ARTIFICIAL INTELLIGENCE IN DIGITAL MARKETING:

A NEW MODEL FOR REVEALING AND MITIGATING BIAS
(A CASE STUDY OF AN INTERNATIONAL SOFTWARE COMPANY)

CATHERINE REED

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I. ABSTRACT

Artificial Intelligence (AI) is transforming modern business and society. As a nascent technology its influence continues to grow across various sectors. In the field of marketing, the potential of AI adoption is particularly pronounced as it offers significant benefits in strategy, content creation, and data analysis. However, alongside these advantages, the increasing use of AI raises critical ethical concerns, particularly around the propagation of bias. This research explores the current and possible bias issues - and how they can be mitigated - in AI driven marketing practices within the context of a global software company.

Two principal forms of AI are currently being leveraged in marketing: traditional AI and generative AI. Traditional AI is grounded in supervised, semi-supervised and unsupervised learning and predictive analytics, whilst generative AI employs large language models to produce dynamic and creative content. Although these technologies can improve efficiencies and personalisation, they simultaneously introduce challenges related to transparency, authenticity, and algorithmic fairness.

Current literature identifies that marketing bias - historically shaped by human judgment - is being compounded by automated systems that inherit and even magnify existing inequalities through their coding, prompting, and deployment. Despite the critical implications, there is a lack of clear governance frameworks and practical guidance for marketers using AI in their activities.

This research employs a qualitative, inductive research approach through an in-depth case study of a leading global software provider. Drawing on a systematic literature review and semi-structured interviews with marketing professionals, the research examines how bias is perceived, experienced, and addressed in AI enabled marketing. The research contributes to both theory and practice by identifying specific areas where bias can emerge in AI usage and proposes a practical, practitioner-informed model for revealing and mitigating such bias within digital marketing.

This thesis builds upon the existing theory of bias propagation in marketing and examines them through a lens of how they can compound via the use of technology. It examines the current usage and implementation of AI within marketing activities and presents that humans are an essential element of successful AI implementation, usage and management within business. The thesis finds that the marketing customer journey and current marketing technology are of vital importance when structuring the implementation of AI in marketing.

The developed model - and accompanying guide on how to operationalise the model - provides actionable insights for both industry professionals and academic researchers. It offers a structured path to more mindful AI implementation in marketing by emphasising the need for internal governance and ongoing training for marketing teams to responsibly interact with AI tools. This research has limitations, however, as it is based on one case-study company in one marketing industry sector, but it can serve as a foundation for future research development in this field of study.

II. DECLARATION OF ORIGINAL CONTENT

I declare that the work in this thesis was carried out in accordance with the regulations of the University of Gloucestershire and is original except where indicated by specific reference in the text. No part of the thesis has been submitted as part of any other academic award. The thesis has not been presented to any other education institution in the United Kingdom or overseas.

Any views expressed in the thesis are those of the author and in no way represent those of the University.

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IV. DEDICATION

To *Ben*, my beloved husband, who immediately supported me when I declared I wanted to do a PhD. Your constant encouragement and taking on so much more yourself, allowed me to achieve this.

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VIII. GLOSSARY

Definition of Framework:

A framework is the structural relationship between concepts. In this thesis, the term framework is used for the Provisional Conceptual Framework that structures findings from the literature review.

Definition of Model:

A model is a dynamic representation of the relationship between concepts and shows the process of applying them – it bridges theory and practical applications. In this thesis, the term model is used for the final operational model that incorporates both literature and primary data that has been thematically analysed.

Definition of Artificial Intelligence:

Artificial Intelligence (AI) includes a wide range of technologies and approaches crafted to mimic human cognition to tackle intricate tasks (Korteling et al., 2021). This refers to a machine's ability to carry out cognitive functions such as perception, reasoning, learning, creativity, and problem-solving (McKinsey & Co, 2023).

Definition of Weak & Strong AI:

"Weak AI" – refers to AI systems trained for specific, targeted tasks. This type of AI comprises the majority of AI applications in use today, such as Siri, Alexa, and autonomous vehicles (Holman, 2023). This literature review focuses on this category of AI.

"Strong AI" – currently exists only in theory, representing a machine with intelligence on par with or surpassing humans. It would possess consciousness, capable of problem-solving, learning, and generating original thoughts (Laskowski & Tucci, 2023).

Definition of Generative Artificial Intelligence:

Generative Artificial Intelligence is a branch of AI techniques that concentrate on producing content like text, images, music, and other forms through machine learning models. These models are crafted to emulate human creativity by studying patterns from available input data, then generating fresh outputs based on these patterns (McCormack et al, 2021). Generative AI falls under the category of "weak AI", learning through machine learning methods.

Definition of Supervised Learning Algorithms in AI:

Supervised learning, a branch of machine learning, employs labelled datasets to teach algorithms how to forecast results and detect patterns (Saravanan & Sujatha, 2018). In contrast to unsupervised learning, supervised algorithms are presented with labelled training data to grasp the correlation between inputs and outputs. This type of machine learning greatly simplifies the process of developing sophisticated models capable of delivering precise predictions. Consequently, supervised learning finds extensive application in diverse industries such as healthcare, marketing, financial services, and beyond (Verma et al., 2021); for marketing this can include lead scoring and audience segmentation.

Definition of Semi-Supervised Learning Algorithms in AI

Semi-supervised learning is an AI method that uses a small amount of labelled data and a large amount of unlabelled data to train models (Verma et al., 2021). These types of AI algorithms are then used as a base for a wide range of tasks – for marketing this can include processing data of customer interactions on a website.

Definition of Unsupervised Learning Algorithms in AI

An unsupervised AI method is defined as when the algorithm is coded to analyse and find patterns in unlabelled data without human guidance (Saravanan & Sujatha, 2018). This AI will use the unlabelled data to find underlying data structures and generate new outputs – for marketing this can include customer segmentation and personalisation recommendations.

Definition of AI Large Language Models:

A large language model (LLM) is a type of artificial intelligence (AI) program designed to recognise and generate text, among other capabilities. The term "large" refers to the extensive datasets used to train these models. LLMs are based on machine learning, specifically utilising a type of neural network known as a transformer model.

Definition of Supervised Learning Algorithms:

Deep Learning - utilises datasets to inform its algorithms. These datasets can consist of unstructured data, including text, images, and code. Deep Learning algorithms are designed to automatically identify distinguishing features, categories, and hierarchies within the data (Holman, 2023).

Machine Learning - necessitates human intervention to review input data but boasts greater accuracy in predicting outcomes. It relies on extensive historical datasets as input to forecast and generate new outputs (Laskowski & Tucci, 2023).

Definition of Marketing Technology Stack:

A marketing technology stack refers to a collection of tools used by marketers to execute and enhance their marketing efforts. Generally known as a MarTech Stack, these technologies are aimed at simplifying complex tasks, gauging the effectiveness of marketing tactics, and optimising spending for greater efficiency. The software curated within these MarTech Stacks have coded "links" allowing them to share data between themselves, for optimised usage. They include CRM systems, digital content asset management, multi-channel nurture tools (email, advertising, personalisation, SEO), website management, virtual events, social media, qualification and analytics.

Definition of Bias:

The definition of bias is nuanced, both a noun and verb, and it applies to both real-world and statistical definitions. The Oxford English Dictionary states "[uncountable, countable, usually singular] a strong feeling in favour of or against one group of people, or one side in an argument, often not based on fair judgement" (Oxford English Dictionary, 2025). Collins Dictionary (2025) further clarifies that "biases can be innate or learned. People may develop biases for or against an individual, a group, or a belief".

This research's assumed definition of bias is a disproportionate weight in favour of or against an idea, thing, or belief, usually in a way that is prejudiced, unfair and closed-minded, against an individual or group. Both conscious and unconscious bias are within this, with the view that unconscious bias is implicit, and conscious bias is systemic.

CHAPTPER 1: INTRODUCTION AND OVERVIEW

1.1 Introduction

This chapter sets out the background to this research study that addresses how companies can identify and mitigate bias propagation when using Artificial Intelligence (AI) in their digital marketing efforts. The research study is conducted as a case study on an international software company. The value and relevance of this thesis come from the exploration into the nascent area of AI and therefore, its currently limited published theory, especially within marketing. In this thesis, a framework is used to create a Provisional Conceptual Framework from the literature. A Model is then produced as a final operational model from both the literature and thematic analysis of the primary data (see Glossary).

This chapter has five sections. Following this introduction, section 1.2 gives a brief background and history of the software industry, marketing industry and AI. In section 1.3, the motivation for this research is explored. Section 1.4 lays out the research objectives and the importance of the research. This chapter is then concluded with a summary section in 1.5.

1.2 Background and Context

1.2.1 Background of the Software Industry

The software industry is a rapidly evolving area of modern business – it enables innovation across sectors (such as healthcare, retail and finance) and enables global economic development (Rangarajan & Tiwari, 2015). As of 2024, the global software market was valued at approximately $736 billion and is projected to reach around $2,248 billion by 2034 (Statistica, 2024). This growth trajectory is fuelled by the following factors: digital transformation, cloud-based solutions and the integration of AI technology (Armbrust et al., 2010). As an industry it encompasses a wide range of products and services, including enterprise solutions, consumer applications and cloud-based platforms. The software industry's globalisation has been encouraged by cross-country collaborations and the increasing influence of emerging markets (George & George, 2024). A large factor of growth has come from the expansion and dominance of big technology corporations headquartered in the USA - Alphabet (formerly Google), Amazon, Apple, Meta, and Microsoft—often called the "Big Five" (Fernandez et al., 2020).

The software industry emerged as a distinct economic sector in the 1960s - due to the commercialisation of computers and the rise of programming as a professional discipline (Campbell-Kelly, 2003). Initially dominated by in-house development within user companies, the creation of Common Business-Oriented Language (COBOL) and FORmula TRANslation (FORTRAN) were among the earliest high-level programming languages developed to address different computing needs for business applications and engineering computations (Kappelman, 2002; Upadhaya, 2023). Government agencies and large corporations were the primary purchasers and users of these languages (Ensmenger, 2012). These languages laid the groundwork for modern programming practices and continue to influence legacy systems today (Upadhaya, 2023). The rise of packaged software and personal computing in the 1980s encouraged the diversification of software. By the 1990s, the globalisation of software production and the widespread adoption of the internet created new market opportunities – this encouraged and allowed companies to access global talent pools and consumer bases (Cusumano, 2004).

Today, the software industry can be broadly divided into several segments: system infrastructure software, application software, software-as-a-service (SaaS), and embedded software. SaaS, in particular, has experienced huge growth due to its scalability, cost-effectiveness and suitability for remote working (IDC, 2022). The market is dominated by global companies such as Microsoft, SAP, Oracle, Salesforce, and Adobe which specialise in enterprise software. Smaller companies and startups own and innovate in niche software areas – such as artificial intelligence, cybersecurity, and mobile applications.

The international nature of the software industry means these companies must adhere to a complex web of regulatory and geopolitical factors. Data protection regulations such as the European Union’s General Data Protection Regulation (GDPR) and the California Consumer Privacy Act (CCPA) impose compliance requirements on these companies operating globally (Greenleaf, 2020). These regulations govern and therefore affect software design, cloud architecture, and data sharing strategies.

In recent years, geopolitical tensions have impacted global software and technology collaboration. An example is the United States and China technology rivalry – spanning from electric cars to AI chips. These rivalries have led to escalating tariff wars, export restrictions and restrictions on market access (Selmi et al., 2020; Segal, 2020). These geopolitical dynamics complicate international operations for multinational software companies and may result in market displacement. These different standards and regulatory regimes have an impact on the correct agreed regulation of new technologies. This is explored further in this research.

1.2.2 Background of Marketing

The software industry has long relied on marketing strategies to bring technology to market to drive its growth and competitive advantage (Kedi et al., 2024). Unlike traditional products, software is intangible and constantly evolving with new offerings and upgrades – this requires a strong value proposition to differentiate in saturated markets that marketing can achieve (Sheth et al., 2024). Effective marketing strategies help software companies educate consumers, establish brand authority and accelerate purchasing cycles (Kedi et al., 2024).

Marketing is the process of promoting a product or service to meet the needs and wants of consumers that ultimately ends in a sale of that product or service (Baines et al., 2017). It involves understanding a target audience for a product or service and communicating that value effectively to drive customer engagement and sales. Its goal is to build strong customer relationships for the company brand and ensure business growth (Sheth et al., 2024).

Like the software industry, the advent of the internet and digital communication technologies in the 1990s was a pivotal moment within marketing. The introduction of websites, search engines and email changed the way businesses interacted with customers – turning marketing digital. This digital marketing capability enabled two-way communication between the company and customer, in contrast to the traditional one-directional advertising that was in place previously (Chaffey & Ellis-

Chadwick, 2019). This rise of digital marketing has enabled software companies to reach global audiences at relatively low cost (Chaffey & Ellis-Chadwick, 2019). The ability to remotely engage with customers is pivotal in cultivating loyalty and driving long-term success (Sheth et al., 2024; Scott. 2024).

A company and their technology that is significant within digital marketing is Google. Since the 2000's Google's search engine marketing and search engine optimisation have become essential tools within marketing to reach audiences via paid and organic search (Iskandar & Komara, 2018; Srinivasan, 2020). Social media companies are also of significance for digital marketing. Platforms such as Meta, X, and Instagram emerged to give marketers direct access to vast audiences and enabled real-time engagement (Kedi et al., 2024; Scott, 2024).

The emergence of big data analytics has influenced marketing strategy and execution. Marketing data allows access to enormous volumes of structured and unstructured data from various customer touchpoints including websites, social media, emails and call-centres. This data, when analysed, provides insights into customer behaviour, preferences, and trends (Mayer-Schönberger & Cukier, 2013; Roetzer & Kaput, 2022). Predictive analytics has become especially important in customer segmentation, lead scoring, and marketing campaign optimisation (Wedel & Kannan, 2016; Sheth et al., 2024).

The arrival of AI has innovated marketing practices (Huang & Rust, 2021), with software companies creating, incorporating and promoting their own versions of AI. These include chatbots, generated content creation and automated customer interactions enhancing digital marketing operations. These AI automation algorithms have boosted marketing workflows with the integration of email, social media, and customer relationship management (CRM) functions. These systems nurture customer leads through automated journeys based on user behaviour, significantly increasing conversion potential while reducing manual effort (Järvinen & Taiminen, 2016). The machine learning algorithms of AI also power content that gives customers personalised experiences. An example of this is shopping on Amazon, where an AI recommends products based on a customer's purchase history to boost engagement and sales (Davenport et al., 2020). Indeed, the retail industry has been at the forefront of implementing AI applications in marketing and other company processes (Jones & Wynn, 2025).

In line with the regulation and governance of software, the rise of data-driven marketing has increased ethical and regulatory concerns. High-profile data breaches can occur and with growing public awareness of how their data can be used, privacy has become a priority. Data usage and consent rules within marketing are subject to the same GDPR and CCPA acts that regulate the overall software technology market (Tadajewski & Brownlie, 2008; Macmillan, 2020).

1.2.3 Background on Artificial Intelligence

AI has its roots deeply embedded in the software industry (Russell & Norvig, 2021). Advances in machine learning algorithms, data processing capabilities, coding languages and computing power have enabled the development of these intelligent systems capable of automating complex tasks. Driven by innovations in computer science and engineering within software companies (including the Big Five) AI technology has increasingly become integral to various business functions, including marketing.

The mainstream adoption of AI in business has evolved over the past decade (Agarwal et al., 2024). The emergence of machine learning in the 1980's allowed for companies to increase data analytics; however, it was not until the evolution to deep learning models in the 2010s that AI capabilities were accelerated (Goodfellow et al., 2016). With this increase in data processing AI algorithms are now widely used within business for predictive analytics, customer data segmentation and integration of intelligent software systems (Zhang et al., 2021).

Within digital marketing AI enables multiple strategic and execution-based marketing activities – from the analysis of large datasets and predicting consumer behaviours to personalised customer experiences (Huang & Rust, 2021). The integration of AI into marketing functions not only enhances operational efficiency it also drives competitive advantage through data-driven decision-making and automation (Davenport et al., 2020). This automation software – specifically chatbots, virtual assistants, and customer profiling is widely used reducing the need for human intervention in routine interactions.

In November 2022, when OpenAI introduced ChatGPT to the wider market, it gave the public access to prompting and using a generative AI with sophisticated natural language capabilities that could produce human-like responses across a wide range of topics. As ChatGPT was made directly accessible on an almost free basis it rapidly reached millions of users worldwide who started using it not only for personal, but professional, tasks (OpenAI, 2022). Due to this successful widespread access to the public technology companies and developers invested and innovated rapidly with new applications for large language models moving AI away from a specialised domain to mainstream use (Trautman et al., 2023).

One of the key benefits of generative AI - that drove its widespread business adoption - is its ability to increase efficiency and productivity (Li, 2020; Roetzer & Kaput, 2022); this is achieved through the deployment of AI in the workforce. The projected spend on AI for marketing over the next five years is set to increase by $71 billion (The Business Research Company, 2025). The upward spend trend reflects companies' perception of AI's potential to automate their customer interactions and enhance performance.

A further area where AI has become mainstream is though the proliferation of smart devices and applications within people's personal lives. Use of virtual assistants (such as Amazon's Alexa or Apple's Siri) and smart home devices has become integrated into everyday life. This personal usage of AI permeates into the workplace by a workforce who want to have AI's ease their workload the same as their personal AI's does (Trautman et al., 2023). In alignment with sections 1.2.1 and 1.2.2, the governance on the regulation of this technology is subjected to law. There are few laws that currently regulate AI coding and issues such as algorithmic bias, data bias and data privacy because of this are explored in this research (UNESCO, 2021).

1.3 Research Motivation

In 2022, the author was asked to begin identifying where AI could be used within their job and department. It was proposed that because AI is the next technological breakthrough, employees should be adopting it and using it at speed. There was little guidance on the outcome of this request or how the adoption of AI was to be managed. Having worked across multiple cultures and marketing teams, the author had been exposed to marketing campaigns that had been recalled due to inappropriate branding, inaccurate transcriptions or unbalanced data segmentation. Generating content and installing data rules without a thorough knowledge or guidance on how to use AI responsibly was an evident concern.

With little guidance on how to approach AI usage within marketing, how to achieve it and use it responsibly, the author turned to academia to help. A preliminary review of academic journals, books and blogs to explore current theory yielded little information for marketing. Due to the nascent area of AI - particularly within a marketing context - there was a dearth of theoretical guidance or a model that supported the authors requirements. It became clear from the literature that AI came coded with bias, that in theory marketeers prompting it could be adding bias and its wider release to the public was going to revolutionise marketing. But the guidance on how to responsibly incorporate it into marketing departments remained elusive. The author felt compelled to research this gap in knowledge themselves and attempt to not only give an original contribution to theory, but also to practice.

In summary, the key problem that motivates this research is the lack of guidance on how to responsibly adopt and integrate artificial intelligence within marketing departments. As AI becomes more integrated into digital marketing there is growing ethical concern about its implementation due to marketings penchant for customer segmentation, targeting, and content personalisation - these can propagate existing stereotypes or marginalise audiences. This thesis provides the opportunity for deep, methodical research into the roots and consequences of such biases, as well as the development of a model to mitigate them. By combining academic rigor with industry insight, the author can contribute to creating more trustworthy and effective marketing practices.

1.4 Research Objectives and Significance

The arrival of generative AI into the workplace has brought about the rapid evolution of the digital landscape and what is possible for businesses striving to maintain a competitive edge (Van Esch & Black, 2021). AI's capability to analyse vast quantities of data, deliver customer segmentation and produce content quickly gives a competitive edge within marketing strategy and execution. This is reinforced by the substantial financial commitment by businesses to purchase AI for marketing purposes. In 2025, the global market for purchasing generative AI for marketing use is valued at $35 billion, with projections indicating an expansion to $106 billion by 2029 (The Business Research Company, 2025). This substantial investment reflects the industry's understanding of the importance of this technology for marketing automation purposes and the reduction of workforce labour time and costs.

Market research shows that 71% of marketeers have reported saving over five hours per week through using generative AI - reducing busy work and allowing more focus on strategic projects – this equates to one month's worth of work in one year saved (Salesforce Research, 2023). Further to time efficiencies, AI also contributes to cost reductions that impact on an improved return on investment (ROI) rate. Generative AI used for content creation reduces labour time by 40% and increases quality of output by 18% (Noy & Zhang, 2023). This is due to content that would have been outsourced to agencies to create and manage can now be done "in-house" by the marketeer to a similar standard. This type of AI usage can increase the ROI for marketing budgets by 38% (Salesforce Research, 2024). This is good news for companies and their bottom-line financial margins, however, this experience is not wholly positive for the marketeers themselves.

Salesforce Research (2023) noted that marketeers are open to the opportunities of generative AI and in using it they feel underprepared by their companies to take full advantage. This is shown by the statistics that 39% of marketeers do not know how to use generative AI safely, and this is compounded by 43% of them stating they do not actually know how to use the technology properly to utilise its full potential. Of interest, consumers are comfortable with brands using AI generated content within their marketing – on the proviso that it enhances their customer experience and that brands disclose they have used AI (Burlacu, 2023). However, this consumer requirement for an AI declaration may not be consistently implemented. The Salesforce Research (2023) noted that 70% of marketeers stated their employer did not provide generative AI training – despite 54% of them believing it is an essential program to use AI successfully within their role. This indicates that marketeers are having to explore unfamiliar ways of working, to develop ways to use AI in their job.

Further research from McKinsey and Company (2025) shows the scale of the gap between marketeers being encouraged to use AI in their work and the responsibility shown by companies. Out of 830 research respondents only half of them reported that the generated AI outputs were reviewed before being used. This is of significant risk for brand reputation and bias propagation if marketeer prompted generative AI is being used without prior review. The research further notes that marketeers report AI outputs for cybersecurity and privacy regulation being prioritised for risk management by their companies, rather than addressing risk in generative AI outputs (Singla et al., 2025).

Bias identification is essential in AI when used within marketing to ensure fairness, accuracy, and inclusivity – AI systems learn from data, which may reflect historical or societal biases. If unchecked, these biases can lead to discriminatory targeting, misrepresentation, or exclusion of certain groups – this not only harms user trust but can also damage brand reputation (Pu et al., 2021). This harm leads to impact on profits and can even lead to regulatory consequences (Unilever Research, 2021). In 2023, the brand Levi's used AI generated models from diverse backgrounds in a marketing campaign. It was criticised by consumers for undermining the brands authenticity and commitment to diversity and inclusion (Baker, 2025).

