individual customers can be calculated” [12] (p. 573). Lueg and Illieva [13] see such profitability information as “a social construction that depends on the–possibly politically motivated–allocation of revenues and costs to which powerful top-management teams as well as accounting and finance educated managers have better access” (p. 2).

In this context, this article addresses three research questions (RQs):

RQ1. What are the critical success factors (CSFs) for the successful deployment of analytics software in industry?

RQ2. Can a conceptual framework be developed to indicate the required pillars for successful analytics deployment?

RQ3. What lessons can be learnt from the application of this framework to the deployment of analytics software at HP Bulmer Ltd.?

Following this brief introduction, Section 2 discusses the research methods used in the study. The RQs are then addressed in Section 3, drawing on the CSF tradition established by Rockart [14] from which the conceptual framework is developed. This is then applied and used as an analytical framework in the case study company. Emergent issues are discussed in Section 4. Finally, Section 5 provides a conclusion to the article, in which the contribution is summarised, limitations of the study are outlined, and possible future research agendas are set out.

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## 2. Research Methods

This study comprises two phases (Figure 1), adopting a qualitative, inductive research approach, and combining a scoping literature review with an in-depth case study. The literature review was structured using the PRISMA extension for scoping reviews, in order to provide a transparent and replicable literature screening process [15]. This process facilitated the exploration of relevant theories and identification of the major issues and challenges spanning business analytics, information systems strategy, and digital transformation. Originally proposed by Arksey and O'Malley [16,17], the approach has been widely applied to map and synthesise existing or emerging bodies of literature within a field [15]. It is commonly used as a preliminary step that can support the development of conceptual frameworks and guide future research directions. Through this exploratory mapping of the literature, the approach provides an opportunity to develop an initial understanding of the key issues and relevant themes [18].

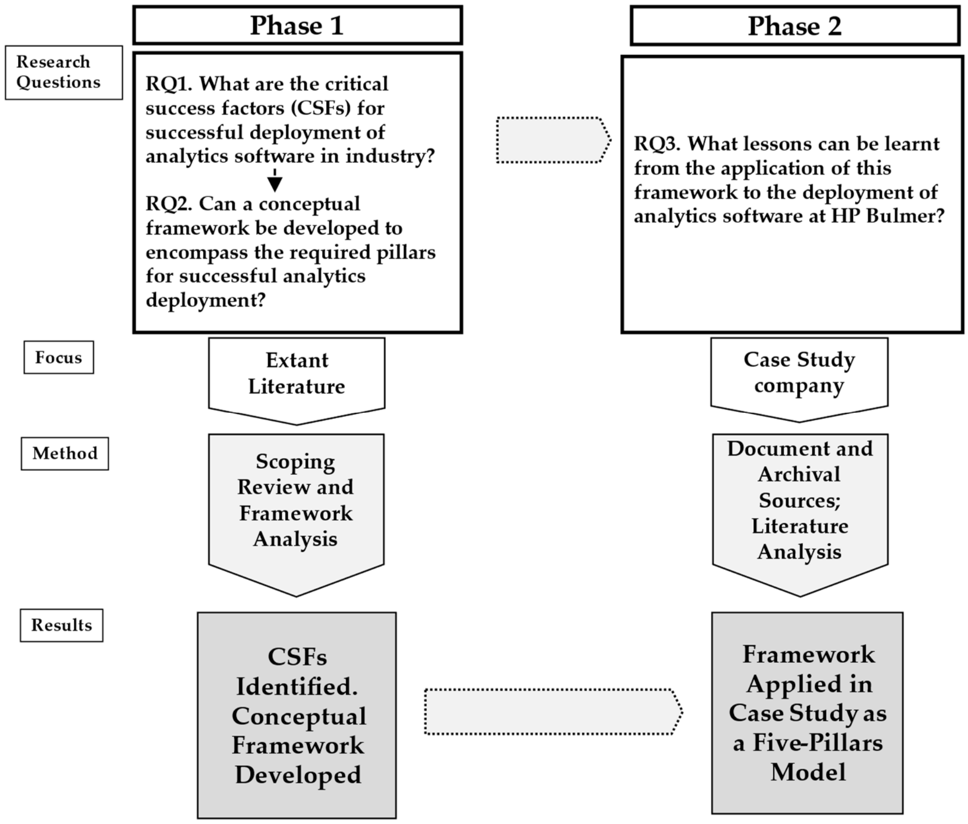


**Figure 1.** The two-phase research process.

In accordance with Snyder's [19] guidance, the review systematically identified, evaluated, and integrated conceptual and empirical studies to generate a conceptual framework, based on a grouping of CSFs into five organisational pillars for the effective deployment of business analytics. This allowed more flexibility in searching for additional sources (Figure 2). This is particularly appropriate for this type of interdisciplinary research, as the study spans analytics, information systems, enterprise software, digital transformation, and strategic management [20].

In addressing RQ1 and RQ2, a number of searches were conducted using search strings in various combinations. These included "critical success factors", "analytics", "digital transformation", "enterprise software", "business intelligence" and "information systems". Academic journals and books were the main source material. No blogs or webpages were utilised within the literature review due to the plethora of academic resources available on the subject. Any literature published before 2010 was excluded, unless it pertained to the history of the topic and its initial ideation such as Rockart's [14] initial identification of CSFs. A snowball sampling approach [21] was used, in which references in the located sources were also examined for their relevance. Overall, this produced 40 sources for further investigation, located in several databases (SCOPUS, Web of Science, ACM Digital Library).

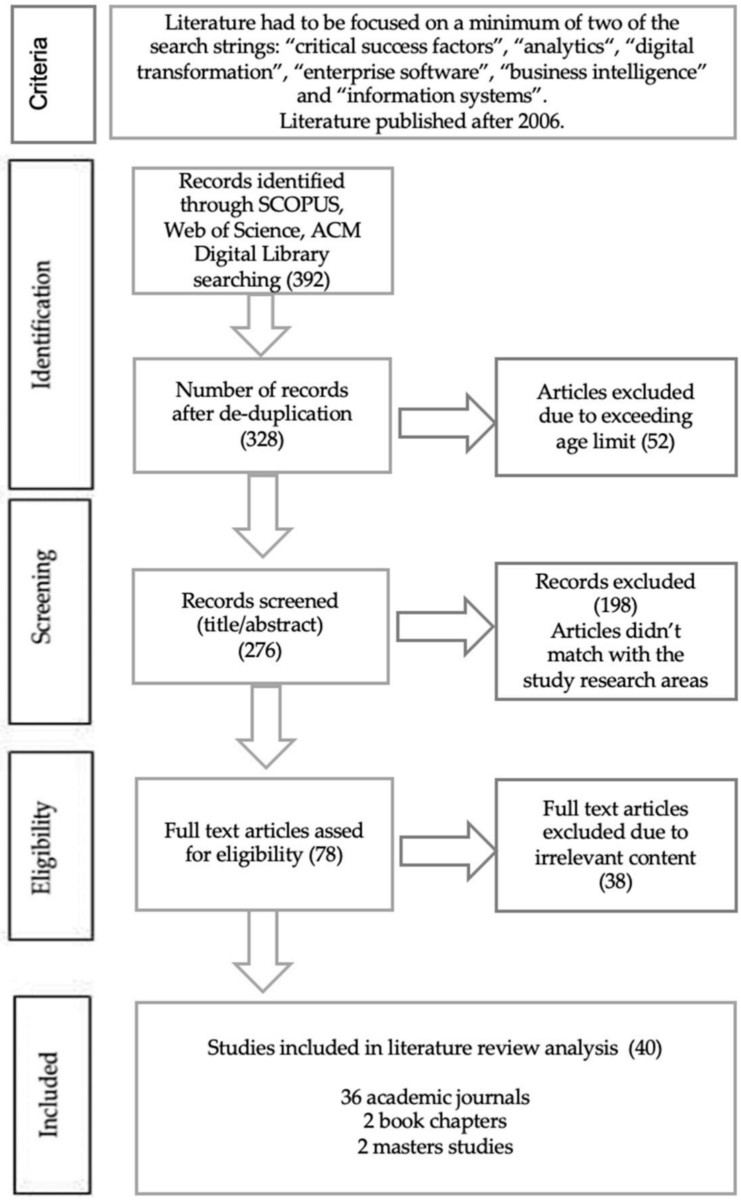


**Figure 2.** PRISMA diagram illustrating the literature screening process used in the study.

A combination of content analysis [22,23] and framework analysis [24] was used to identify and classify the CSFs for the deployment of analytics software in the source literature. Framework analysis is particularly suited to applied research where the aim is to generate structured, theory-informed insights that are grounded in empirical and conceptual evidence [25]. It enables the systematic reduction, categorisation, and synthesis of large bodies of qualitative material while maintaining transparency and analytical rigour. This method is particularly effective in informing the development of robust conceptual frameworks, as it explicitly links empirical evidence to higher-level analytical constructs [24]. During the literature review, as CSFs emerged, they were mapped into a framework, using qualitative content analysis to identify recurring themes, patterns, and conceptual relationships within the CSF literature. In a first stage, open coding was conducted manually across the reviewed literature to identify individual factors discussed as influencing analytics implementation success. In a second stage, codes were grouped around related concepts into higher-order analytical categories. Through this process fourteen CSFs were identified. These CSFs were then aggregated into five broader conceptual pillars through iterative comparison and conceptual abstraction. This systematic and transparent approach strengthens the validity of the resulting conceptual framework and provides a rigorous foundation for the subsequent case study analysis.

The conceptual framework derived from the literature analysis allows for theoretical insights to emerge inductively rather than by testing predefined hypotheses. Conceptual frameworks play a central role in organising and explaining complex phenomena in management and information systems research. Jabareen [26] defines a conceptual framework as "a network, or a plane, of interlinked concepts that together provide a comprehensive understanding of a phenomenon" (p. 51). This emphasises that conceptual frameworks do not merely describe reality but actively structure how it is interpreted. This is particularly important in interdisciplinary domains such as business analytics, where technical, organisational, and political dimensions intersect [27]. Conceptual frameworks support analytical generalisation by linking empirical observations to theory, rather than to populations [26,28]. They also enhance transparency and rigour for the study by making explicit the relationships that underpin analysis [29].

In Phase 2 of the research, the conceptual framework was applied in a qualitative case study of HP Bulmer Ltd., using a retrospective, interpretivist approach. HP Bulmer Ltd. (hereafter referred to as "HP Bulmer" or "Bulmer") was the world's leading independent cider maker in the 1990s, with an annual turnover of over £335 million in 1999/2000. In the 1990s the company steadily grew pre-tax profits, which were maintained at between £20m and £30m per annum until 2000–2001. In 2001–2002, following the resignation of the managing director, departure of the finance director, and investigation by Deloitte-Touche (Bulmer's auditors), Bulmer's pre-tax profits were re-stated as just £4.4m. This resulted in the collapse of the share price and takeover of the company in 2003. It is relevant as an analytics case study because throughout the 1990s, the company grappled with the challenges of using analytics systems to provide reliable profitability information, particularly customer profitability, to support strategic decision making. Three separate analytics projects were undertaken, but none of them was able to adequately support a profit-led culture within the company. The case study builds upon the analysis in Phase 1 of this study to explore why this happened. The Bulmer case study is of particular interest because the collapse of the company has not hitherto been examined from this perspective. At the same time, it is of relevance to the debate on analytics, as a key focus of the IT strategy at the time was on providing a stable systems portfolio and appropriate tools capable of generating timely and accurate management information to guide strategic and tactical decision making in the sales and marketing domain.

Case study research is well suited to exploring complex socio-technical phenomena within their historical and organisational contexts, allowing complex organisational concepts to be examined in real-life contexts [28]. Here, data is drawn from documentary sources in the public domain, including company reports, press coverage, analyst commentary, and related publications and conference materials. The search strategy was, in the main, intuitive, where some sources were located via appropriate internet searches, whilst other documents were available in personal archives accessible by the authors.

Stake [30] identifies three types of research case study, intrinsic, instrumental, and collective, but notes that a case study can sometimes be both intrinsic and instrumental, and this is the case here in the Bulmer case study. The intrinsic case is usually exploratory in nature, where the researcher may have a particular interest in the case itself, whereas an instrumental case study aims to explore a specific issue, possibly developing theory or generalisations. Stake emphasises that in both intrinsic and instrumental case studies, the opportunity to learn is a key objective. The intrinsic case strives to capture the richness and complexity of the case. Data triangulation can be fostered through the examination of multiple sources of evidence, such as participant interviews, observations and organisational documents, which increases the validity and reliability of the data obtained [28]. Here, 22 sources were used and cited to support the construction of the case study narrative.

These sources are analysed thematically, guided by the five-pillars model, while remaining open to emergent themes. The combination of the scoping review and case study provides theoretically informed insights into the organisational, technological and political conditions shaping the success or failure of business analytics initiatives. Yin [28] emphasises that the strength of case study research lies not in statistical generalisation but in analytical generalisation, whereby empirical findings are generalised to theory rather than to populations. This approach is adopted in the case study analysis in response to RQ3. It is also appropriate for this study to use documentary and archival sources, as this aligns with established guidance for historical and organisational case studies, enhancing construct validity [28,31].

## 3. Results

This section comprises three subsections, addressing each of the RQs in turn. In Section 3.1, the literature relating to information systems and analytics deployment is examined and fourteen CSFs of relevance are identified. In Section 3.2, the conceptual framework is developed, grouping the CSFs into five main pillars and specifying six categories of operational mechanisms that enable the organisational change required for successful analytics outcomes. In Section 3.3, the case study of HP Bulmer is presented, using the five-pillars model to compare and contrast the three analytics projects pursued by the company over a ten-year period.

### *3.1. RQ1: What Are the Critical Success Factors (CSFs) for Successful Deployment of Analytics Software in Industry?*

The concept of CSFs was introduced by Rockart [14] as a means of helping managers identify the limited number of areas in which satisfactory performance is essential for organisational success. The CSF concept was further developed and applied in the recent literature to synthesise research on information systems, strategic management, and business analytics. CSFs are context-dependent, linked to strategy, and shaped by structures—these can be industry-specific, organisational or within the external environment [3]. Bullen and Rockart [32] operationalised the CSF approach, positioning it as a bridge between information needs and information systems design. Within IS research, CSFs have been widely used to analyse enterprise systems, software deployment, and technology-enabled change [33–35]. Applied to analytics software, the CSF approach is particularly relevant as analytics initiatives typically span multiple domains [36], encompassing managerial, organisational, and governance factors [37,38].

Recent research increasingly conceptualises analytics capability as a core organisational competence underpinning digital transformation and data-driven decision making. Big data analytics capability (BDAC) refers to the organisational ability to collect and analyse large volumes of complex data to generate actionable insights and improve strategic decision making [39]. Empirical studies demonstrate that firms with strong analytics capabilities achieve improved financial and market performance when analytical talent and knowledge management processes are aligned with organisational strategy [39]. Research on digital entrepreneurship suggests that BDAC can stimulate innovation and organisational growth by enabling firms to exploit new digital opportunities and improve responsiveness to market conditions [40]. This highlights the growing relationship between analytics capability and organisational agility, effectively showing that the use of big data enables firms to respond more quickly to changing market conditions and enhance competitive performance [41]. Within the broader digital transformation literature, analytics capability is increasingly viewed as a dynamic organisational capability that supports digital innovation and strategic adaptation [42]. The effectiveness of analytics capability depends on complementary organisational factors such as digital culture, governance structures, and managerial commitment [40]. This clearly shows that analytics deployment is a socio-technical process embedded within organisational transformation rather than simply a technological implementation [43]. These recent contributions strengthen the argument that successful analytics deployment requires coordinated development across technological infrastructure, data governance, organisational processes, and leadership commitment.

Top-management support is one of the most consistently cited CSFs. Rockart [14] argued that executive commitment is essential to ensure that information systems address strategic priorities. Subsequent research confirms that senior leadership sponsorship legitimises analytics initiatives, secures resources, and resolves cross-departmental conflicts [38]. The determined support of senior management of a company is imperative: "the will to change is of no use if there is not adequate involvement of the company's owners, managers and human resources. . . it is essential to have the support and direct involvement of the company's management, who must provide sufficient confidence to carry out the necessary changes to adapt to the market's most current and sophisticated technologies" [44] (p. 4). Clear business objectives and strategic alignment are also emphasised. Analytics systems that are deployed as technology-driven projects [45–47], rather than as enablers of specific strategic goals, are less likely to succeed [48,49]. Bullen and Rockart's [32] work highlights the importance of linking CSFs to strategy, suggesting that analytics initiatives should be explicitly designed to support organisational success factors. User involvement and change management constitute another major theme. Analytics software often alters decision rights, workflows, and power structures [46]. Resistance from users, lack of trust in data, and poor adoption have been identified as frequent causes of failure [50]. Effective communication, training, and participatory design are therefore CSFs and software implementation must be aligned with organisational priorities and governance structures to support sustained strategic impact [51].

As analytics systems are fundamentally data-driven, data quality emerges as a central CSF in the literature. Numerous studies identify poor data quality—inconsistent and incomplete data—as a primary barrier to analytics success [50,52]. Data governance structures play a crucial role in addressing these challenges. Strong governance defines data ownership, standards, and accountability, enabling consistent and reliable analytics outputs [52,53]. Without governance, analytics initiatives risk producing conflicting results that undermine managerial confidence and limit use in strategic decision making [54], indicating the importance of scalable and integrated data infrastructure. Data warehouses and, more recently, data lakes and cloud platforms can provide the foundation for enterprise analytics [9,55,56]. However, infrastructure alone is insufficient; its design must reflect organisational CSFs and analytical priorities, echoing Rockart's emphasis on focusing information systems resources on critical areas.

Human skills and organisational culture are repeatedly identified as CSFs. Analytics software requires a combination of technical expertise, statistical competence, and business domain knowledge [8]. The shortage of analytical talent has been widely reported as a constraint on effective deployment [34,38,57]. Beyond individual skills, organisational culture influences how analytics is used. A culture that values evidence-based decision making and is willing to challenge intuition is more likely to benefit from analytics investments [50]. Rockart's [14] CSF framework implies that cultural factors shape which information is considered critical and how it is acted upon. Cross-functional collaboration is another recurring CSF. Analytics initiatives typically span IT, finance, operations, and marketing, requiring coordination across functions. Studies of business intelligence (BI) competence centres highlight the value of dedicated structures that integrate technical and business perspectives [58].

While technical and organisational factors are well documented, the more recent literature highlights governance and decision making as critical yet underexplored CSFs. Analytics systems generate insights, but value is only realised when insights inform decisions and actions [3,7,38,59]. Governance mechanisms define who has authority over analytics priorities, models, and interpretations [59]. Poorly defined decision rights can lead to analytical paralysis or selective use of data to justify pre-existing agendas [60]. This aligns with Rockart's original insight that CSFs are shaped by managerial priorities and political realities [14]. Senior executives must not only sponsor analytics initiatives but also be willing to act on analytically derived insights, even when they conflict with established or emerging strategies or power structures [57]. Without such commitment, analytics risks becoming a reporting exercise rather than a driver of strategic transformation.