The aim of this thesis is to develop an original contribution to theory and research in the field of AI usage in digital marketing. It is specific to the industry of marketing, and while it is researched on a case study company, it can be leveraged by other companies for their marketing departments. This research aims to address the following research objectives:

RO1: To analyse current and possible bias issues in coding, prompting and deployment of AI in Digital Marketing

RO2: To develop a conceptual framework for analysing bias issues in the use of AI in Digital Marketing.

RO3: To develop and validate a model, entailing appropriate guidance for practitioners, for revealing and mitigating bias in AI deployment in Digital Marketing.

The current transfer of academic knowledge of AI implementation and the biases within marketing into practice is currently lacking and this gap is justified and explored throughout this research. In addition to the contribution to theory this research aims to give business leaders a model they can implement in practice within their marketing departments. According to the AI Marketing Report (Kasumovic, 2024) only 27% of businesses are providing training to their marketing teams to support their use of AI effectively – this gives a broad scope of improvement required – especially with the projected investment in AI spend for marketing over the next five years. This research provides a model for these businesses to utilise and implement to support their training for their marketing departments.

This thesis contributes to academic theory in a few areas. The first is in the theory of bias propagation and management within marketing. This research builds upon the existing theory of bias propagation in marketing and examines them through a lens of how they can compound via the use of technology. This research considers where bias is present and can be propagated when marketeers use AI.

The second theoretical area is the implementation of new technology into a business setting. This research focuses on AI technology specifically and how it can be successfully implemented into marketing. It examines the current usage and implementation of AI within marketing activities and presents that humans are an essential element of successful AI implementation, usage and management within business.

The third theoretical area is the evolution around digital marketing and the technology it currently uses that AI enhances. Throughout this research the importance of the customer journey and marketing technology is justified and explored. Conclusions drawn from the model analysis shows the importance of the infrastructure of the marketing technology stack when implementing AI in marketing. This research applies the developed model to the specific discipline of marketing. While it is studied on a case study company it is applicable across the marketing industry.

Research questions that are relevant for this thesis align with the three research objectives. What are the current and possible bias issues in coding, prompting and deployment of AI in Digital Marketing? What conceptual framework can analyse bias issues in the use of AI in Digital Marketing? What model entails appropriate guidance for practitioners, for revealing and mitigating bias in AI deployment in Digital Marketing? As the research objectives and questions are of the same nature, for the purposes of this thesis it will focus on addressing the research objectives.

1.5 Chapter Summary and Thesis Structure

To maintain competitive advantage companies are required to embrace AI and incorporate it into their technology systems. Marketing is an industry that is valued for its ability to deliver exceptional customer experiences. With AI's capabilities for data analytics, customer automation and ease of content generation it is essential that marketing departments are quickly enabled to utilise AI responsibly. The impact on company ROI and streamlined workforce hours is impressive within the marketing context and so companies should begin focusing on implementing AI as a requirement for a modern digital marketing department.

In this chapter the background of the software industry, marketing industry and AI evolution was explored. It covered the motivation for this research, the initial research gap and the three research objectives. This thesis is comprised of eight chapters (figure 1.1).

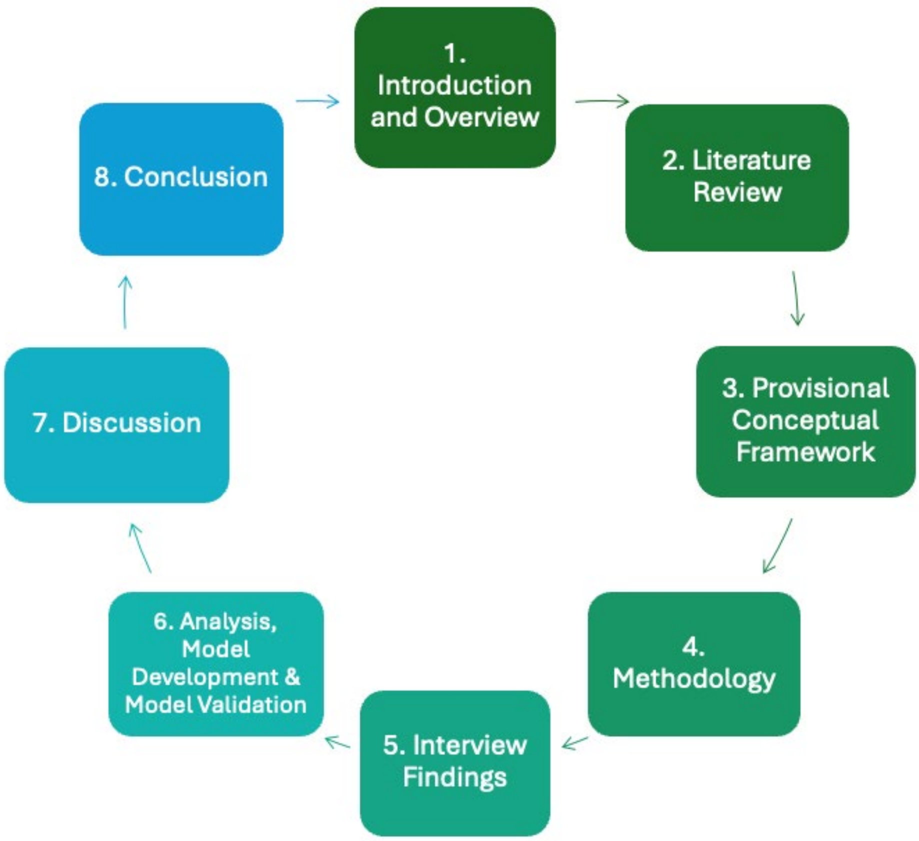


Figure 1.1: Structure of this Research Thesis

After this Introduction, chapter 2 focuses on the Literature Review. The literature review is conducted as a systematic review of the current theoretical literature. It explores the literature on artificial intelligence in marketing, bias theory in marketing and AI and the importance of the marketing customer lifecycle. It identifies the current theoretical frameworks that are available to identify and mitigate bias from AI deployment in digital marketing. The outcome of this chapter is the identification of key themes that are used for the construction of the provisional conceptual framework.

Chapter 3 establishes the Provisional Conceptual Framework (PCF). Within this chapter the key themes identified from the literature review are explored through their interactions. These interactions are reviewed through cross-tabulations of the literature and researcher knowledge to justify them. The outcome of this chapter is the identification of the core concepts and emergent themes that are the basis for the primary research questionnaire design and interview focus areas.

Chapter 4 sets out the research Methodology. This research is conducted as inductive with the researcher taking the stance of interpretivism. It is mono-method qualitative research on a case study software company. The timeline for this research is cross-sectional. Within this chapter there is justification for the pre-interview questionnaire and the focus areas from the PCF analysis. This chapter reviews the thematic analysis method employed for the primary research findings and how the cross-tabulation analysis from the PCF chapter is used to support the thematic analysis.

Chapter 5 presents the initial Interview Findings from the thematic analysis of the qualitative research. It codes the data into specific concepts that are cross-referenced with the data from the cross-tabulations of the PCF. This cross-referencing is done to justify the research outcomes with both literature and primary data. These initial themes identified are further explored in chapter 6 with full justification using quotes from the interview data.

Chapter 6 further explores the Interview Findings from chapter 5 and justifies them through the thematic analysis. Questionnaire and interview quotes are used to justify, critique and review opposing views on the identified focus areas and PCF. This deep analysis is used to evolve the PCF into the final model by justifying the areas of improvement and any gaps identified. The outcome of this chapter is a new model for revealing and mitigating bias in AI deployment in digital marketing. This new model is accompanied by a guide that gives appropriate guidance for practitioners on how to apply the model in practice.

Chapter 7 is the Discussion of the final model proposed in chapter 6. It reviews the emergent issues that arose in participant questionnaires and interviews that are recommended for future research opportunities. It discusses the implications of the findings for the wider marketing industry and the model's relevance to existing theory and practice.

Concluding this research is chapter 8, Conclusion. This chapter addresses the three research objectives and outlines its contribution to theory and practice. It addresses the limitations of this research and areas for future research. This chapter finishes with the researchers' final reflections on the research process.

CHAPTER 2: LITERATURE REVIEW

2.1 Chapter Introduction

This literature review is concept-centric in its approach, letting the topic guide exploration into current literature and philosophical concepts, rather than researching in a chronological or author-centric way (Webster & Watson, 2002). It provides a foundation for addressing RO1: to analyse current and possible bias issues in coding, prompting and deployment of AI in Digital Marketing.

This chapter is structured into seven sections. Following this introduction, section 2.2 explores the current literature on Artificial Intelligence (AI) exploring its recent widespread access and how it has begun making an impact within marketing departments and marketing technology. This section explores the concept of the Marketing Technology Stack which is an important technology grouping in this research. Section 2.3 explores current bias theory and how bias can manifest within marketing. Section 2.4 brings together the theory and literature on AI, bias and marketing to explore the current research frameworks that are available to provide structure to using AI in marketing and identifying possible bias issues. Section 2.5 explores the theory on the marketing customer lifecycle and the customer journey. It analyses the uses of AI within marketing interactions with customers dependent on their purchasing journey and what stage they are at. Section 2.6 reviews the current landscape for AI creation through big technology companies and how they are currently regulated by law. This chapter then is summarised in section 2.7.

Xiao and Watson (2017) argue that a robust literature review must find the current frontier of knowledge about its subject and find the current research gaps to build new investigation and theories. A range of typologies are available to researchers when conducting a literature review: systematic or narrative (Xiao & Watson, 2017). This literature review is conducted as a systematic review, using RO1 as the driver for the literature research. By analysing all the available research, the review facilitates a comprehensive and objective critique of other marketing frameworks. This provides the basis for the provisional conceptual framework that is tested using the primary research conducted in this study (figure 2.1).

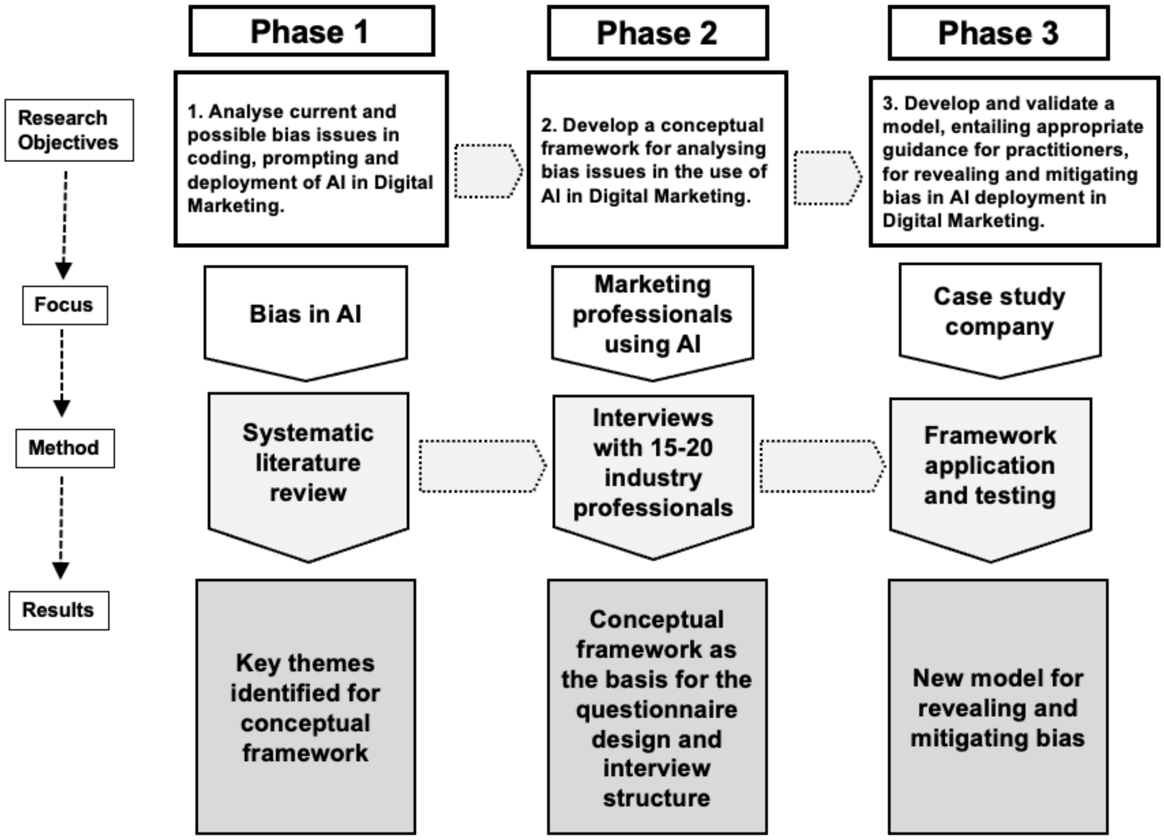


Figure 2.1: The Research Process Flowchart
(Source: Thesis Author)

Artificial Intelligence (see glossary – section VIII) is conceptualised by some authors as the Intelligence Revolution: “AI draws strength from the Internet, finally starting a major revolution comparable to the previous technological revolutions” (Li, 2020, pp 12). The Intelligence Revolution will change our society in many regards, but it is at risk, like any new and existing technology, of being misused if not correctly regulated. Countries are beginning to implement AI laws and rules for businesses and individuals, to use AI safely, ethically and within boundaries but gaps within regulations and fast-developing AI models mean this is not always covered by current law. Within businesses, marketeers are being encouraged to use AI for marketing strategy, execution, and optimisation, from dynamic content creation to data profiling, but with little implementation guidance (Roetzer & Kaput, 2022).

A Gartner survey in late 2023 revealed that 63% of marketing leaders plan to invest and adopt AI into their marketing practices within 24 months, which leaves a high percentage of 37% marketing leaders who have no plans to use AI within their marketing campaigns or workforce within two years (Stamford, 2023). For those who do invest in using AI in marketing, they will see an increase in productivity of more than 40% in the next five years (Buczek et al., 2023).

Bias exists in everything we do, and those biases are already well documented as being perpetuated in marketing through the marketeer (Gerhard, 2008) – this is further explored in section 2.3.2. The aim of this research is to mitigate these biases. Currently, there is limited worldwide AI governance (explored in section 2.6), and this lack of governance for companies creating AI, permeates into a lack of governance for employees using it within their companies. This results in compounding and amplifying bias in self-learning algorithms used by company employees.

Current research offers frameworks for how you can use AI for marketing strategy, and these are explored in section 2.4.1; the researcher found no evidence of an "implementation" framework that exists to mitigate bias when executing marketing campaigns. Current literature only gives frameworks that are used for strategic marketing practices (Huang & Rust, 2021). In this literature review there is an exploration of marketing techniques that use AI and where the bias can be propagated at each stage of the customer's marketing journey; current gaps in the literature are clearly noted.

A PRISMA (Preferred Reporting Items for Systematic Review or Meta-Analysis) flow diagram is used by the researcher to determine the relevance of the literature for this review (figure 2.2). This clear visual overview shows the different stages the researcher took in the systematic review of the literature – firstly identifying relevant literature, screening it and assessing it for eligibility. Due to the nascent area of AI, any literature that was over 20 years old was excluded for the topic of AI. Literature older than 20 years within this literature review is relevant to bias theory within marketing. Each piece of literature also had to have focus on two core areas from RO1 at once to be eligible – marketing, bias or AI. This rigor benefits this research by providing clear and reliable conclusions while reviewing large amounts of literature. From this PRISMA review 183 significant sources were identified and are represented in this literature review (appendix 1). These 183 literature sources are comprised of 108 academic journals, 13 book chapters, 16 online analyst papers and 46 grey matter sources (such as blogs and newspaper articles).

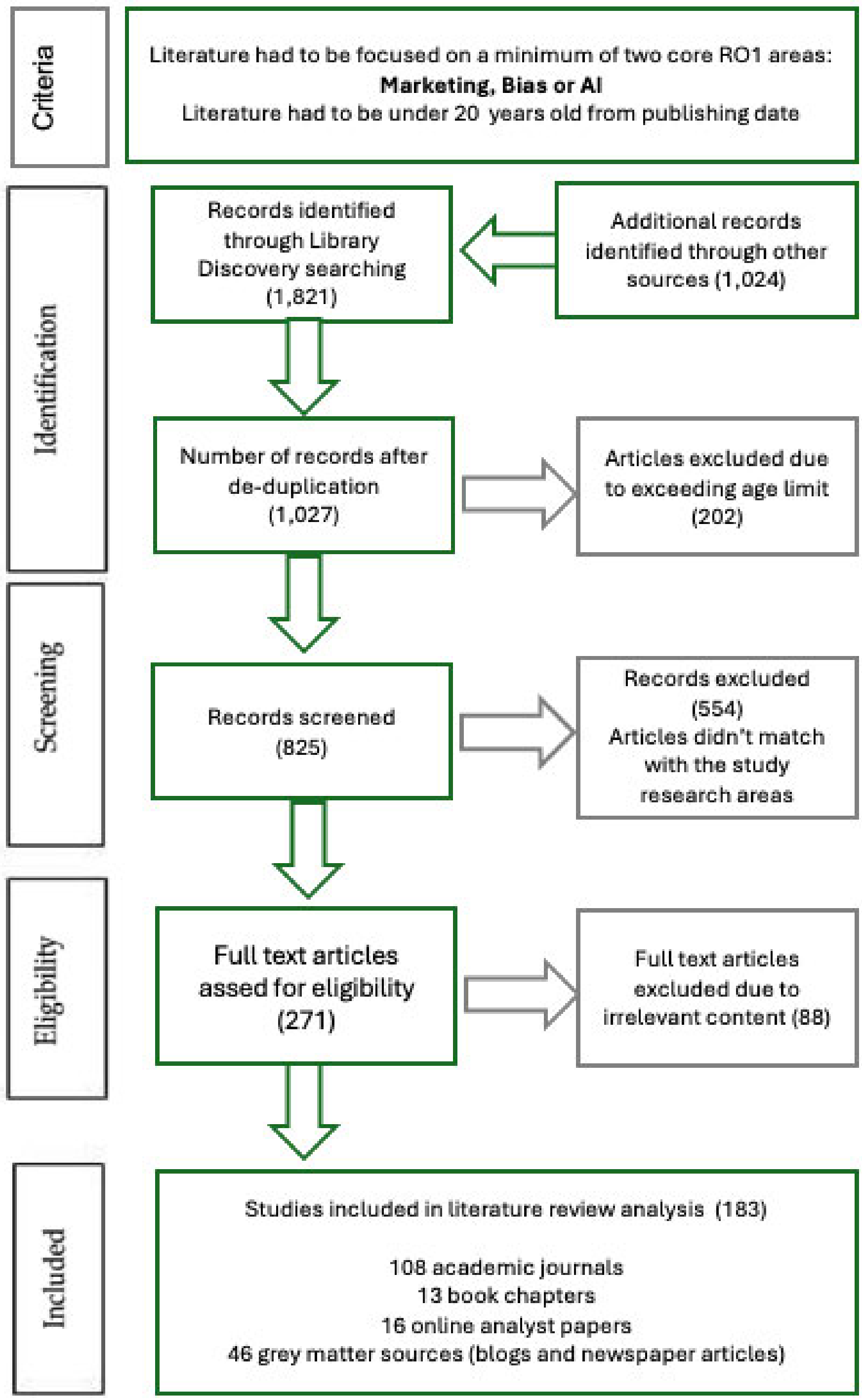


Figure 2.2: PRISMA Flow Diagram of Systemic Review Adapted by Research Author

Source derived from: Rethlefsen & Page. (2022)

This literature review is the discussion of the selected 183 significant sources of literature. This review encompasses methodologies, findings, and variables in the extant literature. Its objective is to offer a comprehensive snapshot of literature for bias mitigation in AI usage in marketing (Arksey & O'Malley, 2005). By prioritising research quality, this review allows inclusivity of multiple viewpoints and research areas (Peters et al., 2015). It maps out the conceptual boundaries of AI usage in marketing to gauge the breadth of current existing research, validate available evidence, and highlight research gaps. The output of this literature synthesis is the ability to categorise the literature against a conceptual framework for testing (Rethlefsen & Page, 2022; Dixon-Woods, 2011).

2. Artificial Intelligence

2.2.1 The Revolution of Artificial Intelligence (AI)

Algorithms that power AI do not know right from wrong and lack empathy - they do not know what empathy is (Crockett, 2020). The AI currently invented is known as Weak AI (see glossary- section VIII). Weak AI has no independent thought, essentially it is “dumb”, and it only knows the rules and input it has been trained on (Heimo & Kimppa, 2019); we should view current day AI as augmented intelligence as it requires a human to use it. Strong AI (see glossary - section VIII) only exists in theory and is not currently invented.

From medicine to construction, the current adoption of AI gives us an initial perspective of how it will be used in society (Heimo & Kimppa, 2019), from productivity apps touted as your own personal assistant, to doctors being trained on surgery simulations for better patient outcomes. For good or bad, the fast development and adoption of AI will impact our lives and Li (2020) argues humans must be ready to see life as we currently know it, become unrecognisable due to AI – “authorities in the field of artificial intelligence believe that, in the near future, the flow of intelligence will surround and support us as calmly as today’s electrical current, providing nourishment in all aspects and completely changing the shape of human economy, politics, society and life” (Li, 2020, p. 14). Walsh (2018) goes further to predict that by 2062 our “modern” world will be completely changed by AI, simplifying, enhancing, and influencing all our lives, from our jobs, and homes, to our healthcare and finances – “the majority of experts in AI and robotics predict we are likely to have built machines as intelligent as us by the year 2062” (Walsh, 2018, p. 3). In this context, it is reasonable to think that AI will bring catalytic change to marketing.

2.2.2 Artificial Intelligence (AI) and Digital Marketing

There are two main types of AI of particular relevance to digital marketing. First, there are learning algorithms – these can be supervised, semi-supervised or unsupervised (see glossary - section VIII), which are used in combination with other technologies within the marketing technology stack (MarTech Stack), supporting and enabling the application of data rules, predictive functionality and other AI-based features (Roetzer & Kaput, 2022). The second is generative AI (see glossary- section VIII) which uses large learning model data sets (see glossary - section VIII) and user prompts to generate new content (Li., 2020). AI empowers marketeers to create higher-quality campaigns, accelerate delivery of these campaigns, attract customers more efficiently, and gain deeper insights into customer behaviour (Santosh, 2024).