The analysis of the relevant literature identified 14 CSFs for analytics project implementation (Table 1). Some of the identified CSFs do not specifically relate to analytics but are evidenced in related and relevant IT contexts. For example, early information systems research on software deployment focused on project management and technical implementation [45], whilst studies of ERP and large-scale enterprise systems identified factors such as top-management support, having clear objectives, user involvement, and effective change management as critical [46,47]. These findings remain highly relevant for analytics software, which similarly requires cross-functional integration and process change.

**Table 1.** Critical success factors for analytics projects with associated pillars.

| Code | CSF | Pillar Alignment | Source |
|---|---|---|---|
| 1 | Adoption of Digital Transformation for Integrated Technology | Robust Technology, Consistent Data | [1,4,5,7,8,11,33,36,38,40,42,48,55,56,58] |
| 2 | Top-Management Support | People Competencies, Political Will | [2–4,10,11,14,32,33,42–44,48,50,53,59] |
| 3 | People Skills and Expertise | People Competencies | [1,3,7,32,33,36,39,42,43,47,48,57–59,61,62] |
| 4 | Data Analysis and Prediction Integrated for Efficiency | Robust Technology, Consistent Data | [2–4,6,34,36,39–41,43–45,47,48,59] |
| 5 | Robust Data Management Practices | Consistent Data, Process Maturity | [1,3,5,10,32,33,39,56,63] |
| 6 | Data Governance, Quality and Integrity | Robust Technology, Consistent Data, Process Maturity | [33,34,36,43,51–55,64] |
| 7 | Processes Integrated with Strategic Intent | Process Maturity, Political Will | [2,9–11,14,32,41,43,51] |
| 8 | Defined Company Strategy | Process Maturity, Political Will | [1,34,40,41,43,51,53,58] |
| 9 | Data and Evidence-Based Decision Making | Consistent Data, People Competencies, Political Will | [32,43,44,49,50,57,60,64] |

**Table 1.** *Cont.*

| Code | CSF | Pillar Alignment | Source |
|---|---|---|---|
| 10 | Investment in Process Creation and Deployment | Process Maturity, People Competencies | [3,11,39,40,45–47,49] |
| 11 | People Training | Process Maturity, People Competencies | [7,36,44,49,51] |
| 12 | Organisational Change | Process Maturity, Political Will | [2,4,46,49,63] |
| 13 | Management Competency for Decision Making | People Competencies, Political Will | [3,34,50,64] |
| 14 | Employee Engagement and Adoption | People Competencies | [14,38] |

The findings contribute to the growing literature on analytics capabilities and digital transformation by demonstrating that analytics success is fundamentally a socio-technical and political phenomenon rather than a purely technological one [40,44]. Although modern analytics platforms provide powerful predictive capabilities [39,43], their organisational impact depends on the alignment of technology, data governance, human capability, political will, and leadership commitment.

### *3.2. RQ2: Can a Conceptual Framework Be Developed to Encompass the Required Pillars for Successful Analytics Deployment?*

Having identified the CSFs (Table 1), each of the 40 source articles was scanned manually to search for concepts relating to analytics in each publication (Table A1 in Appendix A). This identified recurring themes, patterns, and conceptual relationships within the literature on CSFs [22,23], which were consolidated in five main themes: robust technology, consistent data, people competencies, process maturity and political will. Coding was applied [26] to the fourteen CSFs in Table 1 and mapped to the five pillars (Figure 3). Some of these pillars are recognised in other studies on information systems, in one form or another. Heeks [61], for example, identified the concepts of people competencies, process adaptability, and organisational structure as well as technology functionality in determining information systems implementation outcomes. This model was adapted by Rezaeian and Wynn [62] to analyse ERP project implementation and was subsequently used in the development of an analytics maturity model [10]. These themes reflect a systemic view of analytics deployment that is consistent with the CSF tradition established by Rockart [14] and reinforced by contemporary research in information systems and business analytics.

The five pillars were identified based on a number of factors evident in the literature. Firstly, technology provides the foundational capability for analytics deployment. The literature emphasises the importance of scalable and integrated technology infrastructure that aligns with organisational analytical needs [45–47]. Secondly, data quality and consistency are consistently identified as central enablers of analytics success [5,36]. High-quality, reliable, and consistent data underpins trust in analytics outputs and encourages managerial use [6]. Thirdly, people-related factors encompass employee skills, engagement, and organisational culture. Analytics deployment requires a combination of technical expertise and business domain knowledge [7]. The fourth theme, process, refers to the alignment of analytics initiatives with organisational strategy and the processes needed for successful implementation [8,55]. Finally, political will emerges as a decisive factor, which is recognised in other studies on information systems implementation. Chang [63], for example, notes that "political behaviour is one of the most important factors determining success or failure in the information systems implementation processes" [63] (p. 79), and

Imran et al. [64] also recognise the significance of this concept in their study of the effect of political will, information technology, and the quality of financial reporting information on fraud prevention. In a business context, political will refers to the strategic and operational commitment of leadership to provide the necessary resources to achieve specific, often challenging, organisational objectives, requiring a sustained effort to drive through change [32,38,60].

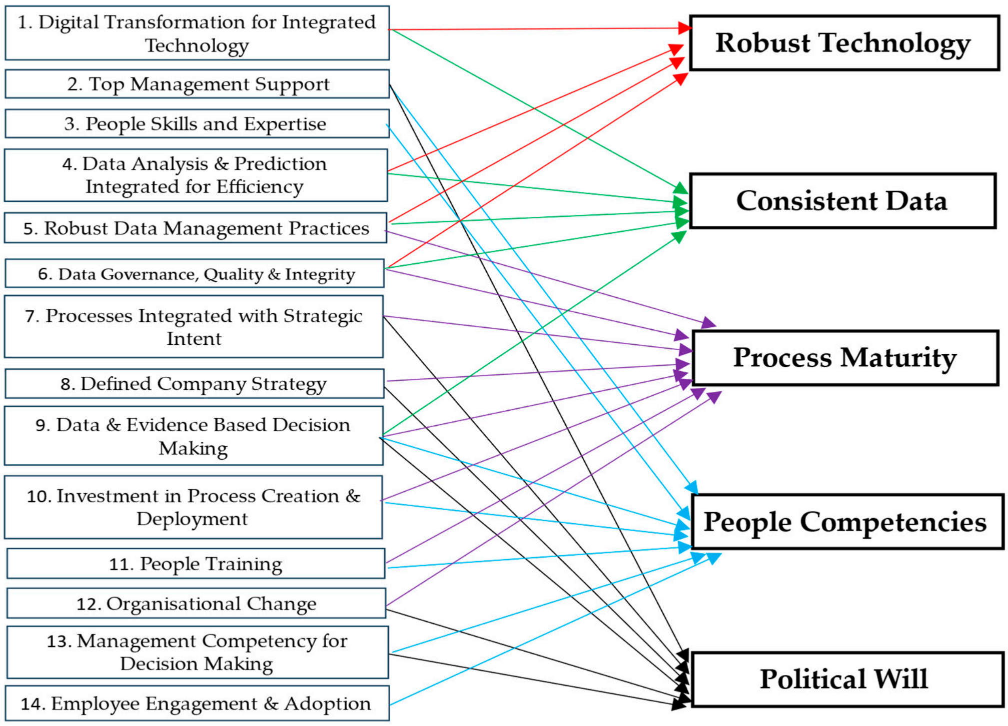


**Figure 3.** CSFs and the five pillars for analytics project success.

Rockart [14] emphasised that information systems should focus on areas critical to organisational success, and the five themes were thus adopted as pillars, providing a clear link between aspirational objectives and core organisational necessities. Analytics systems that lack clear strategic objectives risk becoming disconnected reporting tools rather than drivers of strategic value [59,60]. These five pillars are mutually reinforcing and systemic. Failure in one area can undermine success in others, underscoring the value of a holistic, systems-oriented perspective.

These five pillars provide the conceptual framework for the ensuing case study of HP Bulmer (Figure 4), reflecting the interdependent and mutually reinforcing nature of these factors. At the core of the model is "analytics-enabled organisational performance", representing the effective use of analytics software to inform decision making and guide strategy. Surrounding this core are the four identified pillars—depicted as interconnected elements rather than as a linear sequence—with a fifth, political will, impacting the other four, emphasising that failure in any single domain can undermine overall deployment success. Analytics systems must support data integration and processing across functional boundaries, often within complex enterprise software environments [14]. Chen et al. [21] argue that analytics technologies only generate value when they are embedded within coherent information architectures that support strategic and operational decision making. Poor data quality has long been recognised as a major barrier to effective analytical systems [31,32]. However, skills alone are insufficient. User engagement and effective change management are essential to ensure adoption and the sustained use of analytics systems. This is particularly important when new tools disrupt established practices and decision rights [29,36]. A supportive organisational culture that values evidence-based decision making and learning enhances the likelihood that analytics insights will be trusted and acted upon [29]. Data governance frameworks, including clear ownership and accountability, are critical in ensuring that analytics systems produce credible and actionable insights. Top-management support and leadership legitimise analytics initiatives by securing resources and signalling their strategic importance [6,12,44]. Clear decision making and a willingness to act on data-driven findings, even when politically or strategically uncomfortable, are essential for realising value from analytics implementation investment [45].

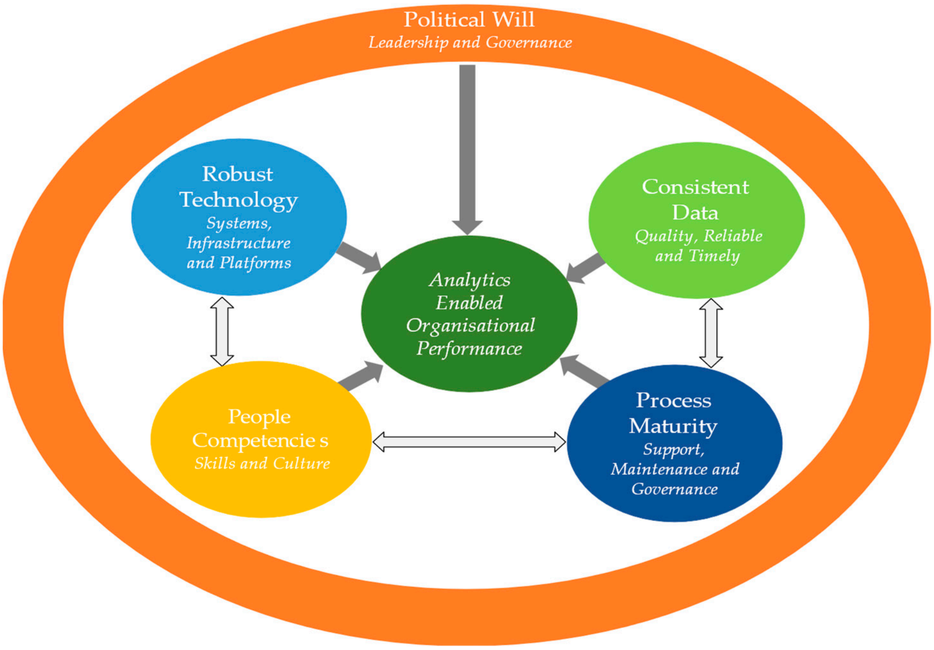


**Figure 4.** Conceptual framework and analytical model: The five pillars for the successful deployment of analytics.

In summary, the five pillars are:

1. Robust Technology: Refers specifically to the digital infrastructure, platforms, and software systems required to collect, process, and analyse organisational data. This element reflects the need for scalable, reliable, and appropriately integrated technologies aligned with organisational analytical requirements [1–3,5–8,10,11,33,38–44,47,48,55,56,58,63,64].
2. Data Consistency: Highlights the critical importance of data quality and reliability and relates to the quality, governance, accessibility, and integration of organisational information resources that underpin analytical activity [2,5,8,10,39–44,47–49,51,55,56,63,64].
3. People Competencies: Captures the human capabilities required to generate and interpret insights, including analytical expertise, data literacy, and organisational culture. This includes analytical and technical skills, business domain knowledge, user engagement, and change management. It also includes the requirement for an organisational culture supportive of evidence-based decision making [1,2,4,6,7,10,33,34,36,38–44,46–51,57–59,63,64].
4. Process Maturity: Refers to the organisational routines, workflows, and decision structures through which analytics is embedded into operational and strategic activities. This element reflects the need for analytics systems to be explicitly linked to organisational strategy and critical success factors, ensuring that analytical outputs address areas of strategic importance rather than becoming isolated reporting tools [1–4,6,7,10,11,14,19,32–34,36–49,51,54,56,59,63,64]. Although process maturity

may incorporate governance practices, the pillar specifically refers to the operational embedding of analytics within business workflows.

5. Political Will: Represents the strategic commitment of senior leadership to support and prioritise analytics-driven decision making, including resource allocation and the authority to act on analytical insights to produce strategic outcomes [1–4,6,10,11,14,19,32–34,36–44,48–51,53,57–60,63,64]. It extends beyond traditional notions of top-management support by emphasising the organisational authority and commitment required to act upon analytically derived insights. It is an overarching component within the framework, enabling and shaping priorities, resolving conflicts, and driving action within the organisation.

To ensure conceptual clarity, the five pillars are defined as analytically distinct but interrelated dimensions of analytics capability. The framework differentiates between operational capability domains (technology, data, people, process) and the strategic enabling condition (political will) that determines whether analytics insights are translated into organisational action. It provides an analytical framework for examining both successful and failed analytics initiatives and offers a structured basis for the empirical case analysis at HP Bulmer.

Analytics-related organisational transformation can be engendered and enabled via a series of mechanisms that support the five pillars. Six main categories of mechanisms can be identified from a synthesis of the CSFs and the literature mapping shown in Table A1 (Appendix A). These mechanisms constitute the organisational infrastructure that translates analytics potential into effective decision making and strategic action. The six categories concern capability development, governance, alignment and communications, data management, process integration, and strategic leadership. Specific mechanisms within each category are shown below.

#### 3.2.1. Capability Development Mechanisms

These mechanisms connect the people, technology, and data pillars by enabling individuals to effectively use analytics systems. They ensure that employees develop the skills and understanding required to interpret and apply analytical insights [1–3,5–8,10,11,36–38,41,43,44,47,49,50,52,54,57–60,64]. They include:

- Training programmes for analytics and data literacy (C1).
- Awareness campaigns on data-driven decision making (C2).
- Cascade briefings from senior leadership (C3).
- Communities of practice for analytics users (C4).
- Cross-functional analytics teams (C5).
- Professional development in analytics and data governance (C6).
- User adoption and onboarding programmes (C7).

#### 3.2.2. Governance Mechanisms

Governance mechanisms link political will, data, and process pillars by providing formal organisational control structures. These mechanisms ensure accountability, consistency, and alignment with organisational strategy [4,9,10,14,32–34,36,40,42,46,48,51,53,63].

- Data governance frameworks (G1).
- Executive analytics steering committees (G2).
- Data ownership and stewardship structures (G3)
- Analytics investment prioritisation processes (G4).
- Ethical oversight and compliance structures (G5).

#### 3.2.3. Alignment and Communication Mechanisms

These mechanisms link political will, people, and process by ensuring that strategy and analytics insights are understood and acted upon. They enable analytics insights to travel through the organisation and influence decision making [1,3,5–7,36–38,43,47,50,57–59].

- Management dashboards and reporting systems (A1).
- Organisational learning and training (A2).
- Executive sponsorship communication (A3).
- Knowledge sharing platforms (A4).

#### 3.2.4. Data Management Mechanisms

These primarily link the technology, data and process pillars, while ensuring that reliable, consistent data flows through analytics systems [1–3,5,7–9,11,33,34,36,38–40,42,45,46,48,49,52–56,58,63,64].

- Master data management (D1).
- Enterprise data architecture (D2).
- Data quality management processes (D3).
- Data integration frameworks (D4).
- Data lifecycle management (D5).

#### 3.2.5. Process Integration Mechanisms

These link process, technology, and people pillars by embedding analytics within operational workflows. They ensure that analytics insights translate into organisational action [2–4,6,9–11,14,32,34,36,37,39,41,42,44,47,48,51,52,56,60].

- Business process redesign incorporating analytics (P1).
- Standard operating procedures for analytics usage (P2).
- Analytics-enabled performance management (P3).
- Feedback loops between operational systems and analytics platforms (P4).
- Continuous improvement processes (P5).

#### 3.2.6. Strategic Leadership Mechanisms

These connect political will with all other pillars, ensuring that analytics initiatives are prioritised and sustained. They ensure political commitment and organisational momentum for analytics adoption [1–5,7,8,10,14,32,33,36–38,41,43,47,49–51,57–59,64].

- Executive sponsorship of analytics programmes (S1).
- Strategic analytics roadmaps (S2).
- Performance incentives aligned with analytics use (S3).
- Accountability for data-driven decision making (S4).
- Digital transformation leadership structures (S5).

Figure 5 indicates how these mechanisms relate to and connect the five pillars. As such, they can act as an action list and agenda for ensuring the five pillars are in place.

In summary, the five-pillars model builds upon existing models of analytics capability and data-driven organisations. Previous studies emphasise the role of data infrastructure and analytical talent in building competitive advantage through analytics [33,47], and more recent research highlights the importance of digital transformation and organisational change in enabling data-driven decision making [38,43,44]. The model presented here provides an integrated framework to ensure analytics technology deployment is aligned with broader organisational transformation processes, enabled through a series of interrelated mechanisms that connect and support the five pillars.