2.2.3 AI Algorithms in the Marketing Tech Stack

A marketing technology stack (MarTech Stack – see glossary, section VIII) refers to a collection of tools and applications used by marketers to execute and enhance their marketing efforts (Purcarea, 2018). These technologies are aimed at simplifying complex tasks, gauging the effectiveness of marketing tactics, and optimising spending for greater efficiency. They are the digital integrated technology tools marketing professionals use to manage, execute, measure, and improve marketing planning, strategy, and execution (Earley, 2021; Ziakis & Vlachopoulou, 2023). The software curated within these MarTech Stacks have coded integrations allowing them to share data between themselves, linked by real-time algorithms, for optimised usage. As shown in Figure 2.3 the MarTech Stack includes CRM systems, digital content asset management, multi-channel nurture tools (i.e., email, advertising, personalisation), Search Engine Optimization (SEO), website management, social media and analytics (Earley, 2021). AI enhances a MarTech Stack through algorithmic improvements, guided decision making and modelling predictive outcomes for personalisation at scale (Flavin & Heller, 2019).

There is a risk of driving hyper-personalisation preferences which come from a biased data set and not understanding nuances in consumer behaviour, leading to suppression of true buyers and other data oversights. MarTech Stack outputs must be constantly reviewed by marketeers, to maintain not only a well-managed marketing buyers’ journey but also ethical data modelling (Roetzer & Kaput, 2022; Ziakis & Vlachopoulou, 2023). These automated marketing decision-making processes could inadvertently perpetuate biases inherent in the data (Buolamwini & Gebru, 2018). Bias is not only in the data – research shows that the AI models themselves learn to “lie to please you…in machine-assisted intelligence analysis”

(Stray, 2023, p. 1). The AI itself learns from the prompter through feedback loops and this learning can create biases within analytical applications driving biased outcomes from the marketing analysts that can impact business outcomes (Stray, 2023).

Figure 2.3: The Main Tools and Applications in the MarTech Stack

(Source: Reed, C., compilation of the MarTech Stack from the literature review, August 24, 2024).

Compounding this is the reduced rate of usage of MarTech Stacks, with the average usage of marketing technology by employees dropping to just 33% in 2023, down from 42% in 2022 and 58% in 2020 (Stamford, 2023). AI enhances the capabilities of the MarTech Stack, yet the declining usage rates indicate marketeers are reluctant to use it. Innovative technologies come with apprehension for humas to adopt and they prefer to rely on their own human capabilities. Although AI bias can impact the operation of these systems within the MarTech Stack, only the prompting of the AI by marketeers is within the scope of this research.

2.2.4 AI and Marketing Content Creation

Li et al. (2020) underscore the significant influence of generative AI on content creation, highlighting its capacity to enhance marketing campaigns through personalised messaging. While AI-generated content can boost efficiency, it also presents challenges concerning transparency and authenticity. Lu and Yuan (2024) build on this and stress the importance of disclosing and properly attributing AI-generated content to uphold consumer trust and mitigate potential legal issues. Zhang et al. (2018) developed a de-biasing framework for coding AI that reduces implicit and explicit biases in AI-generated content. However, the focus was on coding the AI itself, not the prompting of the AI by a user. Garg (2022) also critiqued the de-biasing framework as reducing content quality.

There are four main pillars of generative AI for marketing: text generation, image generation, audio generation and video generation – all extremely useful within marketing, where a diverse and abundant content strategy is key to connecting with prospective customers (Huang & Rust, 2021).

2.2.4.1 AI Text Generation

Text AI streamlines content creation processes, freeing up valuable time for marketers to focus on strategy and innovation (Haleem et al., 2022). Automated content generation tools can produce blog posts, social media updates, and email newsletters with minimal human input, ensuring a consistent flow of high-quality content across channels (Nair & Gupta, 2021). By harnessing the power of natural language processing and generation, text AI enables marketers to create compelling content at scale, tailor messages to specific demographics, and optimise campaigns for maximum impact (Rabby et al., 2021).

This is of significance in the marketing world, where 26% of marketing budgets are spent on content creation and 4% on localising that content into multiple languages (Brenner, 2023; Kotzsch, 2023). The average “large company”, defined by Deloitte research as having 100,000+ employees and $1B turnover per year, spends approximately 13% of their overall budget on marketing each year (Kemp, 2024). The top five marketing channels giving the highest ROI in 2024 are social media shopping tools, web, and search engine optimisation (SEO), paid social media content, email marketing and content marketing. All these five marketing channels utilise AI for quick content generation, rapid testing in market and data profiling.

No monetary figures are in current research for projected savings on text content production; however, in 2024 Databox reported that companies save between 25% and 74% of marketeers time when using generative AI for content creation (Rudan, 2024). Increasing the time saved on content production is the AI available for localising marketing content. AI powered machine learning localisation gives near perfect translation to all the world's languages; this has dropped localisation spend for companies to almost zero and can be used by marketeers themselves rather than outsourcing to a specialist translation service. Alongside this, AI software used for content localisation has reduced localisation timelines from an average of six-weeks of human translation down to 24 hours. This not only keeps marketing spend low, but it also gives centralised control to marketeers whilst also giving them more time. This increased ROI from using AI in marketing will continue to favour digital marketing channels, where AI is seamlessly integrated.

This increased production volume, as well as money saved to scale advertising efforts, allows marketeers time to personalise communication. Through analysing customer data and their persona preferences, AI algorithms can generate content that resonates with individuals on a deeper level, increasing engagement and conversion rates (Haleem et al., 2022). Marketing personas themselves can drive bias; with strict pre-selected rules of job titles, demographics, company turnover and industries they group a prospective customer into groups. However, not all those within the persona groups will be accurate as the group rules may have been selected with bias from the human inputting them. There will be outliers within these persona groups that will be ignored or discriminated against. This persona bias is explored further in this literature review.

Alongside text content being generated, AI-powered chatbots provide instant assistance to customers, enhancing their shopping experience and building brand loyalty (Rabby et al., 2021). The research into the ethical ringfencing of AI chatbots is mixed with generic guidance of ensuring that AI generated content aligns with brand values and maintains authenticity to avoid alienating customers. This still leaves it to the marketer to proactively maintain authenticity, with limited research into how companies should be monitoring use of AI, such as using algorithms to monitor and refine the AI algorithms that the chatbots learn from (Arsenijevic & Jovic, 2019).

2.2.4.2 AI Image Generation

Marketing is a creative industry, and while the strategic targeting of data is the core of marketing, the creative imagery is what consumers physically see in front of them, from what they see on their TVs, to print adverts viewed while catching the train (Scott, 2024). They are seeing it because they have been targeted correctly, through the correct medium, but the creative imagery is the “hook” for the consumer to engage with the brand - this is targeted advertising. Image generative AI enables the analysis of user-generated content and social media imagery, allowing marketers to decipher consumer preferences and trends swiftly. This facilitates personalised campaigns that resonate with specific demographics, fostering deeper connections and higher conversion rates (Haleem et al., 2022; Santosh, 2024).

The marketeers can select imagery based on their consumers persona profile, select the creative design theme, and create images within moments, with multiple images to A/B test, to gain more optimisation (Nair & Gupta, 2021). Campaigns that would have taken weeks to brief a creative agency, set content review cycles, select imagery, and then receive final files, can now be conducted within a day by the marketeer. With algorithms adept at recognising patterns, sentiments, and objects within images, marketers can tailor visual content with precision, at scale, with low cost and high ROI (Scott, 2024). While up to 74% of time is saved in this process, it opens companies to unmoderated marketing content being visible to consumers. A creative agency would have had a standard operating and delivery process for clients, with a moderation step to validate that no advertising laws were broken or discriminatory imagery was present. A marketeer can now produce content with ease in-house, but process steps still need to be in place to mitigate risk.

Generative AI imagery tools, such as DALL-E use Google Images as their data for their large language model. Sun et al. (2024) investigated gender bias in Google Images by comparing census labour statistics with occupational images from web searches. Their findings showed that women were underrepresented in male-dominated occupations, while men were overrepresented in female-dominated fields. Additionally, the images depicted more women than men with smiling faces and downward-angled heads, especially in female-dominated jobs compared to male-dominated ones. The study also found that all images for "white collar" occupations exhibited Eurocentric aesthetic qualities, such as the absence of Afro-Caribbean hairstyles, highlighting a beauty bias (Henning, 2022).

Not just generating images, AI drives image recognition technology to streamline content moderation and management across marketing platforms, such as social media channels, website banners and email creative (Haleem et al., 2022). It efficiently filters through vast amounts of visual data, ensuring brand consistency and compliance with community guidelines.

Innovative applications extend to augmented reality (AR) and visual search. AR experiences powered by image AI captivate audiences, offering immersive interactions that display products in realistic settings. Visual search capabilities simplify the path to purchase, enabling consumers to find desired items effortlessly by uploading or snapping a picture (Rabby et al., 2021).

Challenges such as ensuring data privacy and addressing algorithmic biases are a concern for image AI. Image captioning is an accessibility advancement to support blind and low vision consumers when using voiceover technology to access websites. Images are given a short description to aid these consumers in understanding what is being shown; these captions can now be generated by generative AI to aid marketeers in enhanced accessibility of their marketing content. These caption generators learn from data that has bias embedded within it, such as Google Images. One such bias is gender bias on male and female features - with AI's consistently mis-gendering images with sometimes funny and often offensive results (Tang et al., 2021). Tang et al.'s (2021) research into mitigation algorithms for AI captioning concludes that further algorithmic rigour is required. They recommend human review of AI-generated captions until algorithms are enhanced further.

Further algorithmic biases are present amongst all generative AI (text, image, audio, and video), and the current limited research available is explored later within this literature review.

2.2.4.3 AI Audio Generation

It is reported that Audio AI enhances communications and marketing across a varied array of tactics. With machine learning algorithms, that learn in-memory, audio AI systems analyse vast data sets to craft personalised, engaging customer experiences (Scott, 2024), from chatbots that answer customer queries in real-time to AI generated audio ads tailored to individual preferences. By deciphering speech patterns, sentiment, and context, these systems deliver messages that feel tailor-made. This not only enhances brand loyalty but also cultivates a sense of intimacy between consumers and brands (Haleem et al., 2022).

Automation of tasks such as content creation and customer support not only save time but also ensures messaging and consistency across all touchpoints of a marketing customer journey (Haleem et al., 2022). Brands can now curate entire auditory universes, from podcasts to voice-driven campaigns, with unprecedented ease and precision (Nair & Gupta, 2021). There are ethical concerns for the usage of audio AI in marketing, concerning data privacy. Scott (2024) states that with responsible deployment, audio AI stands poised to revolutionise marketing, amplifying brand voices while forging deeper connections with audiences. The need for guidance on how to use AI for marketing is identified, but there is no conceptual framework on how businesses can utilise audio AI with the appropriate safeguards in place, to keep not only data secure but also prevent over data profiling to a biased level.

Audio AI also offers automatic captioning for all languages via automatic speech recognition (ASR) and AI. This automatic captioning for audio, like image captioning, is used for accessibility for deaf and hard-of-hearing consumers. It is also used within marketing for localisation purposes, for generating localised subtitles from audio in videos, digital events, and inbound chat services (Kopalle et al., 2022). As with image captioning the algorithms for audio AI are propagating bias, with research by Tatman (2017) showing that YouTube's voice recognition is 13% less accurate for women than men. Linguistic minorities speaking English with a regional accent also had less accurate results, with American and Received Pronunciation accents getting the best results. Scottish accents had less accurate results than New Zealand or Australian accents.

Koenecke et al. (2020) built upon this research and showed that ASR misidentifies more words from speakers who are black, have accents, or speak any other language than English. Examining voice recordings from an online event and using the top five ASR tools available from Big Tech vendors they proved an average word error of 35% for black speakers, compared to 19% for white speakers (Koenecke et al., 2020). They propose using more diverse data for AIs to create more inclusive ASR outputs that will be more reliable when used in marketing endeavours.

2.2.4.4 AI Video Generation

Businesses are using AI-created videos to produce compelling, personalised video content at scale, tailored to specific demographics, preferences, and behaviours (van Esch & Black, 2021). Like image generative AI, video AI has access to AI-powered virtual reality (VR) and augmented reality (AR); marketeers are creating video marketing campaigns offering immersive and interactive brand experiences.

One significant application is in targeted advertising. AI algorithms analyse vast amounts of data to create customer profiles, enabling marketers to craft videos that resonate deeply with their target audience. These videos can be customised based on factors such as location, interests, purchase history, and browsing behaviour (Raj, 2023). An example would be on a company website and AI-generated videos highlighting various products based on a user's past purchases or interests. This leads to an enhanced customer journey for consumers through dynamic product recommendations, interactive storytelling, or immersive experiences that adapt based on user input (Kastenholz, 2024).

Quickly created, with access to a repository of "actors" images and voices to use, AI generated videos are invaluable for A/B testing and optimisation. Marketeers can quickly create and test multiple versions of a video to identify which resonates best with their audience. This iterative process leads to more effective campaigns, improved conversion rates, and higher ROI (Raj, 2023).

Recent advancements in digital technologies have significantly enhanced the capacity to create lifelike videos and audio using sophisticated computer graphics and AI algorithms. This has blurred the line between authentic and fabricated media, posing challenges in discernment. While such computer-generated media finds practical use in various fields, they also introduce concerns regarding privacy and security (Chadha et al., 2021). "Deepfake" technology exemplifies these concerns, coined from "deep learning" and "fake," allowing the alteration or masking of faces, voices, and expressions in images or videos. Employing techniques rooted in deep learning and AI, deepfake manipulations are increasingly difficult for humans to detect, presenting potential risks in the realm of media authenticity. These “deepfake” algorithms have no attributes of good or evil, and this technology has been widely used for negative purposes by humans (Yu et al., 2021). Brands are already attuned to monitoring their brand reputation, and AI software itself is used to detect and flag when a video is an AI deepfake (Pu et al., 2021), which companies are using to continue to safeguard their brands.

When marketers are utilising AI software to create marketing videos and audio voiceovers for a range of marketing tactics (from advertising to inbound chat) they are creating their own deepfakes. By selecting AI-generated human presenters to bring authenticity to videos and not declaring they are AI-generated leads to a view duplicity from the company (Chen et al., 2025). There is no current literature available on training and ringfencing for marketeers within ethical parameters when they create deepfake marketing videos. There is limited research or training on mitigating bias when selecting the race or gender of the AI-generated human appearing in these videos. There is also a dearth of research on bias in these video creations in a Eurocentric style, even if destined to be used in non-European and non-Westernised countries.

The closest research to regulate current AI video usage in marketing is from Whittaker et al. (2021), who used a conceptual framework approach to drive a research agenda for deepfake use in marketing. Referring to deepfake technology as “the phantom menace”, there were more open questions than answers, as part of their output, as this was the first paper to position deepfake videos in the marketing narrative. Their findings included guidance for brands to disclose the usage of deepfake technology, and they concluded that deepfakes will enhance the perception of emotional intelligence to consumers when interacting with chatbots that now have a face, and that the consumer will have no idea they are not speaking to a real human which in turn can cause ethical trust issues. This aligns with the general research output from Lu & Yuan (2024) to add a disclaimer to all AI-generated content to disclose its usage to consumers.

Bynder (2023) uncovered that 55% of marketers are already using generative-AI when creating content, with 54% utilising it for content drafting, 30% for content repurposing and 27% creating tone of voice documents. There is no definitive research that gives clear numbers on how many of these companies are declaring the usage of AI, but it will not be 55% - otherwise there would be labels for generative AI on TV adverts, radio adverts, print adverts, artwork, etc., in our own daily lives. There is speculation that the number of undisclosed AI-generated content from brands is high, and we can see the implication of this from new laws and governance being introduced. From March 2024, YouTube has added AI disclosure rules where Brands must clearly state AI usage when they are posting videos that use deepfake audio or visual content (Lee, 2024). This does not apply to individual influencers and vloggers (video bloggers). In late March 2023, President Biden issued an Executive Order for laws governing the usage of AI which will impact disclosure by brands (Robins-Early, 2024) and within Europe, from March 2024, the European Parliament enforced the AI Act. It is the world's first comprehensive legal framework for AI, providing EU-wide rules on data quality, transparency, human usage, and accountability (Nahra et al., 2024).

While the public perception of deepfakes comes with negative connotations, the application within movies and gaming is being met with positive reaction. Split-second personalisation is a hyper-personalisation experience being applied and tested for movies and gaming, with the sole intent of keeping you hooked for longer, spending more in-game credits and letting you control your interaction with a storyline (Welsch, 2024). OpenAI, the company behind Chat-GPT, have been reported to be pitching their latest AI-powered video tool to Hollywood directors, from several different film studios (Buckley et al., 2024). Hollywood using AI-generated films would allow them to instantaneously produce at scale, a role-play led movie, where the watcher through a VR headset, can choose the course of the movie, what happens to its characters and storylines. The cloud-hosted AI can stream the hyper-personalised movie to the viewer and because deepfake videos look completely real, there will be no impact on viewing quality (Welsch, 2024).

The application of hyper-personalised videos in marketing is currently not well-defined. There is currently a dearth of research literature on the creation and usage of hyper-personalised videos within marketing. As adoption evolves, it can be assumed it will have a clear application of hyper-personalisation for videos in marketing from advertising videos and product demo videos to virtual events and webinars.

2.3 Bias

Within businesses, marketeers are being encouraged to use AI for marketing strategy, execution, and optimisation, from dynamic content creation to data profiling, but with no standard implementation and usage guidance.

2.3.1 Bias Theory

Bias is determined by a myriad of factors, often stemming from societal influences, personal experiences, and cognitive processes (Delgado-Rodriguez & Llorca, 2004). Cultural upbringing plays a significant role, shaping beliefs and attitudes towards various groups or ideas. Media representation, family dynamics, and educational backgrounds all contribute to bias formation. Additionally, individual experiences and interactions create cognitive biases, such as confirmation bias, where we seek information that aligns with preconceptions (Lo Iacono, 2023). Emotional responses, like fear or empathy, can also sway personal bias (Smith & Noble, 2014). Biased representations themselves not only limit the narrative scope we collectively share but also shape public perceptions of individuals' roles and capabilities (Liu & László, 2007).

While bias in general is perceived with a negative connotation, not all bias is inherently bad depending on the context (Nosek et al., 2022). Bias can serve as a useful tool in decision-making processes. Marketing strategies can leverage bias to target specific demographics effectively (Davidson, 2011). In art and literature, bias can provide unique perspectives and storytelling angles that resonate with audiences (Matthews & Wacker, 2008). Moreover, bias can foster a sense of belonging and identity within communities, reinforcing shared values and cultures (Hussain & Jones, 2021).

2.3.2 Bias in Marketing

Bias in marketing is well documented (Smith & Conrad, 2020) and it happens within every marketing touchpoint. This is because it is driven by humans who themselves are biased in every decision they make. Marketing ultimately is helped by bias within buying consumers, and it tries to predict their purchasing habits to communicate to them at the “perfect” time. Conick (2018) agrees with this statement but argues that marketing lacks a uniform framework and terminology for how bias is present.

Dowling et al. (2020) agree and through further research form a compelling argument on how bias could be grouped in marketing “key findings according to three classes of deviations (nonstandard preferences, nonstandard beliefs, and nonstandard decision making) across the four phases of consumer purchase decision making (need recognition, pre-purchase, purchase, and post-purchase)” (Dowling et al., 2020, pp 3). By focusing on behavioural economics, they argue that it is a mixture of the customers, the marketeers and the marketing content itself that propagates bias – this research focuses on the marketeers and marketing content bias.

2.3.2.1 Marketing Workforce

To thoroughly investigate bias in marketing, the requirement is to not only research the bias in marketing output, but also the marketing workforce, who’s own social-environmental views need to be understood. Marketeers are the humans using AI for their marketing campaigns - without understanding bias propagation their marketing activities can perpetuate stereotypes, discrimination, and inequality (Gerhard, 2008). Acknowledging and mitigating bias is crucial in these fields to ensure fairness and accuracy.

Marketing is a female dominated industry, with the split of 62% female, to 38% male employees (EMR, 2023). Alongside this, research in 2021 identified demographics of marketing managers as being predominantly white, making up 79.5% of the workforce, with almost 50% of the workforce under the age of 39 (Data USA, 2021). Furthermore, 42% of marketing managers identify as middle class, the biggest percentile of class group (Rogers, 2022); the combination of being white and middle class also dictates higher pay and promotion opportunities, than those who are not.

The implications of these demographic characteristics are explored further in section 2.4.2.

2.3.2.2 Marketing Strategy and Execution

Dowling et al. (2020) created a conceptual framework of their behavioural bias research to map the three bias areas against a marketing customer journey (figure 2.4). They built upon Lemon and Verhoef's (2016) research that a customer journey is not linear, but a cycle of phases based on customer need. It is a unique perspective on where bias propagation can enter a marketing purchase journey from preferences, beliefs and decision making.