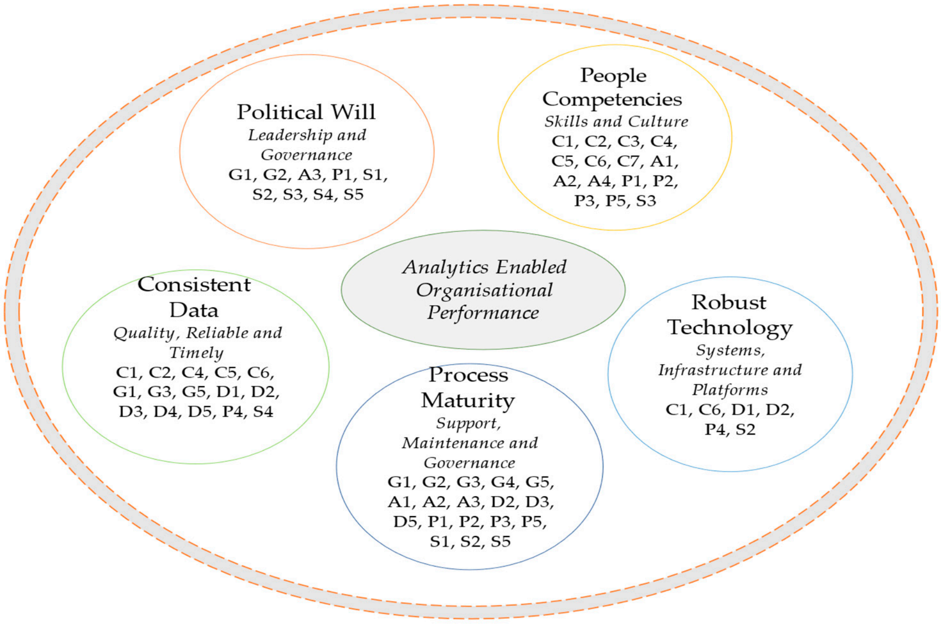


**Figure 5.** Enabling mechanisms for the five pillars.

### *3.3. RQ3: What Lessons Can Be Learnt from the Application of This Framework to the Deployment of Analytics Software at HP Bulmer Ltd.?*

In the late 1980s, HP Bulmer consisted of three separate divisions (cider, soft drinks, and wines and spirits) with a set of systems running on proprietary hardware that struggled to meet the varying needs of these three business areas [65]. With market share being a prime business objective, year-end "fast finishes" were the norm. The absence of modern integrated systems meant that management information was generally inadequate, lacking consistency and not reported in real time. In particular, control and visibility of expenditure on sales promotions at critical times in the financial year were problematic.

In the early 1990s, with the "Beer Orders" [66] about to radically change the long alcoholics drinks market, Bulmer engaged consultants to examine strategic options. As a result, the company embarked on a new strategy, centring on its core cider business, and dispensing with its wines and spirits and soft drinks businesses and brands. "The board... resolved to focus the business on profit from premium brands rather than volume sales of its 400 lines and to continue geographical expansion by developing foreign markets for cider. The company divested non-core businesses (pectin manufacture; soft drinks) and automated production and distribution" [67] (p. 2). Many of the more peripheral activities of the company were also closed down, including the small number of pubs owned by Bulmer and the steam museum on the Hereford site. Some of the less profitable cider brands were also discontinued—the emphasis was to be on profit, not volume sales.

In parallel with this change in strategic direction, Bulmer embarked on a major systems replacement and technology upgrade programme [68,69], which included projects to provide accurate and timely customer and product profitability information allowing the tracking and analysis of promotional expenditure. These are discussed below.

#### 3.3.1. Spreadsheet-Based Analytics Prototyping (1992–94)

The first attempts to develop reliable profitability information came from the company's market research department, where the departmental manager put together an extended spreadsheet system to provide profitability data. The system was not formally supported by the IT function—it was "end-user computing"—but IT provided the cost and sales data from their corporate systems as best they were able [70]. This nascent profitability data was made available to the senior sales management at the head office in spreadsheet form, and as printed reports for the field-based national account managers, who were not equipped with laptop computers at that time.

Whilst there was an evident need for such information, it was viewed as unreliable, as data from the feeder systems was inconsistent or lacked specificity at customer and product levels. Writing in the Computing journal in 1994, Sweet [71] reported “to stay ahead, Bulmer needed sound management information and the ability to react swiftly to changing conditions, but the company’s existing computer systems simply did not provide the sort of financial details which were required” [71] (p. 37). In addition, there was also no cross-company process in place to support, manage and exploit the system, which thus remained largely as a pilot driven and owned by the market research department.

#### 3.3.2. Financial Management System (FMS) (1993–98)

Faced with the serious problems relating to the inconsistency of data, a new project was launched in 1993. It was based around a multi-dimensional spreadsheet system—PC Express—which was purchased from the software company IRI. This provided the flexibility and analytical capabilities to handle the large amounts of data that were now becoming available from some of Bulmer’s newly implemented systems for sales and distribution, keg installation management, and financial ledgers [72]. In September 1994, a report in the Financial Times [73] noted “when Bulmers decided to change its focus from a volume-driven to a profit-oriented company, it realized that it would need new analysis tools” [73] (para. 1). The Bulmer’s commercial director observed “we will be able to track the effectiveness of our spend, whether it be on distribution, packaging, promotions, or producing our products. . . we can then take out cost where necessary” [73] (para. 9). This type of system has been termed an OLAP (online application processing) application, because it has the capability to process large amounts of data on request. Jones [74] noted at the time “OLAP is emerging as an important technology because it offers greater flexibility for functions such as end-user reporting or enquiries” [74] (para. 4). This benefit was also emphasised by the Bulmer’s IT director: “OLAP tools are much more intuitive to the way the human mind thinks and acts,” adding “the human mind can think in multi-dimensions more easily than in terms of a relational database. Give users an ad hoc enquiry relational database tool, and they will soon be stumped; an OLAP database is much easier to understand” [75] (p. 14).

The system was intended to be used by the company’s 40 field-based national account managers, and some of its brand managers, financial controllers and analysts in the head office. The IRI company was acquired by Oracle during this period, and the product was rebadged “Oracle Financial Analyzer”. This was to the benefit of Bulmer as it engendered better integration with its financial and manufacturing systems which were also acquired from Oracle. The total cost of the project was approximately £400,000 over the five-year period, with benefits estimated at £1.1m [76].

In 1997, the IT director and systems project manager provided an update on the systems’ status [77]. They reported a range of key issues yet to be resolved. As regards the data, some of the cost feeds (general sales force costs, cost of credit, distribution costs) required further analysis, meaning that the profitability figures produced by the system were not robust. There had also been teething problems with the system itself—version 4.5 of the software could not handle the data volumes involved, which forced a migration to a new version (4.6.) of the software, running under the UNIX operating system. There had also been problems with the communications links between the central system and the field-based national account managers, which were resolved with the migration to the new version of the system. Education and training remained a key issue, with some of the intended users still struggling to use the system effectively.

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The 1997 presentation recorded that the system was in operation and being used by 35 field-based national account managers, plus 15 brand or finance managers at headquarters [77]. Volumetric reporting for the company's top 60 customers was available to all users, and cost drivers and the means to report them had been identified, but further analysis was required on the cost feeds. Account and brand planning and forecasting capabilities were being used, and interim profitability reports and promotional spend analysis were available for head office users.

Although the project was in part successful, and had delivered significant bottom-line benefits [76], the data availability problems persisted in some areas of the business, notably with newly acquired brands that were heavily promoted at the end of the 1996-7 financial year. This highlighted the issues around data governance in the company, which acted as the catalyst for formal recognition of data ownership and maintenance responsibilities by appropriate business functions. Despite the persisting problems around data availability and quality, the company continued to grow its profits over this period, with pre-tax profits reaching £30.1m in 1996/7 (Figure 6).

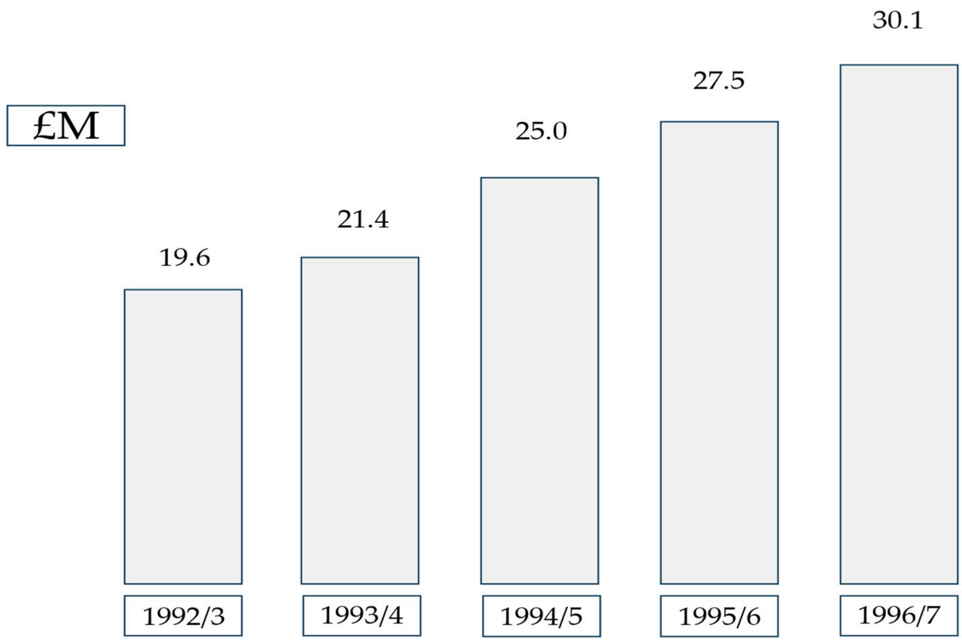


**Figure 6.** HP Bulmer's growth in pre-tax profits 1992/3 to 1996/7. Based on [78].

#### 3.3.3. Profit Management Programme (PMP) (1998–2001)

In 1997, the then managing director left the company shortly after the acquisition of Inch's cider company for £23m in 1996. The new managing director engaged consultants Arthur Andersen to re-engineer processes and improve internal communication and culture. A range of cross-company projects were set up, involving company staff working with the consultants in three streams of activity focusing on technology, people and process issues. One project—named the Profit Management Programme—entailed a detailed review of the functioning of FMS and aimed to address the key issues of process simplification, data availability, and management control. Analysts from the consultancy supported Bulmer's IT team in resolving the data issues, notably relating to accurate allocation of costs by customer and by product. In addition, a further analytics tool—JDA Boost—was acquired to run alongside FMS on the national account managers' laptops to provide improved data analysis functionality.

Some of the information generated by this initiative regarding the relative profitability of customers and products was highly significant (Figure 7), and for just a short period in 1998-9, the five pillars for the support of successful profit management analytics were in place—the technology, the data, the user ownership, the management process, and the political will to act upon the data. Then, in 1999, the company's new business strategy—to "generate profit and cash to invest in growth"—had the clear goal of becoming a £1 billion turnover company by 2004 [79]. Volume growth became the driving force, which heralded a range of strategy shifts within the company—new products were developed apace, additional staff were recruited to new middle management positions, and the company acquired companies or agreed partnership arrangements in the USA, South Africa and China to add to its existing overseas companies in Australia and Belgium. In 2000, Bulmer acquired The Beer Seller, a wholesale drinks distribution company, giving them a new route to market whereby Bulmer could deliver their brands into pubs and clubs across the UK. The aim was to make Strongbow® *the* national and international cider brand.

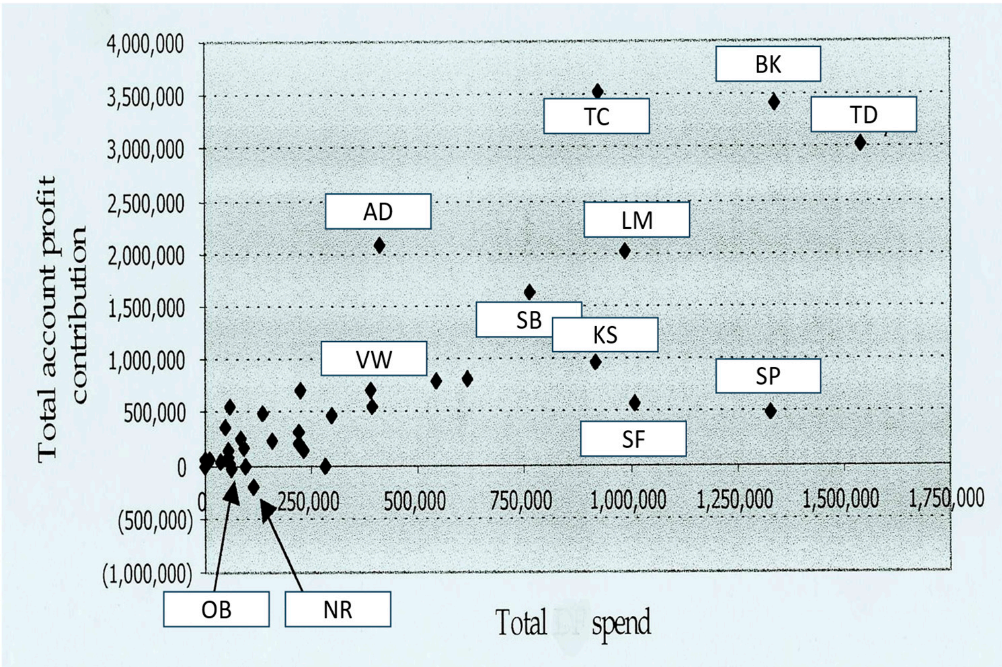


**Figure 7.** Total account contribution vs. support spend by customer, 1998-9. Customer labels are not representative. Source: [79].

Initially, this strategy appeared to bear fruit—the Annual Report of 2000/2001 [80] showed turnover up 57% year on year at £526m, with pre-tax profits up 1% at £28.6m, and Strongbow® "firmly established within the top ten highest selling long alcoholic drinks" in the UK [80] (p. 5). In the IT arena, the company was increasingly viewed as being at the forefront of successful technology deployment in the drinks industry, notably in pioneering new eBusiness applications across the extended supply chain [81]. However, events rapidly went from bad to worse for the company after 2001. Following a series of profit warnings in 2002, Bulmer's share price collapsed, at one point dropping to as low as 75p, having reached a high point of over £5.00 in the late 1990s. Greene [82] noted "a company that had once been worth £250 million was now worth £60 million. 280 of the 1000 employees were made redundant to try and cut costs, and many of the apple-growing farmers agreed to being paid over six months" (para. 43). Blackwell [83], writing in the Financial Times in 2002, when the company called in a "turnaround specialist after its fifth profit warning in 9 months" [83] (para. 1), noted "the latest warning predicts £14.5m of exceptional charges to be taken in the year to April 2003" [83] (para. 5). In addition, the board expected a further write-off of £4.7m in "capitalized investment in product development" and a further write-off of "up to £22m for goodwill associated with acquisitions in the US" [83] (paras. 5–6). Blackwell [83] also notes that the resultant level of debt (£110m) put the company in breach of most of its banking covenants. The chairman at the time noted that they were now trying to "correct what may have been the overoptimism of the management in the past" [83] (para. 8).

In 2003, Bulmer was bought by the Scottish & Newcastle Brewery for £278 million, and in 2008, Heineken and Carlsberg jointly acquired Scottish & Newcastle (S&N) in a £7.8 billion deal completed in 2008. Bulmer now survives as a brand name, but with operations in Hereford scaled back considerably. What once was a proud independent drinks company with a dynamic management culture in the mid-1990s, is now principally a cider plant within a large international drinks business, employing a few hundred staff, where once there had been over 1000 employees in the 1990s.

Table 2 assesses the three analytics projects pursued at Bulmer in the 1990s, which aimed to provide customer and product profitability analysis. It suggests intermittent failure, for varying reasons, to control promotional spend, which was a key issue in the resignation and departure of the managing director and finance director, respectively, in 2002. The irony is that in 1999, having finally managed to get the required combination of stable technology, reliable data, the necessary people skills and an established process in place, the political will that had been a key driver for these projects throughout the 1990s evaporated after the turn of the century as the company pursued its ambition of becoming a £1billion turnover company by 2004.

**Table 2.** The three analytics projects at HP Bulmer in the 1990s.

| Pillar/ Project | Robust Technology | Data Consistency | Process Maturity | People Competencies | Political Will |
|---|---|---|---|---|---|
| 1992–94 End-User Prototypes [69] | No. Standalone departmental spreadsheets were stable, but not suitable for a corporate system. | No. Data was assembled on an ad hoc basis from disparate sources. | No. There was no cross-company process or procedure for data governance, ownership or maintenance. | No. Restricted to the marketing research manager and his assistant. National account managers were not adequately briefed or trained. | Yes. Moving to a profit-led culture was supported by senior management. |
| Financial Management System (FMS) 1993–98 [72–77,84] | Partially. The PC Express product was adequate but automation of integration with feeder systems was problematic. | No. Allocating appropriate cost data from a variety of transaction processing systems was an ongoing problem. | Partially. Data ownership and maintenance responsibilities were recognised and appropriate staffing and procedures were in place. | Yes. IT project management, data maintenance, and end-user (national account managers) competencies were well advanced. | Yes, but data and process issues thwarted successful implementation. |
| Profit Management Programme 1998–2001 [78,79,83] | Yes. The FMS was stable and well supported. The JDA Boost product was available for national account managers for further analysis. | Yes. The allocation of costs by customer was largely resolved. Automated update of FMS was in place. | Yes. Processes were reviewed and verified. Data governance was in place. National account managers were trained and supported. | Yes. IT support skills, data maintenance competence, and end-user training were well advanced. | Yes, initially, but soon undermined by broader corporate ambition. |

It is not realistically possible to track the evidence of all the change mechanisms (Figure 5) across the three analytics projects, although the PMP project promoted many of these mechanisms within the company. That level of scrutiny is not feasible in a retrospective case study based on secondary sources, although a more selective assessment is feasible. In this context, the 14 CSFs were reviewed across the three projects embarked upon in the 1990s, in which the three most relevant change mechanisms for each CSF were selected from the 31 listed above in Section 3.2. This gave each CSF a clear analytics orientation and provided a logical basis for assessment (Table 3). A red–amber–green classification was made for each CSF across the three projects, based upon an examination of the project documentation and the summary narratives contained above. A degree of interpretation was allowed to accommodate the time lapse since the Bulmer case; for example, digital transformation was evidenced more as a technology-driven process of re-engineering in the Bulmer projects. If none or one of the change mechanisms was in place, a red assessment was made; if two were in place, an amber rating was given; and if all three conditions were met, a green assessment was given.

**Table 3.** Meeting the CSFs in the three analytics projects at HP Bulmer (R = not met; A = partially met; G = met).

| Change Mechanisms/Analytics Projects/CSFs | Change Mechanisms | 1992–94 | 1993–98 | 1998–2001 |
|---|---|---|---|---|
| 1. Adoption of Digital Transformation for Integrated Technology | D4, P1, S5 | R | G | G |
| 2. Top-Management Support | A3, G2, S3 | R | G | A |
| 3. People Skills and Expertise | C1, C6, A4 | R | A | G |
| 4. Data Analysis and Prediction Integrated for Efficiency | C5, D4, P4 | R | A | G |
| 5. Robust Data Management Practices | G3, D1, D5 | R | A | G |
| 6. Data Governance, Quality, and Integrity | G1, G5, D3 | R | A | G |
| 7. Processes Integrated with Strategic Intent | G4, P1, P3 | R | G | A |
| 8. Defined Company Strategy | G1, D2, S2 | G | G | G |
| 9. Data and Evidence-Based Decision Making | C2, A1, S4 | R | A | A |
| 10. Investment in Process Creation and Deployment | C6, G4, P5 | R | G | G |
| 11. People Training | C1, C4, A2 | R | G | G |
| 12. Organisational Change | G3, P1, S5 | R | G | G |
| 13. Management Competency for Decision Making | C2, C6, G2 | R | G | G |
| 14. Employee Engagement and Adoption | C3, C7, A3 | R | A | A |

This analysis suggests that all CSFs were met by the end of the 1990s, with the exception of four CSFs that still remained only partially met: top-management support, processes integrated with strategic intent, and data and evidence-based decision making, which all relate to political will (Figure 3), plus employee engagement and adoption, which was a direct consequence of the failure to fully meet the other three CSFs noted above. This indicates that analytics deployment, and more generally digital transformation, are not simply technological upgrades, but involve the alignment of technical subsystems (technology, data, process) with organisational elements such as people and political will. The HP Bulmer case provides a useful illustration of how analytics capability can lose strategic value even when technical components appear relatively stable.