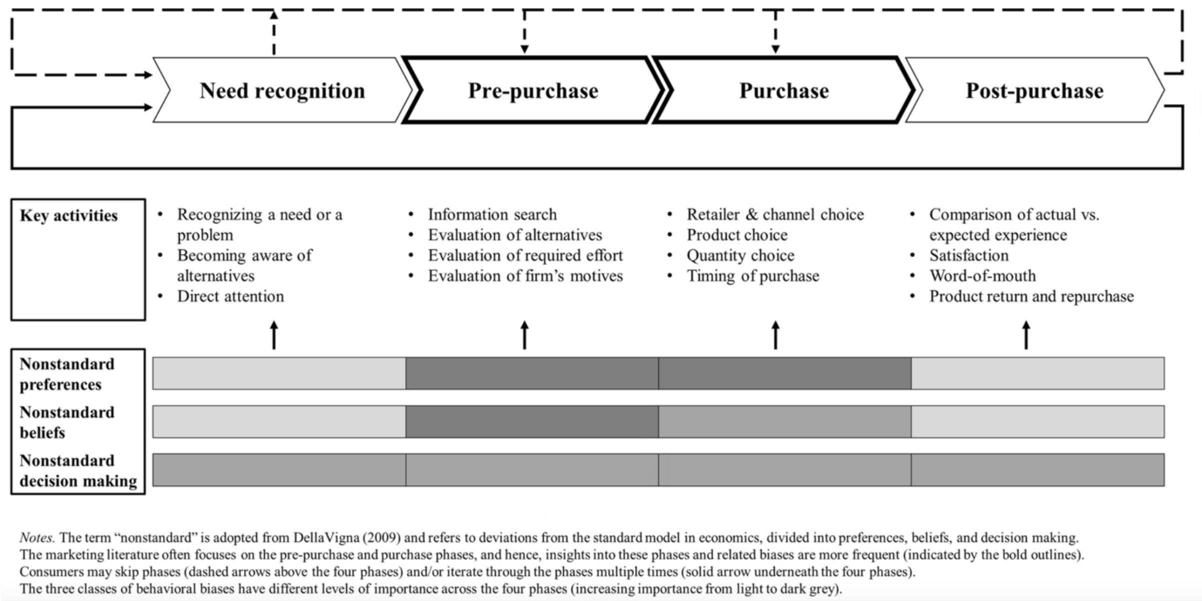


Figure 2.4: Conceptual Framework from Dowling et al. (2020) - four phases of consumer purchase decision making, and how these are influenced by the three classes of behavioural biases.

If companies have a prolific presence on "organic" marketing channels, then their marketing materials will be visible to outlier consumers who have nonstandard needs. Organic marketing channels are the channels that are not paid for and organically grow Brand value. These channels include website, non-paid social media, blogs, search engine optimisation, telesales activities that are free (LinkedIn messaging and cold calling), email campaigns and online events.

However, companies with limited organic marketing are at risk of not being able to mediate overt bias risk by “playing the field”. Their targeting of specific consumer groups will be hyper-targeted and driven by the marketeer in a biased view that only extremely specific groups are purchasing products. It can be stated that the marketing strategy itself is the basis of the bias and is created and instigated by a biased human (Garcia & Martinez, 2020). Mapping bias by marketing customer journey phase will be further explored in section 5.

2.3.3 Research Bias Focus

Trying to understand the true scope of bias is hard, and some authors suggest it permeates all our thoughts, lives, and deeds (Lo Iacono, 2023); trying to then scope out biases inherent to marketing requires a detailed revision of current literature. When researching bias, focus areas should be utilised to attain true understanding of the research area (Smith & Noble, 2014).

Many authors concur that the core biases in marketing amplify societal stereotypes (Kellaris et al., 1996; Wan et al., 2020; Dowling et al., 2020). These fit into six core bias themes: affinity bias, ageism, binary bias, confirmation bias, cultural bias, and gender bias (table 2.1).

Affinity bias	Preferring and rewarding those who look, behave, and have the same views as you.
Ageism	Negative judgement and discrimination based on age, at all age stages.
Binary bias	Comparing two groups, individuals or beliefs and judging them, rather than reviewing on their individual merits.
Confirmation bias	Wilfully giving greater weight to evidence that confirms personal views, selecting only views that agree with our own.
Cultural bias	Prioritising own cultural norms and values, with judgement of other cultures.

Gender bias	Preference for one gender over another, usually stereotypical views of gender specific roles in society.

Table 2.1: Table showing the top six categories of bias within marketing.

(Based on: Kellaris et al., 1996; Wan et al., 2020; Dowling et al., 2020)

Listing the biases from the literature review in Table 2.1 does not privilege them as more important than other biases. It allows space to detail how these biases are the most common in marketing and can be perpetuated when marketeers use AI. As this research develops, and other biases are uncovered within the primary research they are added into the category mix as required. Manifestations of bias are not easy to ringfence into set groups, and this occurs in multiple subtle ways within the six main marketing biases. They are both conscious and unconscious, implicit, and explicit and they also manifest in overlapping ways.

2.3.3.1 Marketing Affinity Bias

Affinity bias in marketing is the inclination to favour individuals or groups who share similar characteristics, experiences, or backgrounds as the marketer. This subconscious bias can significantly influence marketing strategies, from the conceptualisation of campaigns to the selection of target audiences and the creation of content (Scott, 2024).

The literature and research on this area are scant. As observed by Fock et al. (2011) while there are few theories on why affinity bias is successful in marketing their theory was that it works best within collectivist cultures. Cultures in Southeast Asia would respond well to Affinity marketing strategies. Most of the literature focuses on affinity bias within marketing teams, such as hiring new colleagues or measuring trust between them. When marketers succumb to affinity bias, they create campaigns that resonate more with their own preferences and perspectives, rather than considering the diverse preferences of a broader audience. It also affects the selection of spokespeople, influencers, and brand ambassadors. Marketers might prefer individuals who mirror their own identity, potentially overlooking talent that could appeal to different segments of their customer base. This results in a lack of inclusivity, misses brand authenticity, and misses opportunities to engage with a wider demographic (Scott, 2024).

2.3.3.2 Marketing Ageism Bias

Ageism bias in marketing involves the stereotyping and discrimination against individuals based on their age, often skewing marketing efforts towards younger demographics while neglecting older consumers. In the USA, AARP Research (2019) stated that 70% of all personal wealth belongs to those of 55 years of age and above; they contribute the highest percentile of consumer spending but represent only 15% of online media imagery (Thayer & Skufca, 2019). This is alienation of a substantial segment of the market that shows brand loyalty. It not only limits the potential customer base for businesses but also perpetuates stereotypes about ageing.

This bias can manifest in numerous ways, such as using younger models in advertisements, overlooking the preferences and needs of older adults and depicting them in ways that diminish older capabilities or make unflattering comparisons (Ivan & Loos, 2023). The same study from AARP Research (2019) revealed imagery showing over-50s in advertisements is seven times more likely than younger adults to be portrayed negatively. This negative impact is multiplied for older representation within minorities.

2.3.3.3 Marketing Binary Bias

Binary bias in marketing refers to the tendency to oversimplify complex consumer data into two distinct categories, such as “interested” vs. “not interested” or “loyal' vs. “disloyal”. This reductionist approach can lead to significant misinterpretations of consumer behaviour and preferences (Fischer et al., 2018). Marketers often use binary categories because they are easy to analyse and can provide clear-cut strategies. However, this approach ignores the nuances and variability in consumer decision-making by focusing only on the extreme ends of consumer behaviour. This results in ineffective advertising, poor customer engagement, and lost revenue opportunities.

2.3.3.4 Marketing Confirmation Bias

Confirmation bias is similar to affinity bias but is the consumer interaction of bias rather than the marketer. It is when consumers favour information that aligns with their pre-existing beliefs or preferences (Bagchi et al., 2020). This cognitive bias can significantly influence purchasing decisions and brand loyalty. Marketers exploit confirmation bias by crafting messages that reinforce the audience's existing attitudes.

Social media and targeted advertising further amplify confirmation bias. Algorithms curate content that matches users' interests, creating echo chambers where individuals are repeatedly exposed to familiar ideas and products (Mohammed, 2023). This repetition increases the likelihood of consumers accepting the marketed messages as truth, thereby reinforcing their biases. However, confirmation bias in marketing is not just about message alignment. It also involves strategic use of testimonials and reviews. Positive reviews from like-minded individuals can validate a consumer's decision, making them more likely to commit to a purchase.

Bagchi et al.’s (2020) research shows that utilising a consumers confirmation bias does not work for quick-decision purchases; however, it does yield positive results for longer-period purchases. Business to business software sales cycles take a minimum of four months to complete, and regularly take a full 12 months (Jain, 2024); it is a prolonged purchase period. There is no current research into confirmation bias within software marketing and how the marketeers are regulating it.

2.3.3.5 Marketing Cultural Bias

Cultural bias in marketing occurs when campaigns, messages, or strategies favour one culture over others, often inadvertently. This bias can alienate diverse customer bases and limit a brand's reach. Historical legacies (such as post-colonialism) shape contemporary consumer behaviour, perpetuating bias in advertising and branding (Yalkin & Özbilgin, 2022). In global companies, marketing is usually managed centrally within Western regions, emphasising the power imbalances in marketing relationships, and reinforcing a scenario where Western brands control the narrative (Gunaratne, 2009).

Language is one area where cultural bias can emerge. In 1985, O'Shaughnessy stated that global businesses run from the USA had an American cultural bias influenced by Western education. This was built upon in 2005 by Usuneir et al. who claimed that the cultures we live in saturate our subconscious minds and it is inevitable that marketers will propagate cultural bias in international marketing. Marketing materials that rely on idiomatic expressions or humour specific to one culture may not resonate or may even confuse and alienate those from diverse backgrounds (Pedersen, 2014). This is especially problematic in global marketing, where messages need to be adapted for diverse cultural contexts to be effective. Transcreation of messaging needs to be conducted to make sure it resonates across languages – it is more than just translation.

Visual creative and content in marketing, such as images and symbols, can carry different meanings in diverse cultures (Usuneir et al., 2005). A colour that is considered lucky in one culture might be associated with mourning in another. Failure to consider these differences can result in marketing efforts that are not only ineffective but also damaging to a brand's reputation. Advertisements frequently adhere to Eurocentric standards, prioritising specific aesthetics, languages, and lifestyles, which marginalise non-Western cultures. This approach not only highlights a lack of diversity but also perpetuates the notion that the Western viewpoint is the benchmark by which all others are judged (Gunaratne, 2009).

According to a 2019 Adobe Cloud report (Adobe CMO Team, 2019), as many as 120 million individuals in the United States do not find themselves represented in marketing advertisements. Although comprising 37% of the population, 66% of African Americans, 53% of Latino/Hispanic Americans, and 51% of Asian Americans express dissatisfaction with how they are portrayed in advertising (Adobe CMO Team, 2019). This lack of representation conveys a perpetuating viewpoint on who society deems 'normal' or 'ideal,' leaving substantial segments of the audience feeling unseen or undervalued (Meda, 2023). Unilever Research (2021) reported that 71% of respondents believe stereotypes in the media are harming the younger generation and one in two people from marginalised communities felt that they had been stereotyped within advertising.

2.3.3.6 Marketing Gender Bias

Gender bias stems from preconceived stereotypes associated with a person's gender. Women are often depicted in domestic settings, focusing on beauty, fashion, and household products, while men are frequently shown in professional roles or using products related to strength and technology (Spielmann et al., 2021). It often leads to the belief that one gender is better suited for specific roles or tasks. This biased portrayal not only limits the perception of gender roles but also alienates audiences who do not identify with these narrow representations.

Research by Unilever in 2016 across all industry advertising showed that 40% of women did not relate at all to the women they saw in adverts. Only 3% of 2016 advertising featured women in leadership roles, and 2% showed women as intelligent. In 2020, when the research was conducted again 98% of advertising imagery was un-stereotypical for both men and women (Unilever, 2020). Cunningham and Roberts (2021), disagree with Unilever Research, their research revealed how gendered experiences and needs are still being misrepresented in current marketing. However, neither the Unilever Research (2020) nor Cunningham and Roberts (2021) research considers those who are non-binary genders. Unilever Research (2021) reported that one in five people believe that advertising does not represent wider society. Leading to the view that the advertising industry will be the next victim of cancel culture – harming brand reputations and loyalty.

2.4 Digital Marketing AI and Bias Perpetuation

2.4.1 Current Research Frameworks

Huang and Rust's (2021) framework (figure 2.5) was one of the first research studies to structure where AI can be used within marketing. It shows how strategic marketing planning is structured across the broad AI landscape, covering marketing research, strategy (segmentation, targeting, and positioning), and operational actions. This three-stage framework leverages AI to enhance strategic marketing, divided into three types of AI: "mechanical AI" for automating repetitive marketing tasks, "thinking AI" for processing data to generate insights and support decision-making, and "feeling AI" for analysing human emotions and social-economic interactions. However, this framework is one-dimensional with general AI terminology mapped to the three areas and there is no focus on application. This is of the same applicability grade as research from Buch and Thakkar (2021) and Yu (2021) that scopes the possibilities of marketing use of AI but does not define the use cases for it.

Figure 2.5: Strategic framework for Artificial Intelligence in Marketing

Source derived from: Huang & Rust (2021)

Building on Huang and Rust's (2021) framework, Haleem et al. (2022) built a comprehensive table overview identifying 23 diverse ways marketeers can apply ChatGPT generative AI in marketing activities. These include audience targeting, creating scripts for advertising, and improving customer service. Nesterenko and Olefirenko (2022) critique Huang and Rust (2021) framework for having no foresight to apply use cases to their research and only focusing on the overall abilities of AI. There is no current research that draws conclusions about the effectiveness of AI-generated marketing and consumers' reactions to it.

Any new deployment of technology within a company requires organisational changes for its successful integration, usually referred to as organisational complements (Brynjolfsson et al., 2019). Jarrahi et al. (2023) argue that the successful implementation of AI, and therefore its value to business', lies in the infrastructure of its adoption not the technology itself (figure 2.6). They propose three complements of people, infrastructure, and process to underpin successful integration for AI (Jarrahi et al., 2023). This links to Huang and Rust's (2021) mechanical, thinking and feeling AI framework (figure 2.5). Correlations between figures 2.5 and 2.7 are: "infrastructure" links to "mechanical AI", "processes" links to "thinking AI" and "people" links to "feeling AI".

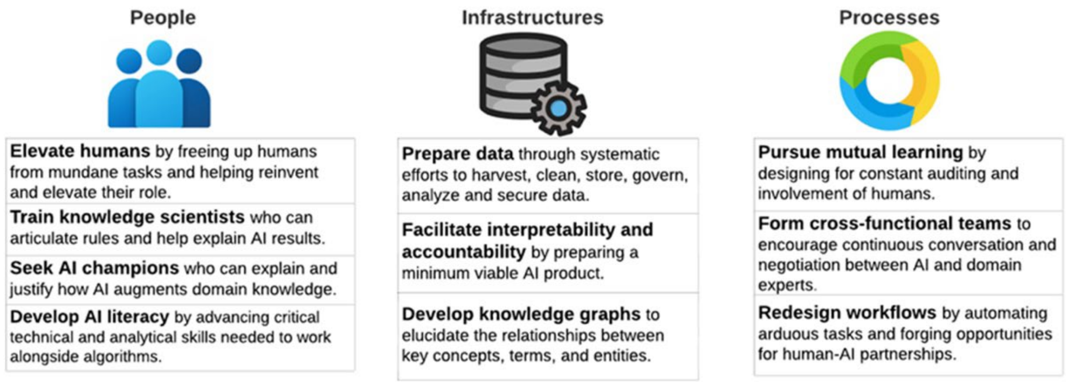


Figure 2.6: Organisational Changes Needed to Accompany AI Adoptions for Knowledge Management

Source derived from: Jarrahi et al. (2023)

This theory is further built upon by Forrester Research who propose the 3E's of AI in marketing are 1) Effectiveness: Improve business outcomes, 2) Efficiency: Cost savings and improved productivity and 3) Effort: Improve customer experiences (Buczek et al., 2023). A further research output that corroborates this "3 areas" of AI usage is Dwivedi et al.'s (2023) research specifically on generative AI bias. They proposed that three areas would help mitigate bias through AI usage: 1) Knowledge, transparency, and ethics, 2) Digital transformation of organisations and societies, and 3) Teaching, learning, and scholarly research.

The literature frameworks discussed in this section are shown in Table 2.2 to clearly show where current authors have focused and the current framework research gap.

Research Framework Focus	Reference	Gap in Framework
Research frameworks that ***map how AI is used in marketing***	Huang & Rust, 2021 Haleem et al., 2022	Where bias is propagated.
Research frameworks that ***show bias within the marketing customer journey***	Dowling et al., 2019	Where AI is used in marketing.
Research frameworks that show ***how to successfully implement AI***	Jarrahi et al., 2023	Where bias is propagated.

Table 2.2: Table of the literature showing current framework focuses and where the research gap is

2.4.2 Human Centred Design

With a focus on the people using the AI and their education on how to use it responsibly, companies can leverage the unique strengths of both humans and AI to achieve adaptability and efficiency. AI is not meant to replace humans but to enhance our abilities. Humans are best at creative tasks, understanding context, and showing empathy. AI excels at repetitive, data-driven analysis and together unlocks a new level of problem-solving (Welsch, 2024).

Human Centred Design is an emerging research area in AI where human empathy and creativity is coded within parameters of the AI (Margetis et al., 2021). Hernández et al. (2023) agree and state it is essential to build public confidence in AI governance and usage. Figure 2.7 shows Schwartz et al.'s (2022) contextual view for developing a socio-technical approach to AI usage and argue researchers should include end-users in software design and usage trainings. Liu et al. (2021) agrees with Margetis et al. (2021) and recommends a human training schedule for employees using AI, to minimise biased outputs.

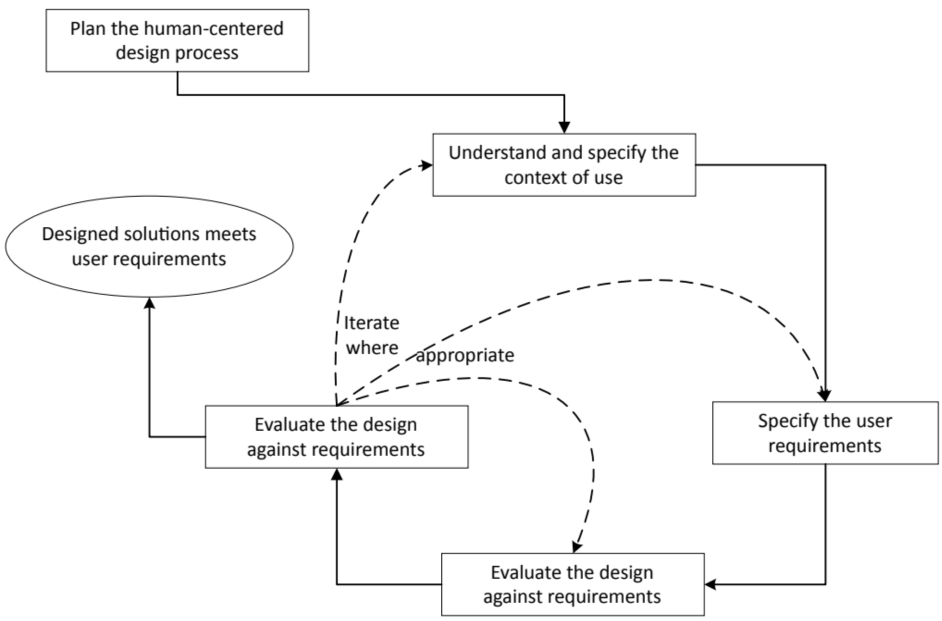


Figure 2.7: Human-centered Design Process for AI Systems
Source: Schwartz et al. (2022)

As noted in section 3.3.1, the average split of genders within marketing is 62% female, to 38% male. Exploring one step further, female roles are predominantly mid-management and junior roles, with most leadership positions (such as CMOs and Directors) being male (EMR, 2023). Kaminski (2023) notes that execution within marketing is the charter of junior "to-do" roles and can deduce that females will do much of the AI prompting work.

The “Bring your own AI to work” movement is seeing 85% of Gen Z, 78% of millennials and 76% of Gen X bringing AI tools to work (Microsoft Lab, 2024); people are feeling comfortable with the technology. However, this comfort level is not equal between females and males with research showing that women are currently using AI less than men (Costa, 2023). Reviewing usage of the top 50 visited AI tools in 2023, 69.5% male users versus 30.5% female users used the AI’s (Sarkar, 2023). Costa (2023) states this is due to the perception that using AI is cheating. It is not clear if women in marketing will be using AI prolifically while doing the main portion of the content creation.

Marketeers themselves can also create unconscious adversarial attacks on AI. AI algorithms are instructed to learn from their prompter to give a more tailored service and are therefore vulnerable to small, imperceptible changes to input data. Prompts from marketeers that change the input data, such as images or text, corrupts the machine learning model for everyone who uses it (Palmer, 2023). With the demographic of marketeers being white, middle-class females (as explored in section 2.3.2.1 Marketing Workforce) and the homogenising of culture and thoughts – there is a possibility of unconscious bias being prompted into and changing companies generative and traditional AI models. This compromises the integrity of the generated content.

2.5 The Marketing Customer Lifecycle

The customer journey has been segmented into four stages (figure 2.4) since 1960, when marketing began to focus on customer decision making for product buying (Lemon & Verhoef, 2016). It has been the core of planning and executing a marketing campaign for decades. Due to the evolution of social media marketing and increase in digital shopping changing buying habits there are now more marketing channels than a decade ago (Moorman et al., 2023). In line with this the customer journey lifecycle has now evolved into further stages, dictated by the company creating these maps for their marketing efforts (Micheaux & Bosio, 2019). This research will be using an eight-stage marketing customer lifecycle map (figure 2.8) that is currently used by the case study company. This eight-stage journey shows content and marketing tactics mapped to granular decision-making stages, split by pre-sale and post-sale. Figure 2.8 is an evolution to the business-to-business (B2B) marketing customer journey proposed by Purmonen et al. (2023) which is also eight stages.

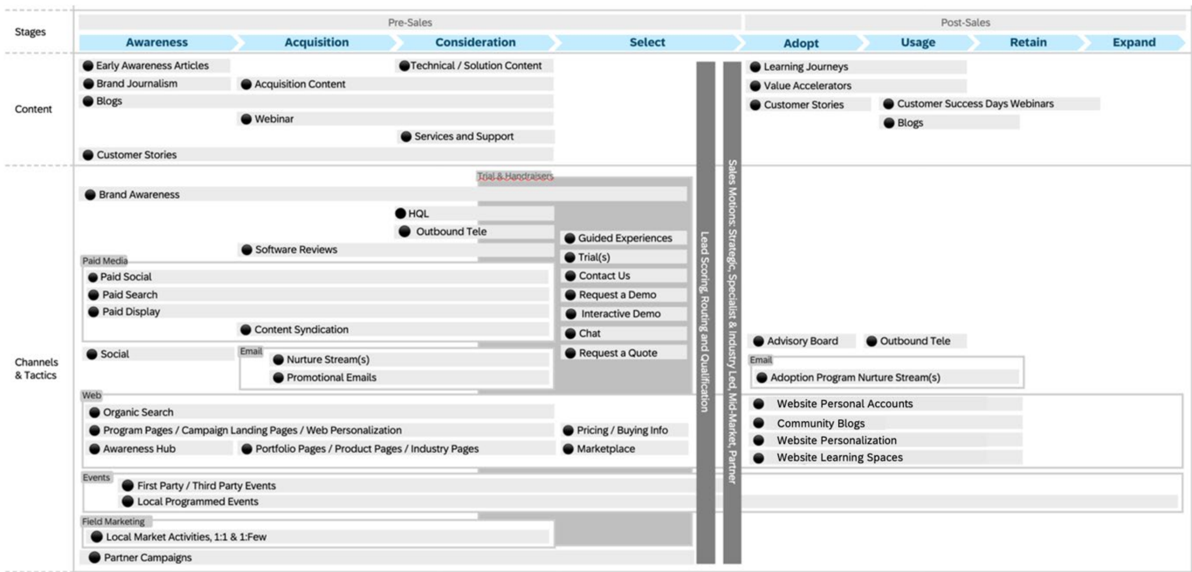


Figure 2.8: Business to Business Marketing Customer Lifecycle Journey Map

(Source: Reed, C., internal case study marketing documentation, June 15, 2024).