## 4. Discussion

The results discussed above raise some issues that merit further discussion. Firstly, the case of HP Bulmer is a cautionary tale for all those businesses pursuing aggressive promotional campaigns, particularly at the close of key accounting periods (year-end, half-year-end, quarter-end). If promotional campaigns are aggressively pursued without the right systems and processes to monitor, record and accrue them in the right accounting period, this can lead to major corporate accounting failures. This is of relevance to company practice today, and not just in the consumer-packaged goods industry, as period-end promotional deals are pursued in many other sectors (e.g., computer hardware and software sales). Bird [84], in her assessment of the promotional spend issues at Bulmer in 1995, noted "monitoring sales in the market for fast-moving consumer goods is a bit like trying to keep track of individual grains of sand as they slip through your fingers. The more products you have, the harder it gets; add special offers and discount schemes and the sales monitoring task can quickly become a nightmare. It may be impossible to spot a flopped promotion until several weeks after its launch" [84] (p. 52). This is clearly a multi-faceted challenge. Analytics systems can provide the technology to support management action, but all of the five pillars discussed above need to be in place to underpin a successful outcome.

Secondly, analytics technologies have evolved considerably since the Bulmer case study from three decades ago. Modern analytics technologies can provide AI-driven, proactive insights, capable of processing very large and sometimes unstructured datasets from a range of sources in real time. Data may come not only from transaction processing systems, as was the case with the Bulmer case study, but also from other sources, such as IoT sensors and social media, plus appropriate third-party sources from outside the company. However, in the context of customer profitability, the accurate and appropriate allocation of cost overheads to individual customers remains a significant challenge. This undermined the credibility of the second analytics project at HP Bulmer and is evident in other similar studies. Van Raaij et al. [12], for example, in their study of a firm producing and selling professional cleaning products, noted that "this process of attributing costs to individual customers is a constant balancing act between increasing the accuracy of the allocation of costs and the efforts that are needed to achieve that increase. Furthermore, the allocation of costs is restricted by the availability of information" [12] (p. 577). Although digitalisation has introduced more powerful and sophisticated tools for analytics projects, accurate and appropriate data allocation remains a key issue. The Bulmer case study also shows that although technologies evolve over time, the organisational dynamics captured by political will remain as the key change dimension in securing successful outcomes. At the same time, the technologies evident in the Bulmer case study—spreadsheets, OLAP applications and field-based laptops—are still in common use today in many organisations. The authors thus maintain that the case study is a valid illustration of the five-pillars model, which remains equally apt today.

Thirdly, the findings complement certain theoretical perspectives put forward by other researchers in the field. Socio-technical theory [43,85], for example, was adopted by Chen et al. [2] in their study of key issues in analytics implementation. Socio-technical theory suggests there are two interdependent subsystems within any organisation. The technical subsystem focuses on "the processes, tasks, and technology needed to transform inputs to outputs", whereas the social subsystem is concerned with "the attributes of people (e.g., attitudes, skills, values) and the relationships among people, reward systems, and authority structures" [86] (p. 17). The main premise is that the social and technical subsystems must be optimised together to foster successful outcomes, and that failure to recognise the social system associated with the design and use of new technology is the reason why many new technology adoptions fail [86]. Further, the theory maintains that any significant

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organisational change instigated through the adoption of information systems must involve careful upfront design to meet the requirements of both subsystems simultaneously [87]. The five-pillars model put forward here resonates with this theory—the technology, process and data pillars make up the technical subsystem, whilst the people and political will pillars comprise the social subsystem—and the Bulmer case study highlights the imperative of managing and coordinating initiatives in both subsystems simultaneously.

The Technology Organisation Environment (TOE) framework is adapted by Radyanto et al. [3] "to develop a theoretical framework for the implementation of data analytics" (p. 345). Their model also includes "hexahelix elements" of "academic, business, corporate, government, media and business assistance in the application of the analytical data process" [3] (p. 345). Similarly, Maroufkhani et al. [88], in their study of big data analytics (BDA) in manufacturing SMEs in Iran, also used the TOE model as their main conceptual framework, and concluded that "the results offer evidence of a BDA mediation effect in the relationship between technological, organisational and environmental contexts, and SMEs performance. The findings also demonstrated that technological and organisational elements are the more significant determinants of BDA adoption in the context of SMEs" [88] (p. 473).

Whilst the TOE framework remains of relevance to IS research, the findings presented here are arguably more relevant in providing a framework geared to the realities of analytics implementation and grounded in the existing literature. The five-pillars model is more closely aligned with the findings of Parks and Thambusamy [89], who suggest that business analytics success is a function of organisational culture (BA skills and BA resources), process (business IT alignment, BA measurement, and BA best practices), and technological (data management, BA techniques, and BA infrastructure) dimensions (Figure 8). There are clearly overlaps between these two models, but the model presented here highlights the key role of political will as a distinct structural condition required for analytics success [44].

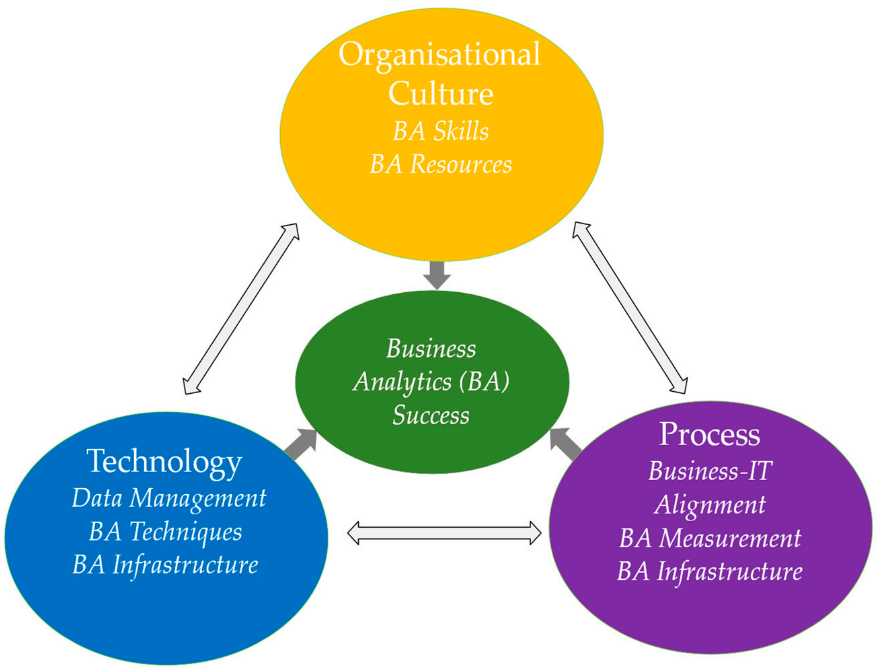


**Figure 8.** Dimensions for business analytics success (after Parks and Thambusamy [89]).

This encompasses both forward-planning and remedial action. This was clearly illustrated in the Bulmer case study, as the necessary resources were made available first for technology investment, then for data maintenance staffing and human skills development, and finally for process improvement, as the deficiencies in the other four pillars were uncovered. Financial and human resource availability is a critical boundary condition for these four pillars that requires the necessary political will for issue resolution and ongoing monitoring and maintenance. In the Bulmer case, this was facilitated by a clearly defined project management structure in which resource constraints were identified and escalated for assessment and resolution through working party and steering group structures. While leadership commitment is often acknowledged in prior work, it is rarely treated as a separate analytical dimension shaping the translation of analytics insight into strategic organisational outcomes [40,43]. The five pillars advance theory by offering an integrated model that connects analytics technology deployment with broader organisational transformation processes.

Finally, as regards the Bulmer case study, this article has put forward one interpretation of events, based on documentary evidence from that era. However, there are other views on this. In 2015, in a letter to the Daily Telegraph [90], the former chairman of the company (from the 1980s and 90s) recalled a conversation he had with Mrs. Thatcher regarding the impact of the increase in duty on the sale of cider. “After what you have done to my company”, he told her, “the only way that I can presently maintain the jobs of loyal and hard-working employees is by selling French water” [referring to Bulmer’s sale and distribution of Perrier water]. He concluded that “while other countries have fostered family companies, our political classes have all too often promoted their sale” [90] (p. 17). Whilst the disproportionate duty on cider versus other long alcoholic drinks has had a negative impact on cider makers at various times in the past, and the effect of the 1989 “Beer Orders” [66] created unwelcome upheaval in the industry, the main reason for company failure in 2002-3 lay elsewhere. In November 2002, the then chairman noted that “following the publication of our results for the year ended 26 April 2002, we identified previously unaccrued promotional expenses of £3.8m” [91]. The uncovering of this £3.8m hole in the accounts was the catalyst for a number of other revelations and write-offs regarding failed investment in overseas acquisitions, new product development and various other initiatives. The former chairman may well have been correct in what he said about selling French water and our political classes, but it was not the main reason for the collapse of the company. The acquisition of HP Bulmer by Scottish & Newcastle in April 2003 ended the Bulmer family’s ownership. The 310p share price offer represented a significant premium, as Bulmer shares had been trading as low as 73½p in November 2002 following the series of profit warnings noted above.

## 5. Conclusions

The current literature on analytics software deployment demonstrates strong continuity with earlier research on information systems and enterprise software, notably concerning the CSF tradition established by Bullen and Rockart [32]. This allowed the identification of fourteen CSFs for analytics project implementation and their grouping and classification as five main organisational pillars that need to be in place for project success. While technologies have evolved, the fundamental challenges around technology, data, people, process and political will remain. Successful deployment of analytics software depends not only on technical implementation but also on organisational readiness, strategic clarity, and the political environment. These insights provided a robust framework for examining the historical case of analytics deployment at HP Bulmer, an in-depth examination within a real-world organisational context.

Although the five-pillars model is a consolidation of existing themes, it has not previously been presented in this form in the context of business analytics. It is not ground breaking research, but is of value in that it is grounded in the existing literature and can be used to plan and monitor analytics projects as well as shed light on what happened in applied case studies. There are a few studies that consider a range of CSFs required for successful analytics deployment [44] and some that make reference to process and people issues as well as technology [10], but none that provide as comprehensive a framework as that presented here. The study moves beyond traditional CSF research, which often treats top-management support mainly as a source of resources. Here, political will is framed as the exercise of authority in managing decision rights, resolving functional tensions, and acting on uncomfortable analytical outcomes. In addition, the distinction between operational capability domains (technology, data, people, process) and the strategic enabling role of political will distinguishes this study from others in the business analytics literature. The five-pillars model provides a framework and checklist that informs both academic research and practitioner understanding. As well as being of interest to researchers in this field of study, the article is of relevance to senior and middle management engaged in the sales, marketing and finance functions.

The Bulmer case study is not seen as an empirical validation of the five-pillars model, but rather as an illustration of how the five-pillars model can be used. The value of the case study thus lies as much in analysing how and why the analytics projects failed in the company, as much as in the application of the model itself. This aligns with the views of Ary et al. [92] who state that "the underlying question in case studies is what are the characteristics of this particular entity, phenomenon, person, or setting?" (p. 392). Yin [28] also argues that in case studies, academics should focus on "what", "how" and "why" research questions—not just answer "what". Case study research is particularly appropriate when the boundaries between phenomenon and context are blurred—"rather than thinking about your case(s) as a sample, you should think of your case study as the opportunity to shed empirical light on some theoretical concepts or principles" [28] (p. 38).

The article clearly has its limitations. It is based on an analysis of current literature and an applied case study, based on secondary documentation. The article nevertheless provides a workable framework for the assessment and management of analytics projects, and a set of mechanisms for establishing the five pillars within the organisation. As such, this study provides a powerful framework that will be of value to analytics researchers as a basis for follow-on initiatives, but also to industry practitioners. The five-pillars model and mechanisms checklist are of direct and practical relevance to senior and middle management engaged in data-driven management and wider digital transformation projects.

Future research could apply and evaluate the five-pillars model and the mechanisms checklist against recent analytics initiatives in different industry sectors. The enabling mechanisms could also be applied and monitored in live analytics projects to confirm their relevance and operational viability. The CSFs could be reviewed and possibly updated to accommodate digital transformation projects involving a range of digital technologies—for example, artificial intelligence, blockchain and robotics. In all such endeavours, the focus should not be on technology alone, but more on the wider organisational factors. Past and current experience confirm that an understanding of the interaction of social and technical factors is key to securing successful outcomes in analytics and related technology projects.

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## Appendix A. Additional Data Regarding the Phase 1 Source Literature

**Table A1.** Classification of emergent themes from the literature analysis allocated to the five pillars.

| Source/Emergent Themes | Technology | Data | People | Process | Political Will |
|---|---|---|---|---|---|
| Vaidya et al. [1] | Advanced analytics | Predictive data | Analytical expertise | Smart manufacturing processes | Strategic intent |
| Chen et al. [2] | Predictive analytics technologies and implementation architectures | Data availability and quality for predictive modelling | Cross-functional expertise and organisational readiness for analytics | Socio-technical implementation processes integrating analytics into decision making | Executive sponsorship and organisational commitment |
| Radyanto et al. [3] | BI supported performance measurement | Data collection and integration | Managerial capability to apply analytical insights | Performance measurement frameworks | Strategic commitment from business leadership |
| Harfoush [4] | | | Organisational change | BI adaptation processes | Leadership behaviour |
| Chaudhuri et al. [5] | BI architectures | Data management | | | |
| Shmueli & Koppius [6] | Predictive analytics models and tools | Data for forecasting and modelling | Analytical expertise and interpretation | Embedding prediction in decision processes | Managerial use of predictive insight |
| Watson & Wixom [7] | BI systems | | Adoption readiness | | |
| Chen et al. [8] | Analytics platforms | Data integration | | | |
| Gao et al. [9] | | Data flows | | Process-centric CSFs | |
| Altundag & Wynn [10] | Advanced analytics systems | Data management maturity | Procurement capability | Strategic integration | Managerial commitment |
| Ajjan [11] | IT portfolio alignment | | | Investment prioritisation | Executive Decision making |
| Rockart [14] | | | | Strategy and CSFs | Executive priorities |
| Bullen & Rockart [32] | | | | IS strategy focus | Top-management support |
| AlMarri et al. [33] | ERP systems | Data integrity | Training and skills | Risk management processes | Leadership commitment |
| Mukred et al. [34] | | Information quality | Decision competence | ERP enabled decisions | Institutional governance |
| Yeoh & Popovič [36] | | Information quality | Information quality | BI implementation processes | BI implementation processes |

**Table A1.** *Cont.*

| Source/Emergent Themes | Technology | Data | People | Process | Political Will |
|---|---|---|---|---|---|
| Davenport [37] | | | | Analytics–strategy alignment | Leadership commitment |
| Wixom & Watson [38] | BI capability | | User engagement | | Senior sponsorship |
| Atlas, Yitong & Khan [39] | Big data analytics infrastructure | Data resources supporting knowledge management | Analytics talent capability | Knowledge management processes | Organisational commitment to analytics capability |
| Song et al. [40] | Digital analytics technologies. | Data-driven opportunity recognition | Digital entrepreneurial capability | Innovation processes enabled by analytics | Institutional and organisational support for analytics adoption |
| Vesterinen, Mero & Skippari [41] | Big data analytics platforms and tools | Integration of market and customer data | Analytical capability development | Marketing agility and adaptive processes | Strategic commitment to analytics-enabled competitiveness |
| Huang et al. [42] | Digital transformation technology infrastructure | Data-enabled organisational capability | Dynamic managerial capabilities | Digital transformation processes | Leadership support for digital transformation |
| Ghafoori et al. [43] | Analytics tools supporting organisational decision making | Data-driven culture and data-oriented management practices | Managerial analytical skills and organisational learning capabilities | Integration of analytics into management control and decision processes | Top-management support promoting analytics as a strategic priority |
| Álvarez-Foronda, De-Pablos-Heredero & Rodríguez-Sánchez [44] | Data analytics technologies | Organisational data access, digitisation of information systems, and analysis of large transactional datasets | Auditor training and development of analytical skills to use data analytics tools | Integration of analytics across audit phases including planning, execution, reporting and follow-up | Executive awareness and organisational support for adopting data analytics within governance and internal audit functions |
| Dearle [45] | Software deployment architectures | | | Deployment processes | |
| Kankaanpää [46] | | | User adoption | Implementation processes | |
| Turulja et al. [47] | Data analysis integration | Knowledge data | Knowledge workers | Knowledge processes | |
| Faruq et al. [48] | AI-enabled analytics | Integrated datasets | Digital skills | Digital transformation | Strategic leadership |
| Thummala & Saxena [49] | | Data-driven metrics | Managerial capability | Program management processes | Evidence-based decisions |
| Kiron et al. [50] | | | Evidence-based culture | | Leadership behaviour |
| Wynn & Brinkmann [51] | | Information quality | Knowledge management | BI in strategy | Governance alignment |

**Table A1.** *Cont.*

| Source/Emergent Themes | Technology | Data | People | Process | Political Will |
|---|---|---|---|---|---|
| Rangineni et al. [52] | | Data quality enhancement | | | |
| Khatri & Brown [53] | | Data governance | | | Governance accountability |
| Zhang et al. [54] | | Data quality discovery | | Data reuse processes | |
| Inmon [55] | Data warehouse design | Data consistency | | | |
| Romero & Abad [56] | Cloud and ERP analytics integration | Big data pipelines | | Platform-enabled processes | |
| McAfee & Brynjolfsson [57] | | | Data-driven skills | | Willingness to act on analytics |
| Wixom et al. [58] | BI competence centres | | Cross-functional skills | Organisational routines | Governance structures |
| Davenport & Harris [59] | | | Analytical capability | Competitive processes | Executive sponsorship |
| Power [60] | | | | | Decision rights and action |
| Chang [63] | Information systems as organisational control and resource mechanisms | Information flows embedded within organisational power structures | Political behaviours among stakeholders during IS implementation | Interaction of political behaviour patterns shaping IS implementation processes | Power dynamics and organisational influence affecting implementation outcomes |
| Imran et al. [64] | Information technology systems supporting financial reporting and fraud monitoring | Quality of financial reporting information and data transparency | Organisational accountability and financial management roles | Financial governance and fraud prevention processes | Political will supporting fraud prevention and oversight mechanisms |

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