The customer journey in figure 2.8 shows four more stages than the customer journey in figure 2.4 – which were need recognition, pre-purchase, purchase and post-purchase. Correlation of figure 2.4 and 2.9 shows need recognition is equal to awareness, pre-purchase is equal to acquisition and consideration, purchase is equal to select and post-purchase is equal to adopt, usage, retain and expand. The evolved customer journey in figure 2.8 shows that there is a content and channel differentiation when a customer is in the two stages of acquisition and consideration that were not investigated in figure 2.4. The post-sale evolution also shows there is distinct differentiation to the stages a customer goes through post-purchase. The nuances of these stages are reviewing in sections 2.5.1 to 2.5.8. Using this map supports the objective aim of researching as a framework synthesis and to conduct a thorough review of literature; important research may be missed if not investigating as an integrated view.

There is a difference between a B2C (business to consumer) and B2B (business to business) marketing customer lifecycle map. A B2B buyer has a longer decision-making process and has an average of 27 interactions with the company (Strong, 2022). A B2B buyers preferred engagement is 67% digital and 33% human to human interaction. These buyers are seeking interactive, immersive and omnichannel engagement (Buczek et al., 2023). The MarTech stack also uses the evolved customer journey to optimise new technology integrations (Early, 2021). Buczek et al. (2023) state that by 2028 G200 firms will utilise data and AI to automate 38% of actions in the buyer journey. There will be more focus on personalisation to dynamically deliver targeted messaging to buyers. Interestingly, the AI usage changes through the technology used across the customer lifecycle. All parts of the journey are underpinned by large language model scoring AI; however, the awareness and acquisition channels use mostly generative AI content (i.e., videos, images and word outputs). The consideration and select stage are predominantly rule based AI (scoring, hyper-personalisation and routing), until the post-sale stage where generative AI comes back to the fore with content creation. Bias perpetuated by the content creator can be common throughout customer journey content and stems from marketers' subjective interpretation and application of AI-generated insights. This can lead to content that perpetuates existing stereotypes or discriminatory practices (Tussyadiah & Pesonen, 2020).

The main biases for this research of affinity bias, ageism, binary bias, confirmation bias, cultural bias and gender bias are often perpetuated at each stage of the customer journey. The main presentations of these biases are explored in sections 2.5.3 to 2.5.8.

2.5.1 Marketing Customer Journey: Pre-sale Awareness Stage

The awareness phase of the Marketing Customer Lifecycle consists mostly of Brand marketing and very early-stage, easily accessed content (such as blogs and customer success stories) that answers high-level consumer questions (Latif et al., 2014). It ensnares the customer to want to learn more and directs them to more specific content in the acquisition stage. AI-generated content bias was explored extensively in section 2.2.4, but the channels which this content is displayed through is also at risk of perpetuating bias.

Paid media is a channel that spans the awareness, acquisition and consideration parts of the map and covers paid social, paid search, paid display and content syndication. It focuses on buying digital “real estate” in publications, journalism blogs, social media sites and Google to display company adverts. Bias is prevalent in data collection, model specification and selection bias due to ad targeting (Chen et al., 2018).

Organic social channels utilises companies owned social media channels (such as Meta, YouTube, X, Snapchat, etc.) and algorithmic bias on these channels can penalise brands. Research into YouTube's algorithm reveals implicit discrimination and bias, favouring middle-class vloggers who produce gender-specific content in collaboration with paid advertising partners. Vloggers creating gender-fluid content or content that defies traditional gender norms are penalised by the algorithm (Bishop, 2018). This has led to a discriminatory hierarchy among vloggers, with the algorithm perpetuating these biases through its machine learning processes. Companies will often use these vlogger influencers to represent their brand.

Websites are at risk of hyper-personalisation and compounding biases in targeting. Utilising AI in marketing customer profiling and targeting must align with privacy regulations to prevent discriminatory practices (Smith et al., 2019). A comment hyper-personalisation avenue on websites is product recommendations. Wan et al. (2020) research focuses on bias against “niche markets” in website personalisation: “these interactions can be biased by how the product is marketed…due to the selection of a particular human model in a product image. These correlations may result in the underrepresentation of niche markets in the interaction data; for example, a female user who would potentially like motorcycle products may be less likely to interact with them if they are promoted using stereotypically “male images” (Wan et al., 2020, pp 618). This research produced a biased limitation equation that used correlation loss to achieve more balanced data; however, it is only for the machine learning AI itself not for a user prompting it with commands.

Company websites are also prone to learning their own company bias using web crawlers. Websites use indexing as a library system - indexing all the pages in a hierarchy that align to the “master” webpage (Schafer et al., 2016). Web crawlers are AI’s that browse these webpages to learn what the webpages are about to retrieve information when needed. These crawlers could fail to capture the diversity of user environments, and compound learned messaging and targeting from within companies (Zeber et al., 2020). Web crawlers also cover the full World Wide Web and index all websites on search engines; constantly learning from the uneven large learning data models such as Google Images - this impacts diversification within search engine optimisation (Weber, 2011).

For search engine optimisation (SEO), AI integrates into nearly every part of their capabilities. Marketing messaging takes guidance from keyword research, categorisation, and topic clustering to produce content. Hyper-personalisation is also perpetuated through SEO, using targeted keyword categorisation to prioritise content and targeting that companies prioritise (Almukhtar et al., 2021). There is also a hyper-focus on comprehensive competitive benchmarking and identifying key opportunities for SEO advancement against competitors.

2.5.2 Marketing Customer Journey: Pre-Sale Acquisition Stage

The acquisition phase of the Marketing Customer Lifecycle is moving the customer towards content with more details on the software they are interested in. Webinars sharing software use cases and customer successes perform well and customers are entered into select nurture email streams to provide them with tailored content as they explore.

Within section 2.2.4 the exploration of using generative AI for online events (such as webinars) was explored through video AI to produce, audio AI to record and translate, and text AI to write scripts. The channels this acquisition content is executed through are similar to awareness channels, covering paid media, web and SEO but with the addition of additional channels explored below.

Sentiment analysis becomes important as customers move along their journey. Social listening becomes an important sentiment monitoring tool for marketing when targeting customer groups (Hayes et al., 2020). AI enhancements allow automatic monitoring and grouping of trending keywords and topic areas. Production of “trending” social media content can be produced and posted automatically to capture more attention. Further sentiment analysis through AI can be gleaned from automating and analysing customer feedback on software review websites (Lumoa, 2025). Keyword analysis supports SEO keyword analysis, as well as blogging topic calendars – it allows marketeers to know what their audience is talking about and produced personalised content quickly.

Alongside sentiment, targeting becomes increasingly important as a customer moves along the Marketing Customer Journey. Correct targeting increases ROI, less customer churn and streamlines efforts for both marketing and sales. Marketing uses sales agreed “Target Account Lists” to target certain companies and personas, however there is bias in persona rules (Lee, 2023). Many companies lack data maturity and will supplement data gaps with Third-Party data lists that can be “unclean” and not correctly validated. Any data used that isn’t validated can drive bias and favour some groups over others; missing key audience preferences which can lead to product misalignment and customer attrition (Wilson, 2023).

Webinars themselves are not just content; they are a marketing channel in their own right. The use of AI within online events includes segmenting event audiences, tailoring content, geofencing advertising, incorporating digital sales (online chat) and the correct form of follow-up afterwards (Buczek et al., 2023). Pre-AI enhancement, these individual parts to an online event would have been set-up separately and connected manually through a human. Now the AI connects these together with little to no human interaction through the MarTech Stack, and it is especially resilient for co-ordinating post-webinar activity when leads are “hot” and need to be followed up (Warren-Payne, 2024).

It is within the acquisition phase of the customer journey that customers begin to be classed as Engaged Contacts. Engaged Contacts are those consumers who are regularly interacting with marketing campaign content (Hill, 2023). Each piece of content has a “Score” attached to it and are weighted based on high to low value content: webinars will have a higher score than a blog for example. This scoring is captured and monitored within the MarTech Stack and AI is used to enhance it (Nygard, 2019). There are scoring thresholds to each stage of the customer journey, and within the acquisition stage an engaged contact is gathering its scores until it reaches the scoring threshold to become a Marketing Qualified Lead. The average number of contents for a contact to interact with is five pieces to reach the scoring threshold.

Paid media, website content and attending a webinar all enhance a customer’s score, however in business-to-business marketing, nurture emails and promotional emails are the main source of a contacts score (Kisielewska, 2022). Email nurture is a set series of emails on product topics that are designed to drip-feed high value content to customers. Made up of between three to ten emails, that lead a customer along a journey they are designed to build a connection and nurture them through to a Marketing Qualified Lead. AI is very important for email nurture, it manages data profiling of customer, segmentation into nurture streams (different nurtures for different product groups), content rules, and contact scoring.

2.5.3 Marketing Customer Journey: Pre-Sale Consideration Stage

The Consideration phase of the Marketing Customer Lifecycle is when an engaged contact is beginning to consider which products to buy. More technical software solution content and services will be consumed by the contact and their score will begin to compound to hit the scoring threshold. Generative AI can be used to produce the technical and solution content and Target Account Lists continue to be used to target specific companies and personas.

Technical content is highly scored, and once an engaged contact is scored highly enough to become a Marketing Qualified Lead, they are routed to Qualification Services for follow up (Brosnan, 2024). However, customers do not have to wait until they reach a score and are contacted – they can ask to be contacted and are known as “hand-raisers”. Contact from a company can take the form of a chatbot, online chat with an agent or request a call-back (Buczek et al., 2023). Generative conversational AI can be leveraged for chatbot services to automate interactions with prospects through personalised conversations. Qualification services will utilise tradition AI enhancements through lead qualification and scoring in real-time. This involves interpret natural language signals to determine next best action to convert to a lead (Buczek et al., 2023).

2.5.4 Marketing Customer Journey: Pre-Sale Select Stage

The Select phase of the Marketing Customer Lifecycle is when the customer makes the final decision on their purchase. In software marketing, at this stage, Qualification Services will be interacting with the contact and will require very specific content such as guided demos and free trials to support a final sale and handover the customer to the sales team (Vashishth et al., 2024). Utilising generative AI to create a personalised e-commerce experience enhances a customer’s experience and likelihood of a sale (Sheth et al., 2022; Permana, 2024).

Traditional AI will support the routing of these leads to sales and remove some confirmation bias of qualification services agents working with their favoured sales agent – the selection will be done on the customers purchasing decisions instead (Buczek et al., 2023). Within other businesses an online marketplace with completely digital sales can be achieved and enhanced with AI serving personalised content. However, for B2B software sales a human is required within the final selection process to not only shepherd the sales process but also provide reassurance to the customer on large software spend (Angevine et al., 2018).

2.5.5 Marketing Customer Journey: Post-Sale Adopt Stage

After a customer has purchased a product, they then enter the post-sale marketing customer journey. This is split into four stages: adoption, usage, retain and expand (figure 2.8). The marketing channels and content generation utilised are the same as all four stages of the pre-sale customer journey, however, the messaging is different.

Once a customer has purchased software, they will require onboarding to help them begin to “adopt” it into their operations. Purchasing the software is only the beginning; bespoke coding between customers’ current systems and their new software will need to occur, and the end-users will need enablement on how to use it (Agnihotri et al., 2017).

Email nurture is the primary digital channel utilised to enable users, offering content such as direct access to support services and how-to guides – education is the main content generation, and the generative AI used will be the same as the ones used for pre-sale content: imagery, text, audio and video. Target account lists are again utilised, and companies are ringfenced into the solutions they have purchased - this removes some of the doubt on data quality as the correct contacts are already identified (Lee, 2023). However, hyper-personalisation can occur where companies may be prioritised due to their spending power in the future.

Online events (such as webinars) are another primary onboarding marketing channel for customers. Scoring is not something that happens within the adoption stage of the customer journey, but data classifying, personalising and then routing to the correct team for support still does. As explored in section 2.5.4, traditional AI gives automation to the webinar platform and follow up for customers (Warren-Payne, 2024).

2.5.6 Marketing Customer Journey: Post-Sale Usage Stage

Once customers have adopted the purchased software into their own technology stack, the marketing materials pivot to getting them to use the software. Education content becomes detailed, and customers are encouraged to access this education as self-service learning journeys. The content produced can be blogs, videos and webcasts which can all be produced by generative AI. Like the “adopt” phase, it is important not to market heavily to these customers and seen to be pushing them to purchase even more product. The marketing materials are more informative, helping the customers and enabling them. This generates long-term loyalty for customers when they feel supported and not pushed to purchase more (Melián & Padrón, 2010).

2.5.7 Marketing Customer Journey: Post-Sale Retain Stage

While customers are adopting their software and becoming enabled the marketing messaging begins to pivot retaining the customers and priming them for upgrading their software (Uncles et al., 2003). Customer loyalty programs begin when the customer makes a purchase; however, it will take time to begin on-boarding them into loyalty programs. There are a few manifestations of loyalty programs including awards, events, advertising, and using them as customer reference (Evanschitzky et al., 2012). While generative AI can be used at this stage of the journey - as the messaging is very specific to individual customers, what product they purchased and the success of deployment – it only has a limited applicability as most of the content generation will need to happen with the customer involved. Similarly, there are limited use cases of traditional AI as each customer will be interacted with directly by a marketeer to celebrate their own individual successes and software implementation.

2.5.8 Marketing Customer Journey: Post-Sale Expand Stage

Once customers are fully enabled and are using their software two marketing motions begin to happen – the first is to upsell the latest version of their software and the second is to cross-sell them complementary software that can enhance their own technology stack (Blattberg et al., 2008). Target account lists once again become important to group customer segments and target them with the appropriate upsell and cross-sell messaging. The selection of software available, as well as the diversity of what customers have purchased, means there are multiple targeting lists ringfencing customers. Traditional AI will be used to ringfence these customers and deliver the correct marketing materials to them with the correct messaging. The most direct forms of marketing for this are email nurture and communication through their sales representative (through email and LinkedIn messaging). Post-sale nurture is "set up" the same as the pre-sale nurtures and therefore are exposed to the same AI usage and data rules as explored in section 2.5.4.

2.6 AI Corporate and Regulatory Issues

As explored in section 2.3, bias is in all aspects of human life. Those biases are already perpetuated within non-AI driven marketing and so it is reasonable to assume that AI usage in marketing will continue bias propagation - as humans interacting with AIs puts bias into them too. Bias within standard AI models used across all industries is recognised; the AI itself can be coded with bias, or compound bias based on its machine learning data sets (Dwivedi et al., 2023; Smith & Williams, 2021; McDuff et al., 2019).

As referenced in section 2.5, data sets used for AI algorithms already have bias in them due to un-diversified data weighted to certain demographics from large language models. Research on AI bias in marketing has identified several dimensions of bias, categorised into algorithmic bias, data bias, and user bias (Smith & Conrad, 2020). Algorithmic bias occurs when AI algorithms produce discriminatory outcomes due to inherent prejudices in the training data (Mittelstadt et al., 2016). AIs that learn from real-world data often inherit the biases represented in that data, these can be binary biases, inequal data parameters and they perpetuate systemic inequalities, especially towards minority groups (McDuff et al., 2019).

Data bias refers to skewed or incomplete datasets that do not adequately represent the diversity of the target population, leading to biased predictions or recommendations (Garcia & Martinez, 2020). User bias involves the subjective interpretation and utilisation of AI generated insights by marketers; they might excessively tailor content based on user data, leading to the reinforcement of pre-existing stereotypes or discriminatory practices (Tussyadiah & Pesonen, 2020).

2.6.1 AI & Big Tech

AI tools and technologies are created by “Big Tech” companies and these companies dominate the technology and software industry; they are Google, Microsoft, Amazon, Apple, Meta, and chip-producer Nvidia (Vallance, 2024). These six companies not only have in-house software development where they will create their own AI programmes, but they also acquire or invest in any challenger company in the AI space. In early 2023, Microsoft invested $10 billion into the company OpenAI who’s generative AI product ChatGPT opened generalised AI usage to the world (Milmo, 2023). Elon Musk in spring of 2024 raised $18 billion of investment funding for start-up x.AI Corp (Lipschultz & Roof, 2024). Where Enterprise Resource Planning (ERP) used to dominate the market, these six AI powerhouse companies are now owning the market share with Nvidia becoming the most valuable company in June 2024 (Randewich & Biswas, 2024).

When researching bias embedded within software and how humans embed their own bias, it is important to understand who are producing the software. Diakopoulos (2016) noted that companies who develop AI usually prioritise efficiency and profit within their algorithms, rather than maintaining data integrity which leads to biased outcomes. Schwartz et al. (2022) agreed and built upon Diakopoulos (2016) research by stating that the humans coding within these dominant corporations will share the same values as the company. This will influence the training algorithms, such as algorithms for profit over data in the decision-making rules of the AI systems. This is known as machine learning heuristics, where AIs are coded to provide a rapid solution that stays within an appropriate accuracy range rather than a perfect solution (Karimi-Mamaghan et al., 2022). Machine learning heuristics rules are built for AI speed (quick in-memory decision-making or content production) to support companies' growth and profits and not for the perfect AI rule set to root out bias. The proprietary nature of these models complicates understanding their decision-making processes and the data they rely on - raising issues of accountability and transparency (Lipton, 2016).

It is important to understand that these software companies are creating AI to enhance their own software offerings (Metz & Thompson, 2024). Their economic base represents the financial incentives and market dynamics that drive the development and deployment of these technologies. It is all about profit and efficiency in a business-to-business context. These large corporations "allow" small start-up companies to create software for the common person to use and then envelop it into their own arsenal by either purchasing the company or controlling a majority stake by investment. It is by coincidence that the "normal" person can use AI software to enhance their own lives – it was created for businesses to profit. In April 2024, the UK Competitions Watchdog announced their concern on the dominance of Big Tech firms. During their investigations they documented an "interconnected web" of AI partnerships between them (Vallance, 2024). At the 72nd Antitrust Law Spring Meeting in Washington in April 2024 it was noted that these companies already dominate the digital space and their controlling the AI space was concerning for transparency, ethical usage, and free competition for businesses (Cardell, 2024).

The global production of AI is also not balanced. Large language models for AI began production at scale in 2020, and by the end of 2023 the USA led the AI production with 61 machine learning models. Europe (including the UK) and China were the second and third largest producers with 25 and 15 models respectively. Over 50% of these models are produced for industry use. The rest are produced for academia, research, and government use cases (AI Index Report, 2024). Cutting-edge innovation and high number outputs from Silicon Valley helps boost stock prices for the “big six” technology companies and will not reflect measured progress with all ethics considered for production.

Software developers in these corporations, who create and code AI, exhibit a significant gender disparity, heavily skewed towards males. Research indicates that only about 8-10% of software developers are female (Kaminski, 2023; Vailshery, 2023). Studies have found that bias can be encoded into AI algorithms by developers, whether intentionally or unintentionally, resulting in biased outcomes due to incorrect assumptions about machine learning capabilities (Sun et al., 2024). These assumptions can stem from both the coders and the AI itself, influenced by its data and programming and the company values being adhered to.

MarTech Stack software is built upon these big tech companies software platforms and their partners software, such as Oracle or Microsoft. Meaning the software marketers use to execute marketing campaigns can be imbedded with machine learning heuristics and large learning datasets from biased data. YouTube’s speech recognition is “powered” by Google Speak Recognition data, and as explored in section 2.7 research shows that the recognition software has bias against accents and languages that are not received pronunciation or white middle-class American. This is also true for both Alexa (the voice powered AI from Amazon) and Siri (the voice powered AI from Apple), both of which who still show biased outcomes for speakers. This is because both Alexa and Siri’s original voice capabilities were built between 2013 – 2018 when the data available was predominately white, male, middle-class American and English speakers within the media. Today Alexa and Siri still work from this original code, and it has not been updated since (Zetlin, 2022). The bias is well documented and yet Amazon, Apple and Google are still to update their machine learning rules to be more inclusive.

This noted bias is continued within Google Images that powers generative AI imagery models. In section 2.6 the research showed the bias in the image data available that will be feeding generative AIs and propagating the gender, cultural and ageism stereotypes in its outputs. Generative text services such as ChatGPT (Microsoft Partner AI) and Google Bard (Google owned AI) are also trained on vast datasets from the internet run by the Big Tech companies; they will inadvertently reproduce and amplify societal biases present in the data (Bolukbasi et al., 2016).

2.6.2 AI Law & Censorship

Despite the dominance of “Big Tech” companies in AI there are laws to try and regulate the creation and implementation of this nascent technology. There are no global regulatory rules for AI (Saito, 2024); different countries, continents and political and economic unions are employing different approaches. In November 2021, UNESCO produced the first global ethical guidance for AI known as “Recommendation on the Ethics of Artificial Intelligence” (UNESCO, 2021). It emphasises human rights, inclusiveness, and sustainability while advocating for a human-centred approach to AI development and deployment. UNESCO's recommendations serve as guiding principles, promoting ethical AI practices worldwide without enforcing legal compliance.

The European Union’s AI Act (European Parliament, 2023) is the first and currently only law on AI regulation to be in place. It is a comprehensive binding regulation that classifies AI applications into four risk categories (unacceptable, high, limited, and minimal) and imposes stricter regulations on high-risk AI, such as biometric identification and critical infrastructure management. The emphasis is on pre-emptive regulation, ensuring that AI systems are compliant before they can be deployed (European Parliament, 2023).

Where these “Big Tech” companies have their main head office will make a difference to their level of regulation, while they may operate globally be required to adhere to some laws their production of AI will be less regulated based on where they choose to produce it. Countries that have stated that AI law is over-regulation, and will harm innovation are the UK, Japan, and the USA. All have chosen a pro-business approach and creating space for innovation. Governance is decentralised and divided as a sector-specific approach. The USA’s National AI Initiative Act of 2020 aims to promote AI innovation while addressing ethical and security concerns. This Act gives guidelines rather than comprehensive laws, with agencies like the National Institute of Standards and Technology (NIST) providing frameworks and standards. This approach encourages innovation by offering flexibility though it risks inconsistency and insufficient regulation (United States Congress, 2020; NIST, 2021). Japan is using its traditional civil law system with its central government creating guidelines and laws governing the legal issues of AI. It focuses on three AI values: human dignity, diversity, and a sustainable society. Japan’s guidelines are only for businesses and government developers and users, and it is assumed the developers are responsible for correct data use. Personal use of AI is excluded from these guidelines.

With these decentralised laws and guidance there are gaps for all AI producing companies to circumvent the law in certain geographical locations. With little regulation of the AIs being built from large language models, machine learning heuristics and sparse data, the bias inclusion and non-regulation is inevitable.

Censorship is also not just the domain of government law, but growing pressure on social media companies to regulate deepfake content shared via social posts has seen a restriction of freedom of speech on social media sites (Welsch, 2024). Generative AIs released to the market in late 2023 are overcorrecting for diversity. Google’s AI Gemini was creating historically inaccurate images and prohibiting harmless text generation believing it was harmful. An example of this is asking for a meal plan including meat to share with neighbours in a bid to encourage healthy eating, the AI extends its safeguarding to decline offering this as meat has been shown to be unhealthy and unsustainable. This over-censorship and over-safeguarding raise key issues that are barely explored in academic literature.

Ghadage et al. (2022) and Zhang and Weiss (2023) critique the scant amount of literature quantifying and guaranteeing fairness in AI large language models that are open to the public and are the basis for many culturally sensitive applications. These range from predictive analytics to marketing analysis. There is sufficient literature on the biased outcomes of not using fairness models in AI but no applicability in industry (Ghadage et al., 2022). Zhang and Weiss (2023) proposed three fairness debiasing algorithms that AI producers can use for unfairness quantification and mitigation to increase results and reduce censorship. However, as Ghadage et al. (2022) observes as regards of the industry use, the onus is on the AI producers to adopt these fairness models. Currently the European Union’s AI Act is the only law to come close to enforcing use of any debiasing algorithms and it can be circumvented due to production location.

The ability to circumvent law based on location allows multinational corporations to allow biases to be embedded within AI machine learning data. Multinational corporations often originate from former colonial powers, which can create a form of neo-colonialism where business practices perpetuate economic inequalities and sustain the dominance of certain global markets (Yalkin & Özbilgin, 2022).

This lack of accountability also raises questions on AI security, as traditional AI systems are targeted by hackers for adversarial attacks (Goodfellow et al., 2014). Attacks usually focus on distorting the input data to change the model. With no laws to govern visibility into security breaches for AI, companies may be hiding occasions where hackers gained entry to their systems and changed the AI model. In the UK, “47% of organisations that use AI do not have any specific AI cyber security practices or processes in place” (Berry, 2024, p 3). This would lead to anyone using such an AI model to potentially encounter manipulated data that could lead them open to a biased outcome. Countries, such as the USA, have begun to use AI to monitor cybersecurity breaches – this has raised concerns within the media on what constitutes cybersecurity and that governments using it are using it as a surveillance tool (Spencer, 2024).

2.6 Chapter Summary

Bringing Together Marketing, AI and Bias

This literature review has begun to address RO1 (figure 2.1), to analyse current and possible bias issues in coding, prompting and deployment of AI in Digital Marketing.

The main theoretical areas explored in this literature review were bias theory, the marketing customer journey, human centred design, technology implementation and the marketing technology landscape (MarTech Stack). Bias theory and the classifications of biases perpetuated in marketing are the backdrop to this research – bias is implicit and understood to be expected within marketing activities and within AI coding, prompting and deployment.

This literature review identified that the current research frameworks available are devolved into the separate areas of marketing, AI, and bias – rather than providing one comprehensive framework.

Dowling et al.'s (2020) conceptual framework (figure 2.4) for bias in marketing helps structure the view of their three identified bias areas against a business-to-consumer's four-stage marketing customer journey. Huang and Rust's (2021) framework (figure 2.5) for where AI can be used in marketing strategy and operations is bolstered by Haleem et al.'s (2022) identification of 23 ways marketeers can use generative AI for marketing. Dwivedi et al.'s (2023) research shows the three key areas for bias within generative AI and is supported by Forrester Research 3E's of AI (Buczek et al., 2023) and Jarrahi et al.'s (2023) three area framework for successful technology implementation (figure 2.6). This then further devolves into Schwartz et al.'s (2022) human-centred design framework (figure 2.7), which only focuses on one of the three areas.

There is no current research to bring these theories together to produce a conceptual framework of where AI is used across marketing and how to confidently mitigate bias perpetuation. From reviewing the literature, the recurring research gap is the lack of literature on the usage and prompting of AI in marketing. With well documented propagation of bias through the data and coding of AI, it naturally is assumed humans will bring bias into their usage of it. The usage of AI through the customer lifecycle (figure 2.8) and the MarTech Stack is of note. As AI becomes more deeply embedded in the customer journey, from lead generation to post-sale interactions, the potential for bias amplification increases. A framework is especially necessary due to the lack of industry standards and enforcement of ethical guidelines for AI usage. The impact of bias hinges on both awareness and management - recognising bias exists allows individuals and institutions to address them, creating plans to mitigate (Carter & Phillips, 2017).

This literature review was structured as a systematic review (figure 2.2) to focus on quality research that gleaned core areas of focus. By evaluating the current literature across AI, it shows that there are clear differences between the types of AI that utilise data and algorithms differently. Researching AI usage in marketing and where bias can be propagated showed the importance of the MarTech Stack and Customer Journey. The MarTech Stack's importance is in implementing AI technology and the importance of the Customer Journey is in its structure as a multi-stage event where AI usage can differ dependant on journey stage. Reviewing the current frameworks showed the importance of the theory on any new technology implementation requiring the People, Process and Infrastructure to be in place within a company.

The four core emergent themes from this literature review are the MarTech Stack, the Customer Journey, the types of AI and the elements of People, Process and Infrastructure. The next stage of the research process flowchart (figure 2.1) is RO2: to develop a conceptual framework for analysing bias issues in the use of AI in Digital Marketing. The next chapter, chapter 3, reviews the building of a provisional conceptual framework using the literature core themes to be tested during the primary research stage to fulfil this research gap.

CHAPTER 3: PROVISIONAL CONCEPTUAL FRAMEWORK

3.1 Chapter Introduction

This chapter sets out a provisional conceptual framework (PCF) for analysing bias issues in the use of AI in Digital Marketing. It sets out to address RO2 to develop a conceptual framework for analysing bias issues in the use of AI in Digital Marketing.

From the chapter 2 literature review, the research gap and core concepts were attained. The research gap is that while there are research frameworks that map AI use in marketing (Huang & Rust, 2021; Haleem et al., 2022), bias within the marketing customer journey (Dowling et al., 2020), bias within AI (Dwivedi et al., 2023) and successful technology implementation (Jarrahi et al., 2023) these are related to specific functions, activities or technologies with no one framework bringing them together. Here the PCF, which builds upon the literature analysis (Reed et al., 2025), aims to achieve this as a basis for subsequent development and validation within the primary research phase. The main themes embodied in the research objectives and in the PCF provide a structure for the development of interview questions and the pre-interview questionnaire. The researcher can build upon these initial concepts by incorporating interview feedback to develop an operational model (Morse et al., 2002).

Jabareen (2009) argues that a PCF is best placed to support theoretical research in complex social phenomena, as “usually, these multidisciplinary phenomena do not even have a skeletal framework” (p. 50). By taking a qualitative systematic approach, the PCF can identify core concepts, then categorise and integrate them by factors and typologies (Victora et al., 1997). Unlike a theoretical framework, a PCF is developed by researchers to propose a solution to the identified research problem (for example, as in Altundag and Wynn, 2024).

This chapter is divided into eight sections. Following this introduction, section 3.2 introduces the PCF and identifies its core concepts. In section 3.3 these core concepts are justified on their incorporation into the PCF and the elements that will be analysed from each of them. In section 3.4 the elements of the core concepts of the MarTech Stack and the Marketing Customer Journey are mapped into axis of tables to explore the interactions between them using data from the literature review and researcher knowledge. Section 3.5 repeats this interaction to analyse the interactions between the Types of AI and the Marketing Customer Journey. Section 3.6 then repeats this interaction analysis between the Types of AI and the MarTech Stack. The axis analysis from sections 3.4, 3.5 and 3.6 is then brought together in section 3.7 in one 3D axis analysis. Within section 3.7 the key emergent themes from these interactions are also explored and distilled into the main themes that will be used to inform the focus areas within the primary research questionnaire and interviews.

3.2 Provisional Conceptual Framework (PCF)

The PCF (figure 3.1) sets out the relationships between the core concepts and elements of these concepts that emerged from the literature review to address RO2. The PCF core concepts shape the researcher's approach to the primary research focus areas. This will aid in understanding how different factors interact between the core concepts to identify focus areas for the primary research phase, entailing use of a questionnaire and interviews. It will inform how the methodology is designed, and this is further explored in chapter 4, Methodology.

The relationship between the literature review and PCF is of great importance, as the PCF incorporates the derived theories from the literature. There are four core concepts identified from the literature review: types of AI, MarTech Stack, Customer Journey and the elements of People, Process and Infrastructure. These four core concepts structure the PCF (figure 3.1). The justification for why these four core concepts were selected from the literature review are explored in this section, section 3.2.

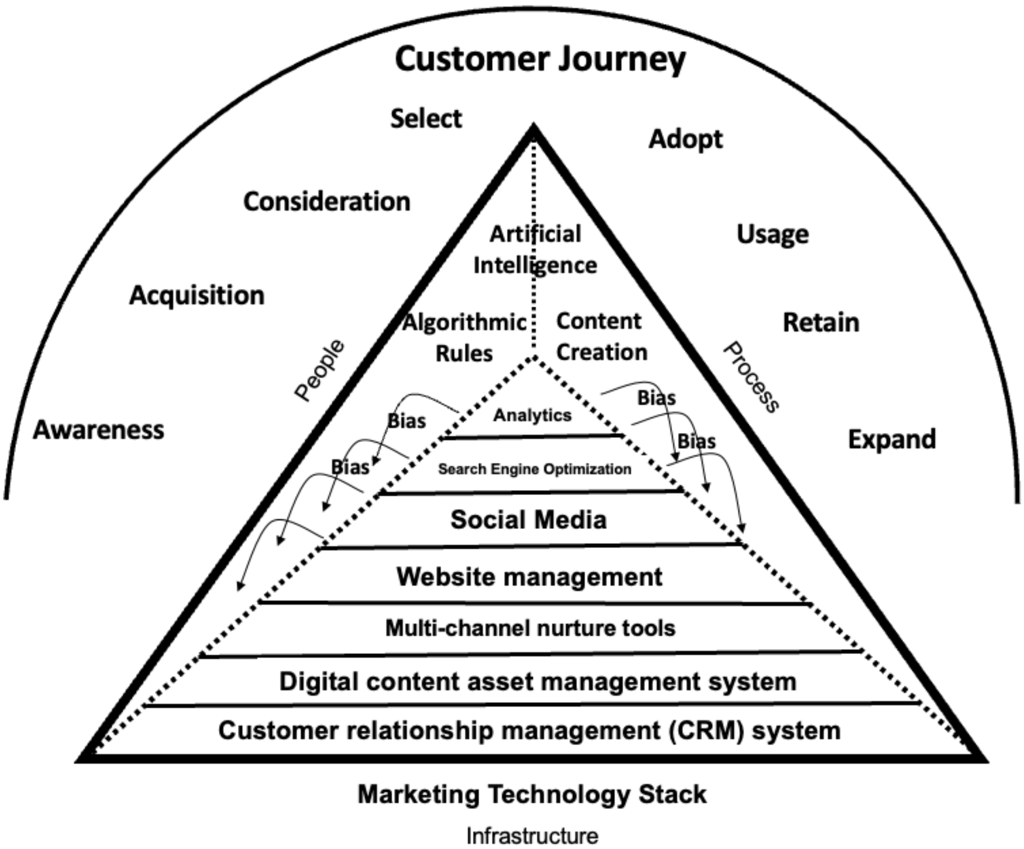


Figure 3.1: Provisional Conceptual Framework

Source: Reed et al. (2025)

3.2.1 Core Concept from the Literature Review: Two Types of AI – Traditional and Generative

For this research the core concept of AI is identified as being split into two types – traditional AI and generative AI (Roetzer & Kaput, 2022). These two types of AI are represented in the PCF as “algorithmic rules” and “content creation” (figure 3.1). The importance of having a delineation into two specific AI influences on marketing is an important focus area from the literature review: generative AI creates, and traditional AI implements rules. In section 2.2.3 Traditional AI was identified as an essential component of the MarTech stack due to its ability to analyse and interpret large amounts of data. This type of AI helps marketers understand customer behaviour, and trends, allowing them to personalise their targeting (Roetzer & Kaput, 2022). As discussed in section 2.2.4, Generative AI was identified as streamlining the content creation process and automating repetitive tasks to create personalised and tailored content at scale in marketing (Lie et al., 2020).

Both AI types are important within marketing for marketeers to engage with their audience in a more meaningful and impactful way to drive better customer experiences and ultimately, increase sales and business growth. The framework by Dwivedi et al. (2023) focused solely on the types of generative AI that can be used in marketing, counting 21 applications of generative AI - showing that focusing on one type of AI for research can be appropriate. However, this research focus to address RO2 requires research on the holistic use of AI in marketing. Researching only one type of AI misses a thorough investigation on how all types of AI are used in marketing. Huang and Rust’s (2021) framework (figure 2.5) segmented AI into three types: mechanical, thinking and feeling AI. Mechanical AI was identified as standardisation, data collection and segmentation. Thinking AI was identified as Personalisation, marketing analysis and targeting. Feeling AI was identified as relationalisation, customer understanding and positioning. Relationalisation was defined as the two-way interaction between two or more humans that shows human emotions. However, the AI’s listed as mechanical, thinking and feeling are all machine-learning AI (identified for this research as traditional AI), that are utilised through the infrastructure of the MarTech Stack. Splitting out traditional AI into three separate areas and splitting generative AI into multiple areas was deemed excessive for this research. Understanding there are many manifestations of both traditional and generative AI is important for this research and is explored thoroughly as part of the primary data and subsequent thematic analysis.

For this research the simplistic core concept of traditional AI and generative AI are selected to enable the research to remain focused on answering RO2. Investigating the application of both traditional and generative AI within marketing is important as they complement and connect with each other – by only focusing on one would not provide a comprehensive review and splitting out the manifestations of AI would be overwhelming.

3.2.2 Core Concept from the Literature Review: The 7 Technologies of the MarTech Stack

For this research the core concept of the MarTech Stack was identified as important to include in the PCF. Within the PCF (figure 3.1) the core concept of the MarTech Stack is represented as the centre of the figure, directly connected to the two types of AI. This is because the MarTech Stack is the software within marketing that enables AI to be used – without it there would be no AI infrastructure. Within the literature review, figure 2.3 identifies the seven most common technologies within a MarTech Stack from the literature. These seven technologies are labelled within the PCF: Analytics, Search Engine Optimization, Social Media, Website, Multi-channel Nurture Tools, Digital Asset Management (DAM) and Customer Resource Management (CRM). There were no frameworks identified from the literature review on how to represent a MarTech Stack and there was no standard agreement on the types of technology that should be incorporated. The seven technologies selected for this research were justified within section 2.2.3 of the literature review as the core technologies that are part of a MarTech Stack due to their repeated identification by other literature.

The MarTech Stack is of importance within marketing as the primary technology stack that allows marketeers to interact with consumers and process their data for a better customer experience (Earley, 2021). For the qualitative research of this thesis, each questionnaire and interview had a section focused on the MarTech Stack (chapter 4, section 4.7). Of note, no additional technologies could be agreed upon by respondents to be added to these originally identified seven technologies. This is explored further in chapter 6 (section 6.3.2); however, it shows the value and importance of the MarTech Stack being included within the PCF and the appropriateness of the seven technologies identified.

3.2.3 Core Concept from the Literature Review: The Eight Stages of a Customer Journey

For this research the core concept of the Customer Journey was identified as being important to include in the PCF. The Marketing Customer Journey is represented in the PCF as the umbrella that incorporates both the two types of AI and the seven technologies of the MarTech Stack. The customer journey chosen for the PCF is based on the case study company journey from figure 2.8. As explored in the literature review, this eight-stage journey - see Buczek et al. (2023) given below - is an evolution of the original four stage marketing journey that originated in the 1960's (Dowling et al., 2020). While utilising the four-stage customer journey would have simplified this research, it would have left out valuable insights on the nuances of a more analysed journey – more steps equal more analysis. Sections 2.5.1 to 2.5.8 detailed the different uses of AI for each of the eight stages and the opportunity to explore this nuance was included within the PCF.

The eight stages of the journey chosen for the PCF (figure 3.1) are awareness, acquisition, consideration, select, adopt, usage, retain and expand. The first four stages are the pre-sale stages, and the latter four are the post-sale stages. These eight stages are designed on the eight-stage journey from Purmonen et al. (2023) that details the modern business-to-business customer journey. This is a more appropriate choice for this research as the case study company also employs a business-to-business marketing model. The four-stage simplified customer journey (Dowling et al., 2020) would be more appropriate for a business-to-consumer analysis, where the purchasing and selling timelines are shorter.

The Marketing Customer Journey is a structured view of where (which channel) a consumer will interact with marketing content. It is structured by content (generative

AI) and the channels through which they are contacted by (traditional AI). The channels in the customer journey is the MarTech Stack technology that are routes to market – such as SEO, Social Media, Web and Multi-channel Nurture. The customer journey, defined as an eight-stage process, allows for a detailed interaction analysis with the other identified core concepts of the PCF. These are explored in sections 3.4 and 3.5 to identify focus areas for the primary research.

3.2.4 Core Concept from the Literature Review: The Elements of People, Process and Infrastructure

For this research the core concept of the elements of People, Process and Infrastructure was identified as important to include in the PCF. Analysis within the literature review showed the organisational structure required for companies to implement AI successfully was “People, Infrastructure and Process” (Jarrahi et al., 2023 - figure 2.7). These three elements are represented in the PCF as surrounding the types of AI and the technologies of the MarTech Stack due to their importance in technology implementation and usage. The three change dimensions of “technology, process and people” are well researched in successfully implementing new technology and software - especially within ERP and CRM projects (King-Turner, 2014). ERP implementation necessitates substantial changes in processes, staff skills, work practices, and technological capabilities (Wynn & Rezaeian, 2015). This mirrors the complexities faced with AI implementation and the utilisation of a people, process and infrastructure framework should be investigated as part of the primary research collection.

The three dimensions from King-Turner (2014) were built upon research by Heeks (2002) that identified four interrelated dimensions of change: technology, process, people, and structure. These are referred to as the “Design-Actuality” gap in Heeks’ original model. This gap represents the disparity between an organisation's current state and the state needed for successful adoption of new systems. This research is not a gap analysis on the case study company’s current system landscape; however, the three elements of change (people, process and infrastructure) are incorporated into the design of the PCF (figure 3.1). In the PCF, the three elements are represented as aligning with the MarTech Stack and Types of AI. This is because the

MarTech Stack is the infrastructure whereby AI is implemented and the AI itself is utilised by people and the processes of deploying it. The elements of people, process and infrastructure are shown as linear within the literature (Jarrahi et al., 2023 - figure 2.7); however representing it as linear was not appropriate in the PCF that required it to be shown as part of the framework itself.

In sections 3.4 to 3.7 of this chapter interaction axis analysis is completed for the core concepts of the PCF. Within these sections the elements of people, process and infrastructure are represented by colour coding to aid in the classification of where these three elements can be utilised to implement AI usage in digital marketing.

3.2.5 Bias Representation in the PCF

Bias is a key focus area for this research and features in the PCF as arrows that detail the cascade of bias that comes from the coding, prompting and deployment of the types of AI and can then proliferate into the MarTech Stack. The justification of bias was evident throughout chapter 2, Literature Review, however it is not a core concept reviewed in the PCF axis analysis in sections 3.4 – 3.7. This decision was made as there is robust research evidence of bias already prevalent within the coding and deployment of AI algorithms (Buolamwini & Gebru, 2018) and the biases within marketeers prompting the AI (Gerhard, 2008). The key focus of RO2 is to produce a conceptual framework that supports mitigating and reducing all bias propagation, not giving the biases themselves a hierarchy. It is therefore assumed that bias proliferates throughout the PCF core concepts. This does not limit additional bias avenues being explored within the primary research and then analysed to explore what types of biases are proliferating through marketing usage of AI.

Within section 3.3, the interplay between the core concepts will be reviewed as tables with axis analysis to show the development of the PCF. The MarTech Stack is the infrastructure element, the marketing customer journey is the process element, and the exploration of people (marketeers) will be part of the analysis of the primary research. It could be assumed that the people, process and infrastructure within companies are main components to mitigate bias perpetuation. This assumption will also be explored within the primary research. By clearly defining these core concepts and their interconnections, this PCF supports identifying emergent themes to explore within the primary research. It also ensures that the study has a coherent structure.

3.3 Provisional Conceptual Framework (PCF) Core Concepts

As noted in section 3.2 there are four core concepts to explore for this PCF. This section explores the interactions between these core concepts and shows how the content was reviewed and developed for the PCF. To conduct a detailed review, the dimensions of the concepts need to be defined. The tables within this section are not the full PCF, but rather they indicate stages in its development.

For the core concept of AI there are two “types”: generative AI and traditional AI (Roetzer & Kaput, 2022). The core concept of Marketing Customer Journey has eight “stages” within it: awareness, acquisition, consideration, select, adopt, use, retain and expand (Buczek et al., 2023). The core concept of the MarTech Stack has seven “technologies”: search engine optimisation, social media, website, multi-channel nurture, DAM, CRM and analytics (Early, 2021). The routes to market within the MarTech Stack are SEO, social media, website and multi-channel nurture. DAM, CRM and analytics are internal software used to measure ROI and structure content and customer data. This research therefore has seventeen elements within its core concepts, giving 112 interactions to explore between them - 2 AI types x 7 MarTech Stack technologies x 8 Customer Journey stages.

It is assumed that the biases explored in chapter 2, Literature Review, are inherent within the thematic data and do not need to be directly noted within the PCF and interactions (Tables 3.1, 3.2 and 3.3). Within Tables 3.1, 3.2 and 3.3 the PCF core concepts are mapped as axis within the interaction tables. Within section 3.4, 3.5 and 3.6 emergent themes are distilled from the interaction tables 3.1, 3.2 and 3.3 – these emergent themes will be the focus areas within the primary research and bias will be explored within these emergent themes in the primary research.

The elements of people, process and infrastructure (PPI) are represented within the core concept interaction tables (tables 3.1, 3.2 and 3.3) as colour coding to show where they are or could be represented. The definition of people, process and infrastructure align with Jarrahi et al.’s (2023) classifications (figure 2.7). For “people” a human will have to be part of the interaction (such as training, complex understanding or prompting), for “process” it is workflows and cross-team collaboration and “infrastructure” as the tools and software used for data and interpretation. Within the PCF (figure 3.1) infrastructure is mapped to the MarTech Stack as this is the infrastructure in place for all marketing operations. The elements of People, Process and Infrastructure are important to the analysis of the primary research as it will support validating the PCF. It potentially can support structuring the research outputs, as these three categories are widely understood within industry aiding implementation of this research’s framework.

The content within tables 3.1, 3.2 and 3.3 are distilled from both the literature review and the experience of the researcher. Literature and corresponding references are mapped into interactions between each core concept. Each interaction is labelled 1 through 94 to allow for easier reference within the main text throughout the rest of this chapter. This mapping of literature into cross-tabulations of interactions was done to provide an initial assessment of how the core concepts relate to each other and allows for emergent themes to be identified between the interactions. These emergent themes are explored in sections 3.4, 3.5 and 3.6 and are then used as additional focus areas within the qualitative research methods.

3.4 Core Concept Interactions: MarTech Stack and Marketing Customer Journey

Table 3.1 maps the seven technologies against the eight stages in the customer journey creating 56 interactions between them that are labelled numerically and referenced in this section. Literature from chapter 2 and corresponding references are mapped into the interactions and the elements of PPI are colour-coded within them. This is the first cross-tabulation to identify emergent themes that can be explored, alongside the core concepts, within the primary research. It begins to address RO2 in justifying the development of the core concepts used for the PCF and how it stands up to analysis between the interactions.

The content inputted in each interaction provides an initial indication of what the MarTech Stack technologies are used for at each customer journey stage. Earley's (2021) research supports using the customer journey to optimise the marketing technology stack through continuous data modelling and learning. All the technology noted has the ability to use AI within it and it is assumed that bias proliferation is already present within any usage of AI through the MarTech Stack or Marketing Customer Journey. Of note is the repetition of typology interactions for the post-sale part of the customer journey and DAM, CRM and Analytics. This is shown by bundling the interactions within the table for simplicity.

	Customer Journey Stages							
MarTech Stack Technologies	**Awareness**	**Acquisition**	**Consideration**	**Select**	**Adopt**	**Usage**	**Retain**	**Expand**
Search Engine Optimisation	**[1]** Keyword targeting (Almukhtar et al., 2021). Paid - Using Target Account Lists to target certain companies. (Chen et al., 2018).	**[2]** Competitive benchmarking (Almukhtar et al., 2021). Online events (i.e. webinars) – full content production (Buczek et al., 2023).	**[3]** Keyword targeting. Advanced topic blogging with keyword analysis. (Almukhtar et al., 2021)	**[4]** Keyword targeting. Advanced topic blogging with keyword analysis. (Almukhtar et al., 2021)	**[5 – 8]** Keyword targeting - education, services guides, customer success stories Advanced topic blogging with keyword analysis. (Almukhtar et al., 2021)			
Social Media	**[9]** Paid - Using Target Account	**[10]** Online events (i.e. webinars) –	**[11]** Organic social messaging from	**[12]** Organic social messaging from	**[13-16]** Organic social media for awareness (no paid targeting).			

	Lists to target certain companies. (Chen et al., 2018). Social Listening for topic and targeting areas (Hayes et al., 2020).	full content production. (Buczek et al., 2023). Paid Social - Using Target Account Lists to target certain companies. (Chen et al., 2018). Social Listening for topic and targeting areas (Hayes et al., 2020).	marketing services reps (Garcia & Martinez, 2020). Retargeting Paid Social - Using Target Account Lists to re-target certain companies. (Chen et al., 2018). Social Listening for topic and targeting areas (Hayes et al., 2020).	marketing services reps (Garcia & Martinez, 2020). Social Listening for topic and targeting areas (Hayes et al., 2020).	Organic social messaging from sales reps – target account lists used to target specific customers. (Garcia & Martinez, 2020) Social Listening for topic and targeting areas (Hayes et al., 2020).
Website	**[17]** Personalisation - Using Target Account Lists to target certain companies (Flavin & Heller, 2019; Earley, 2022).	**[18]** Optimisation of internal linking webpages to enhance user navigation (Earley, 2022). Online events (i.e. webinars) – full content production (Buczek et al., 2023).	**[19]** Personalisation - Using Target Account Lists to target certain companies (Flavin & Heller, 2019; Earley, 2022).	**[20]** Guided experiences and free trials (Vashishth et al., 2024; Sheth et al., 2022). Marketplace to buy software (Permana, 2024).	**[21 – 24]** Online events (i.e. webinars) – full content production (Buczek et al., 2023). Personalisation - Using Target Account Lists to target certain companies (Flavin & Heller, 2019; Earley, 2022).
Multi-channel Nurture Tools	**[25]** Promotional emails only - data profiling, segmentation, rules, scoring (Nygard, 2019; Roetzer & Kaput, 2022).	**[26]** Nurture & promotional emails – data profiling, segmentation, rules, scoring (Nygard, 2019; Roetzer & Kaput, 2022).	**[27]** Contact us and inbound qualification services (Arsenijevic & Jovic, 2019). Lead qualification and scoring (Nygard, 2019).	**[28]** Contact us and inbound qualification services (Arsenijevic & Jovic, 2019). Lead qualification and scoring (Nygard, 2019).	**[29-32]** Nurture & promotional emails – data profiling, segmentation, rules, scoring (Nygard, 2019; Roetzer & Kaput, 2022). Online events (i.e. webinars) – full content production (Buczek et al., 2023).
Digital Asset Management (DAM)	**[33 – 40]** Central repository for storing digital assets such as images, videos, documents, and other media files. Organisation of assets using metadata, tags, categories, and folders.				

	Advanced search capabilities, including keyword searches, filters, and saved searches to quickly locate assets. Track and manage multiple versions of assets. Facilitate the sharing and distribution of assets across various channel platforms. Support workflows for asset creation, approval, and publishing, including collaboration tools and task management. (Earley, 2022; Flavin & Heller, 2019; Haleem et al., 2022)
Customer Resource Management (CRM)	**[41- 48]** Contact suppression rules. Data modelling algorithms. Contact routing rules. Contact scoring rules. Generate predictive analytics - customer behaviour. (Arsenijevic & Jovic, 2019; Nygard, 2019; Roetzer & Kaput, 2022).
Analytics	**[49 – 56]** Dependent on data maturity – large database required. First-party & third-party data targeting. Generating forecasts. (Welsch, 2024; Lee, 2023; Wilson, 2023)

Table 3.1: Showing MarTech Stack and Customer Journey Interactions - content indicates what the technologies are used for with references from the literature review. Literature identified is from correlating topic sections in the literature review.

Colour Key: **Purple** = People, **Blue** = Process, **Orange** = Infrastructure

When reviewing the interactions between the core concepts, repetitive input of the literature into multiple interaction areas suggests there are emergent themes that can be further explored to robustly research RO2. While themes are usually identified within interview analysis, identifying initial emergent themes within the PCF interactions allows for robust testing of any emergent topic areas that can be explored within the interviews to attain more in-depth data.

Emergent Theme in Table 3.1: Pre-sale vs Post-sale Marketing Customer Journey

The variations on interactions during the pre-sale stage of the journey (awareness, acquisition, consideration and select) are more nuanced than the post-sale (adopt, usage, retain and expand) stages. This is evident from the individual technologies referenced in interactions [1, 2, 3, 4, 9, 10, 11, 12, 17, 18, 19, 20, 25, 26, 27 and 28] for pre-sale stages. This theme is identified by the amount of relevant literature to support it. However, the literature on post-sale stages was limited to a few examples, rendering interactions [5 – 8, 13 – 16, 21 – 24 and 29 – 32] as bundled together. This suggests that the recommended focus for this research should predominantly focus on the pre-sale interactions for the primary research to granularly explore those nuances. Primary research on the post-sale stages can be simplified by investigating the umbrella themes emerging in Table 3.1.

Emergent Theme in Table 3.1: Targeting and Testing

Targeting of target account lists is detailed within Table 3.1, particularly within CRM [41 – 48] and Analytics [49 – 56]. It is applicable to all eight of the customer journey stages and therefore is a repetitive theme. The targeting of ringfenced customer lists is of particular importance across the customer journey as it is outbound targeting. The MarTech Stack straddles both outbound and inbound targeting, applying scores and rules to the incoming customer lead. An emergent theme found in tables 3.2 and 3.3 are on “personalisation”, “targeting”, and “data-modelling”; the targeting and testing identified here complement these other emergent themes.

Emergent Theme in Table 3.1: Analytics and Predictions

Like the targeting and testing emergent theme, the themes on scoring, profiling and routing rules [41 – 48] are repeated areas in Table 3.1. Their importance feature within the multi-channel nurture interactions [25 – 32], across all eight of the customer journey stages. This focus on analytical predictions [49 – 56] within the MarTech stack is seen across the full eight stages of the marketing customer journey within CRM [41 – 48] – meaning it is of great importance to a successful customer experience. This aligns with the same focus area found within Table 3.3, in section 3.6.

Emergent Theme in Table 3.1: People, Process and Infrastructure

The classification for what PPI means within these tables was explored in section 3.3. Of note throughout Table 3.1, is there is no interaction that has just one element of People, Process or Infrastructure - there are always at least two components mapped to the interactions - with all three elements of PPI applied to 28 interactions [1, 2, 3, 4, 5 6, 7, 8, 9, 10, 11, 17, 18, 19, 21, 22, 23, 24, 27, 28, 29, 30, 31 and 32]. These interactions with all three aspects of PPI are evenly spread across the channels that interact with consumers (SEO [1 – 8], web [9 – 16], social media [17 - 24] and nurture [25 – 32]. Digital Asset Management (DAM) [33 – 40], Customer Resource Management (CRM) [41 – 48] and Analytics [49 – 56] have a weighting of Process and Infrastructure, where People were not represented - this is due to the automatic algorithmic capabilities that do not require human intervention. People feature with both infrastructure and process across SEO [1 – 8] and social media, [17 – 24] showing that a human must direct activities in some way for activities that are “customer facing”.

The emergent themes identified in this section are cross-referenced against the emergent themes from section 3.5 and 3.6 to produce the final emergent themes in 3.7 that are used as additional focus areas within the qualitative research methods.

3.5 Core Concept Interactions: Type of AI and Customer Journey

Table 3.2 maps the two types of AI against the eight stages in the customer journey creating 16 interactions between them that are labelled numerically and referenced in this section. Literature from chapter 2 and corresponding references are mapped into the interactions and the elements of PPI are colour coded within them. This is the second cross-tabulation to identify emergent themes that can be explored, alongside the core concepts, within the primary research. It continues to address RO2 in justifying the development of the core concepts used for the PCF and how it stands up to analysis between the interactions.

	Customer Journey Stages							
Types of AI	**Awareness**	**Acquisition**	**Consideration**	**Select**	**Adopt**	**Usage**	**Retain**	**Expand**
Generative AI	[57] Content produced for advertising: images, videos, text and audio (Haleem et al., 2022; Rabby et al., 2021).	[58] Content produced for acquisition stage: whitepapers, eBooks, etc (Haleem et al., 2022; Rabby et al., 2021). Online events (i.e. webinars) – full content production, tailoring content (Buczek et al., 2023).	[59] Content produced for consideration stage: whitepapers, eBooks, etc. AI Chatbots – text, audio (Haleem et al., 2022; Rabby et al., 2021).	[60] Content produced for Select stage: Guided experiences and free trials (Haleem et al., 2022; Rabby et al., 2021). Inbound qualification services: contact us and chatbots (Rabby et al., 2021; (Arsenijevic & Jovic, 2019). Marketplace to buy software (Permana, 2024).	[61 – 68] Personalised generated content at scale. Content produced for usage, retain and expand stage: emails, how-to guides, webinars, etc (Haleem et al., 2022; Rabby et al., 2021). A/B testing on email and content wording and structure (Nair & Gupta, 2021).			
Traditional AI	[69] Using Target Account Lists to target certain companies	[70] Using Target Account Lists to target certain companies	[71] AI Chatbots – routing rules/suppression rules (Rabby et al., 2021).	[72] Contact us and inbound qualification services	[73 – 80] Using Target Account Lists to target upselling and cross-selling software to specific companies and personas (Flavin & Heller, 2019; Earley, 2022; Meda, 2023).			

	and personas (Flavin & Heller, 2019; Earley, 2022; Meda, 2023).	(Flavin & Heller, 2019; Earley, 2022; Meda, 2023). Webinars - segmenting event audiences, geofencing (Buczek et al., 2023).	Using Target Account Lists to target certain companies (Flavin & Heller, 2019; Earley, 2022; Meda, 2023).	(Arsenijevic & Jovic, 2019).	Nurture emails and webcast routing rules (Nygard, 2019; Roetzer & Kaput, 2022).

Table 3.2: Showing Type of AI and Customer Journey Interactions - content shows where the literature suggests AI is relevant to the customer journey with references. Literature identified is from correlating topic sections in the literature review.

Colour Key: **Purple** = People, **Blue** = Process, **Orange** = Infrastructure

When reviewing the interactions between the core concepts, repetitive input of the literature into multiple interaction areas suggests there are emergent themes that can be further explored to robustly research RO2. Table 3.2 identifies possible AI deployment in the eight stages of the customer journey. It reviews how the two types of AI are evident at different stages of the customer journey but does not link them to any particular technology. This a general assessment of AI usage against each stage in the journey.

In Table 3.2 there is evidence of the Marketing Customer Journey stages leveraging both generative AI and traditional AI to enhance personalisation, targeting, content generation, and data analysis – similar to the MarTech Stack technologies. It is assumed that bias proliferation is already present within the two AI types.

Emergent Theme in Table 3.2: Content Generation

There is detailed application of generative AI across the eight stages of the customer journey [57 - 68] in table 3.2. The literature identified shows that content generation is detailed across the four main pillars of generative AI: text generation, image generation, audio generation and video generation. It shows they can be used for content production for certain journey stages [57, 58, 59] and for specific purposes such as online events [58]. This repetitive representation, but with differing uses, is of interest to explore further as an emergent theme.

Emergent Theme in Table 3.2: Targeting and Testing

Targeting of customer target account lists [69, 71, 73 – 80] is repetitive within table 3.2 and reinforces the “personalisation”, “targeting” and “data-modelling” emergent theme from Table 3.1. As noted from Table 3.1, targeting of ringfenced customer lists is of particular importance across the customer journey as it is outbound targeting. While a customer’s journey is not a linear path (Lemon & Verhoef, 2016), specific targeting of customers allows for increased interactions no matter how many times they interact with a company. With the B2B customer journey averaging between 8 to 14 interactions the continued targeting is important to optimise sales (Buczek et al., 2023).

Emergent Theme in Table 3.2: People, Process and Infrastructure

All 16 interactions in Table 3.2 include the element of infrastructure [57 – 80], which is aligned to the MarTech stack in the PCF. The largest weighting is for all three elements of PPI with only generative AI used for awareness [57] not including the process element. This representation of PPI across 15 interactions [58 – 80] represents how the usage of AI requires people and process to be involved, not just the technology itself. Interestingly, people and infrastructure interactions [57, 59, 60 – 68] are focused just on generative AI across seven of the eight customer journey stages, showing the reliance on humans to prompt AI. People are removed from some of the interactions [71, 73 – 80] within traditional AI, this is where a customer enters the consideration phase of their journey and automated routing and scoring begin. This indicates that marketeers (people) are channelling efforts to the very beginning of the customer journey to drive higher quality interactions with prospective customers. Allowing automated scoring, routing and follow up to happen when their customers are already engaged.

The emergent themes identified in this section are cross-referenced against the emergent themes from section 3.4 and 3.6 to produce the final emergent themes in 3.7 that are used as additional focus areas within the qualitative research methods.

3.6 Core Concept Interactions: Type of AI and MarTech Stack

Table 3.3 maps the two types of AI against the seven technologies creating 14 interactions between them that are labelled numerically and referenced in this section. Literature from chapter 2 and corresponding references are mapped into the interactions and the elements of PPI are colour coded within them. This is the third cross-tabulation to identify emergent themes that can be explored, alongside the core concepts, within the primary research. It continues to address RO2 in justifying the development of the core concepts used for the PCF and how it stands up to analysis between the interactions.

	MarTech Stack Technologies						
Types of AI	**Search Engine Optimisation**	**Social Media**	**Website**	**Multi-channel Nurture Tools**	**Digital Asset Management** (DAM)	**Customer Relationship Management** (CRM)	**Analytics**
Generative AI	**[81]** Content generation with SEO keywords (optimised organic ranking) (Haleem et al., 2022; Almukhtar et al., 2021)	**[82]** Paid social personalised generated content (Haleem et al., 2022; Rabby et al., 2021). Social media content generated from social listening (Hayes et al., 2020).	**[83]** Personalised generated content (Haleem et al., 2022; Rabby et al., 2021). Software reviews – automate and analyse customer feedback (Lumoa, 2025).	**[84]** Personalised generated content (Haleem et al., 2022; Rabby et al., 2021). A/B testing on email and content wording and structure (Nair & Gupta, 2021).	**[85]** Personalised generated content (Haleem et al., 2022; Rabby et al., 2021). Localisation of content (Haleem et al., 2022). Generating descriptions for accessible content (Tang et al., 2021).	**[86]** Generate predictive analytics - customer behaviour (Ghadage et al. 2022; Zhang & Weiss, 2023).	**[87]** Generate forecasts (Welsch, 2024; Lee, 2023; Wilson, 2023).
Traditional AI	**[88]** Targeting rules. A/B testing on keywords. Metadata matching rules.	**[89]** Social listening targeting rules (Hayes et al., 2020).	**[90]** Personalisation rules. A/B testing on website. (Flavin & Heller, 2019; Earley, 2022).	**[91]** Nurture & promotional emails – data profiling, segmentation, rules, scoring. (i.e. by product based on	**[92]** Automating tagging and categorising content (Haleem et al., 2022).	**[93]** Contact suppression rules. Data modelling algorithms. Contact routing rules. Contact scoring rules. (Nygard,	**[94]** Persona rules. Analysis of customer data (Flavin & Heller, 2019). Dependent on data maturity – large

	(Almukhtar et al., 2021)			interaction) (Nygard, 2019; Roetzer & Kaput, 2022).		2019; Roetzer & Kaput, 2022).	database required (Lee, 2023). First-party & third-party data targeting (Wilson, 2023).

Table 3.3: Showing Type of AI and MarTech Stack Interactions - content shown is where the literature suggests AI is relevant to the MarTech Stack, with references. Literature identified is from correlating topic sections in the literature review.

Colour Key: **Purple** = People, **Blue** = Process, **Orange** = Infrastructure

When reviewing the interactions between the core concepts, repetitive input of the literature into multiple interaction areas suggests there are emergent themes that can be further explored to robustly research RO2. Table 3.3 looks at how the two types of AI are evidenced in the different technologies in the context of marketing. This table is specific to marketing function and shows how the MarTech Stack technologies can leverage both generative AI and traditional AI and is evidenced in each technology. This blend of technologies aims to improve customer engagement, optimise marketing efforts, and drive business outcomes. Again, it is assumed that bias proliferation is already present within the two AI types.

Emergent Theme in Table 3.3: Targeting and Testing

As evidenced from Tables 3.1 and 3.2, targeting and testing are important emergent themes to explore. The analysis from table 3.3 takes this further by showing how personalisation should also be represented as both types of AI contribute to personalisation efforts [82 – 85 and 90]. Hyper-personalisation was a key bias research area noted within chapter 2, section 2.2.3. Personalisation at scale can use biased data and without a human to review nuances in consumer personas and behaviours it quickly drives suppression of true buyers and unethical data modelling

(Flavin & Heller, 2019; Roetzer & Kaput, 2022; Buolamwini & Gebru, 2018). It is important to include personalisation within data analysis on targeting and testing.

Emergent Theme in Table 3.3: Analytics and Predictions:

Scoring, profiling and routing rules are another focus area that is repeated and evident in Table 3.3. This analytics focus can be found across interactions that give structure and to customer data [91, 92, 93 and 94]. This is evidenced as predictive analytics for customer behaviour and forecast generation which falls under traditional AI usage. Generative forecasting [87] and A/B testing [84, 88, 90] also supports these analytical prediction tools being of importance within the MarTech Stack and therefore worthy of investigation as an emergent theme.

Emergent Theme in Table 3.3: People, Process and Infrastructure

In contrast to Table 3.1 and 3.2, the representation of PPI elements are more weighted to “people and infrastructure” interactions [81 – 85] and “infrastructure and process” interactions [83, 85 -89 and 92 – 94]. There are only three interactions that include all three PPI elements [85, 88 and 90]. This indicates that more of the MarTech stack doesn’t require human interaction or day-to-day management by a human. The human interactions within AI are focused solely in generative AI, which would manifest as prompting the AI. People interaction also only appears to be focused to the front of the MarTech stack [81 – 85] where additional human oversight would be required for creative purposes. The People element doesn’t touch CRM [93] and Analytics [94] as AI used here has already been coded and would be automated for usage. It appears from the literature that process isn’t as pronounced when generative AI is in usage [81 – 84], this will be investigated as part of the primary research as an emergent theme to investigate if processes are in place to regulate human usage of generative AI.

The emergent themes identified in this section are cross-referenced against the emergent themes from section 3.4 and 3.5 to produce the final emergent themes in 3.7 that are used as additional focus areas within the qualitative research methods.

3.7 3D Core Concept Interaction: MarTech Stack, Marketing Customer Journey and Type of AI

Tables 3.1, 3.2 and 3.3 show the 112 interactions between the PCF core concepts, but they remain devolved. Making it one view (table 3.4), shows a 3-dimensional representation of the three core concepts of types of AI, the MarTech Stack and the Customer Journey and the interplays between their typologies. If Table 3.4 is illegible for reading, please refer to tables 3.1 – 3.3 for clarification.

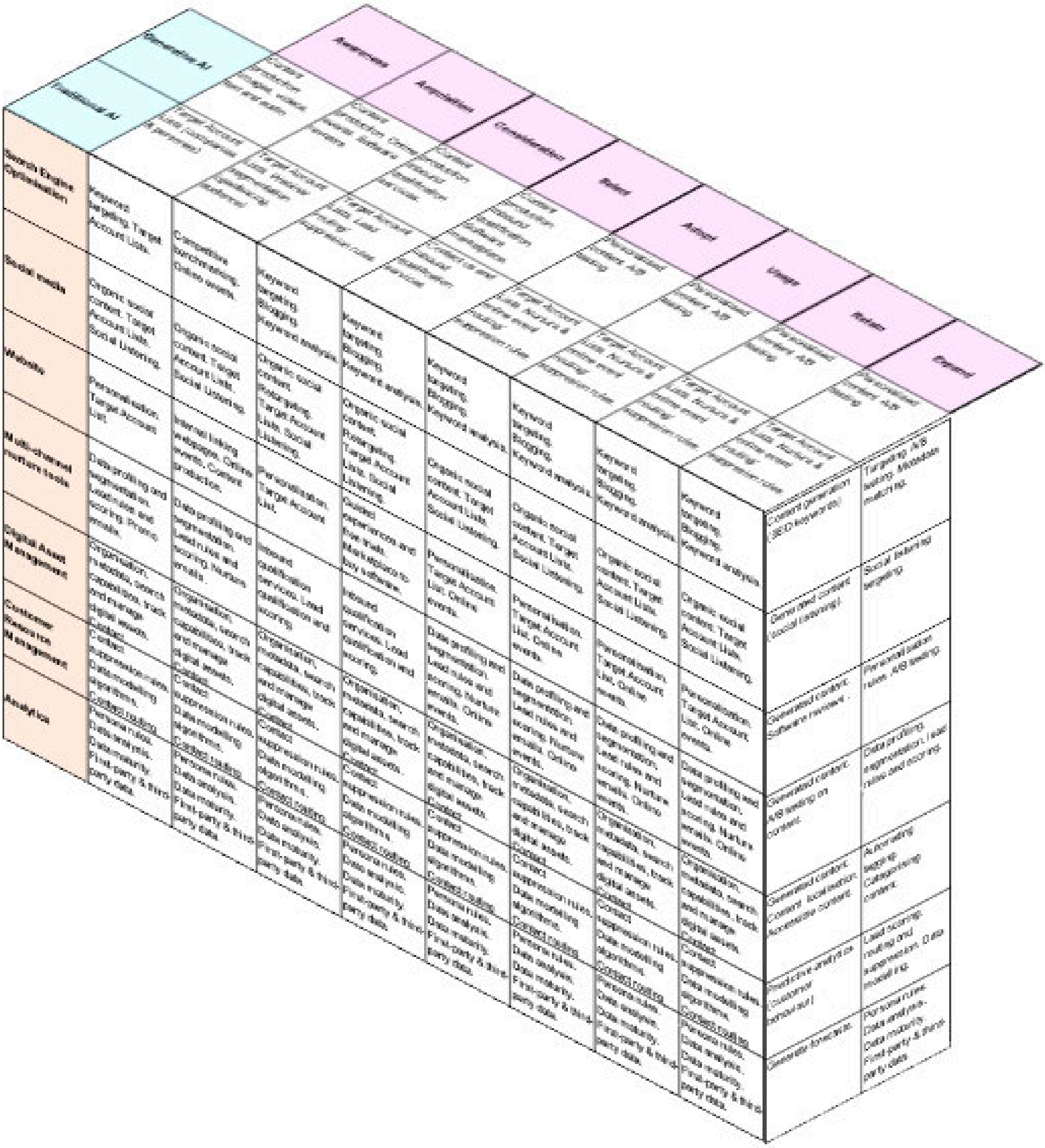


Table 3.4: 3D Model of the Core Concept Interactions

The emergent themes from Tables 3.1, 3.2 and 3.3 are used as focus areas within the design of the questionnaire and interview questions. It was important to identify any additional areas of interest from the core concepts to be explored within the primary data. While it has added additional complexities to this research by adding in additional emergent themes, the research objectives are complex and therefore the complexities within each core concept required further exploration. By structuring the literature against the PCF core concepts as the cross-tabulations in tables 3.1 – 3.3 it allowed for additional review and rigour against the selected literature. If the themes were repeated in Tables 3.1, 3.2 or 3.3 then they were included as emergent themes – if they did not repeat, they were excluded. Mapping the literature correctly against the concepts and exploring additional and repeated themes within these tables gives confidence in the selection of the core concepts themselves.

Throughout Table 3.1, 3.2 and 3.3 the reoccurring emergent themes have been identified – giving 10 emergent themes. However, this would be too many to take forward with regards to additional complexity and many of the emergent themes either overlapped or complimented each other. Therefore, four emergent themes have been identified throughout sections 3.4, 3.5 and 3.6 these are: ‘Pre-Sale Customer Journey’, ‘Targeting and Testing’, ‘Analytics and Predictions’ and ‘Content Generation’. These emergent themes will be incorporated as additional focus areas for analysis within the primary research.

Emergent Theme #1: Pre-Sale Customer Journey

The pre-sale part of the Marketing Customer Journey (awareness, acquisition, consideration and select) has more nuanced interactions than the post-sale portions (adopt, usage, retain and expand). Post-sale marketing tactics utilises the same marketing mechanisms as the pre-sale portion (i.e. nurture email and webinars) and so can be investigated as part of the interview process and applied to the post-sale afterwards. Focusing on the pre-sale will give the research the full overview of the marketing tactical mix, while reducing the focus to only four stages of the customer journey. Notable for the customer journey, there is a weighted representation for all three PPI areas across each stage, the interplay of how they interact will explored in the primary research.

Emergent Theme #2: Targeting and Testing

Focus on correct personalisation and targeting was a reoccurring interaction in the core concepts and relates to all three concept areas. The capability of the MarTech Stack is in its detailed ability to target. Specific targeting occurs across the different stages of the customer journey, and traditional AI utilises machine learning targeting. The focus in tables 3.1 – 3.3 on targeting showed it aligns with infrastructure and process repeatedly. For personalisation targeting and testing it also aligns with people, as the marketeers themselves need to select and manage the personalisation content, specific targeting and monitor progress.

Emergent Theme #3: Analytics and Predictions

The importance of analytical predictions is found throughout the interaction tables and the PPI weighting shows a higher weighting to process and infrastructure within the DAM, CRM and Analytical part of the MarTech Stack. This software processes the profiling, scoring, routing and forecasting for customers on their pre and post purchasing journey. The interactions mostly happen within a traditional AI landscape.

Emergent Theme #4: Content Generation

All content creation interactions included both people and infrastructure – people for the marketer using the technology and infrastructure for the MarTech capabilities. Identifiable processes were not always found for generative AI uses (text, image, audio and video). The use of this generated content was found across all stages of the customer journey, but only in the front view of the MarTech stack – where externally facing channels (such as social media and SEO) are used.

The structure of the thesis analysis and how they align to the research objectives can be identified in Figure 3.2. Each stage shows the research objective mapped to the analysis method used and chapter it relates to. It diagrammatically shows the linkage between the core themes identified from the literature review and from this PCF chapter. The result of the core themes of the literature review were to inform the structure of the PCF. The core and emergent themes of the PCF will inform the questionnaire and interview design and focus areas. The justification for why there are emergent themes identified is found throughout this chapter. This figure enables a simplified view of the complex data analysis methods deployed throughout the research, and that are explored further in chapter 4, Methodology.

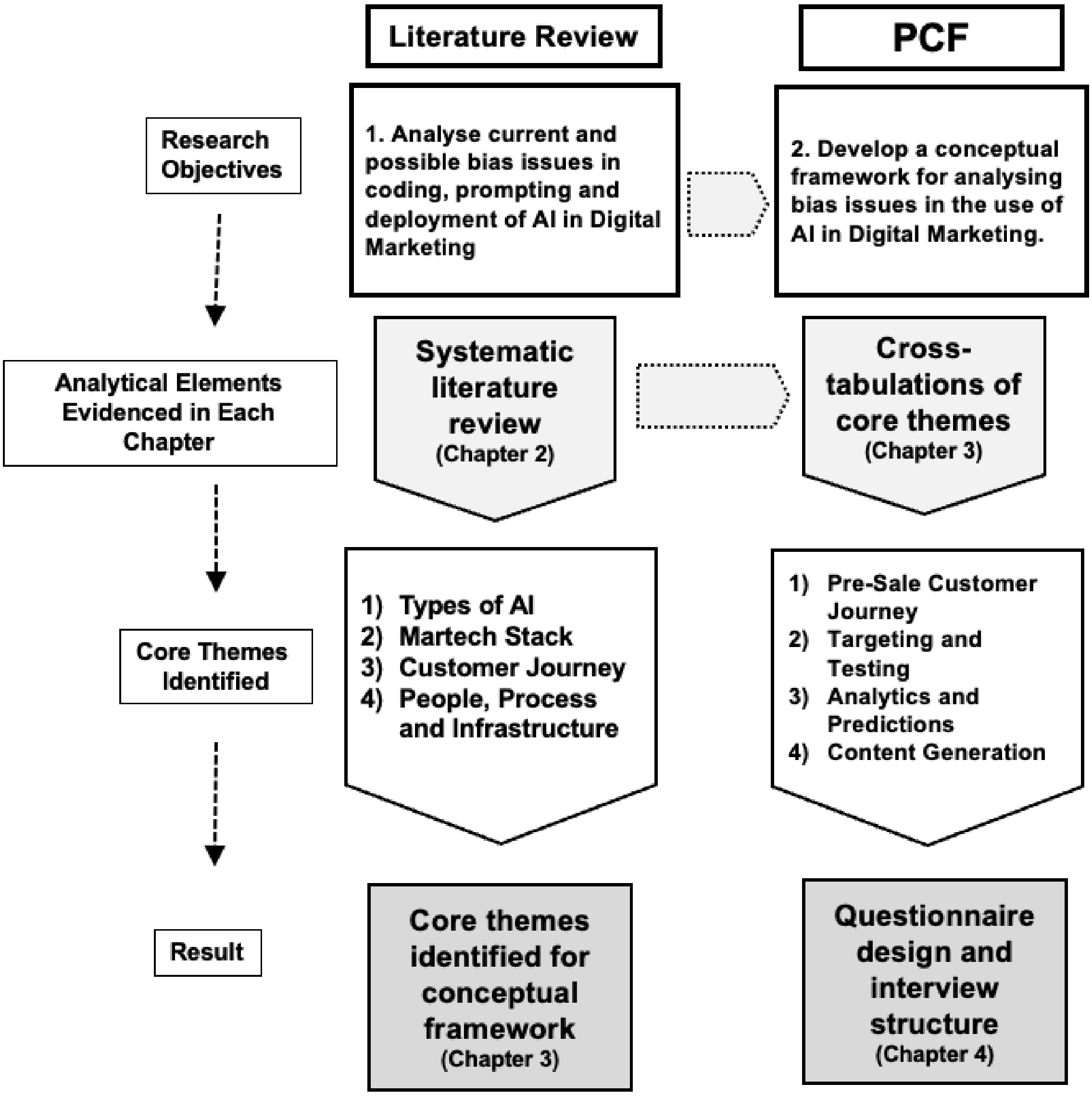


Figure 3.2: The Research Methodology Flowchart

(Source: Thesis Author)

3.8 Chapter Summary

In this chapter, a Provisional Conceptual Framework (PCF) was created to address RO2 to develop a conceptual framework for analysing bias issues in the use of AI in Digital Marketing. This PCF was designed to fill the research gap identified in the literature by integrating the previously separate literature framework areas of AI, marketing, and bias into a single comprehensive model.

Section 3.2 introduced the PCF structure and section 3.3 justified the selection and representation of four core concepts in the PCF. The PCF structures the four core concepts from the literature review: types of AI, the technology of the MarTech Stack, the stages of the Marketing Customer Journey and the elements of People, Process and Infrastructure. The PCF highlights the critical distinction between generative AI (focused on content creation) and traditional AI (focused on algorithmic rules), noting that both play significant roles in enhancing marketing effectiveness. These two AI types intersect with the MarTech Stack and the Marketing Customer Journey at multiple points, shaping how marketers reach and engage with consumers. The elements of People, Process, and Infrastructure were integrated into the PCF, underscoring their significance in shaping AI-driven marketing practices. These elements highlighted how human involvement, structured processes, and technological infrastructure interact to influence AI's role in marketing. The PCF also represents bias as implicit within AI due to the literature review showing how bias is already proliferated from being coded either with bias or through biased data.

Through the cross-tabulation analysis of the core concepts in sections 3.4 – 3.7, four key emergent themes were identified. This was achieved by mapping literature to each of the core concept interactions and adding additional colour coding for PPI representation. These emergent themes are: 'Pre-Sale Customer Journey', 'Targeting and Testing', 'Analytics and Predictions', and 'Content Generation'. The Pre-Sale Customer Journey emerged as a focal point due to its nuanced interactions. Targeting and Testing emphasised the need for precise personalisation and audience engagement strategies. Analytics and Predictions demonstrated the importance of scoring and profiling across the marketing journey, and Content Generation underscored the role of AI in producing personalised and scalable marketing content. These emergent themes are used as additional focus areas to explore when creating the questionnaire and interview questions in chapter 4, Methodology. This chapter serves as a foundation for the further primary research, where the PCF will be validated and refined – this will ultimately contribute to a more comprehensive understanding of AI's impact on marketing practices.

CHAPTER 4: METHODOLOGY

4.1 Chapter Introduction

This chapter sets out the overall philosophy, research paradigm and explains the method of primary research that will be used to capture and analyse the data required to answer RO3 – to deliver a model for revealing and mitigating bias in AI deployment in digital marketing. Throughout this chapter the methods used are justified by clearly showing their link to the research objectives, literature (chapter 2) and the PCF (chapter 3).

Figure 4.1 shows the three research objectives for this thesis - this research's second objective is to "develop and validate a conceptual framework for analysing bias issues in the use of AI in Digital Marketing". This research so far has been conducted as inductively for theory development - having leveraged literature research to produce a PCF. This methodology chapter continues with phase 2 (figure 4.1), to prepare for the interviews with 15-20 industry professionals. The research aimed for 15-20 interviews - the number achieved was 18. The research tests the conceptual framework for robustness and applicability across industry by focusing on the core concepts from the PCF and literature review.

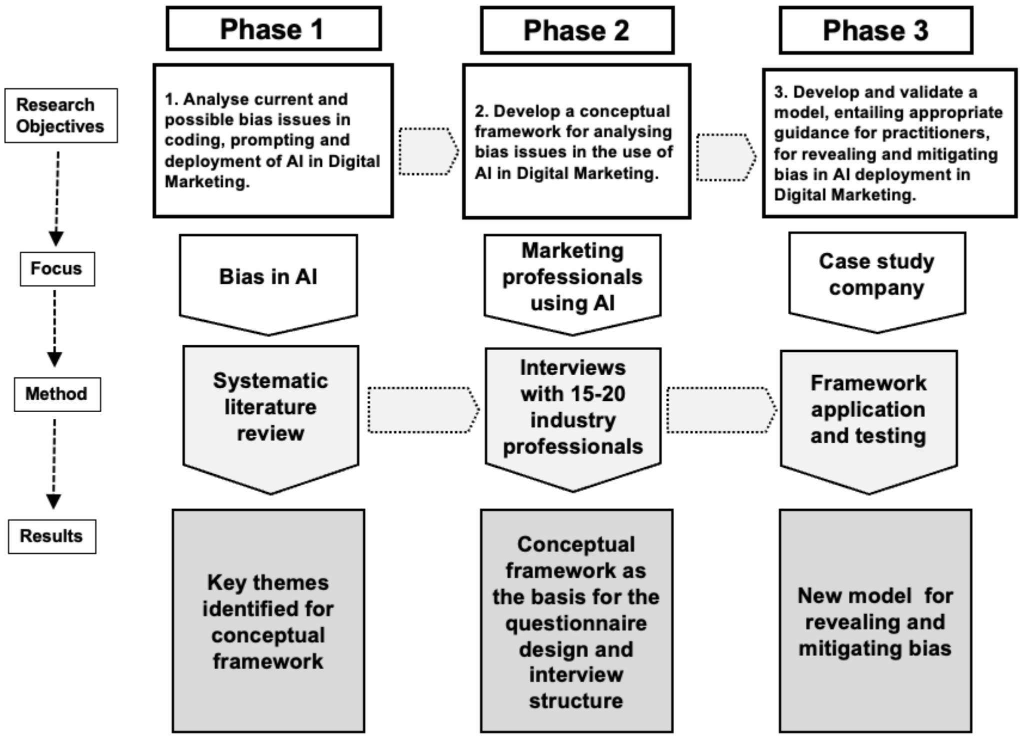


Figure 4.1: The Research Process Flowchart - brought forward from chapter 2 for reference.

(Source: Thesis Author)

The methodological and philosophical frameworks for this research are modelled on and organised in alignment with the research onion concept by Saunders et al. (2012) (figure 4.2). Highlighted on Figure 4.2 are the methodological choices selected for this research. The structure of this chapter's topics aligns with the research onion to give structure and alignment to give a clear vision on the methodological goals and how it will occur. This structure offers a comprehensive approach to developing and presenting a methodology in research. The model is widely used because it provides a clear framework that will allow the researcher to systematically work through each stage of the research process, ensuring that no critical aspect is overlooked.

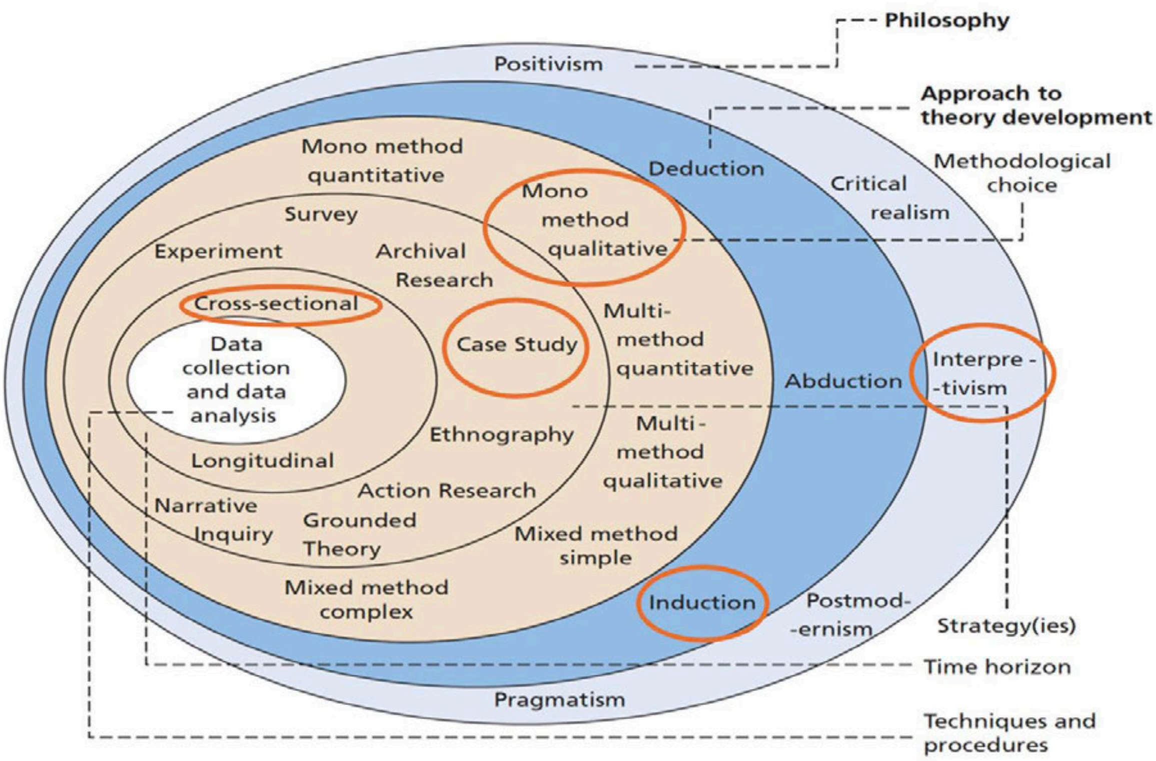


Figure 4.2: Research Methods - Research Onion (methodological selections highlighted)

Sourced from: Saunders et al. (2012)

The Research Onion is divided into layers, starting with the most general aspects of research (philosophies) and gradually narrowing down to the most specific details (techniques and procedures). This layering helps this chapter to be logically organised - beginning with the research philosophy (e.g., positivism, interpretivism) and moving through stages like research strategies (e.g., experiment, survey) and data collection methods. This hierarchical structure encourages careful consideration of each stage's impact on subsequent decisions, promoting coherence between the research's theoretical underpinnings and its practical execution. It also promotes critical thinking, as the researcher will justify each methodological choice, aligning it with their research objectives.

This chapter is divided into nine sections. After this introduction, section 4.2 sets out the philosophy of this research. Section 4.3 covers the approach taken to research theory. Section 4.4 identifies the methodological choice, with section 4.5 justifying the methodological strategy chosen. In section 4.6, the time horizon for this research is reviewed. In section 4.7, the data collection strategy is established and reviewed, focusing on the ethical conduct of the researcher, the design of the pre-interview questionnaire, and the interview structure. Section 4.8 goes on to establish the data analysis strategy once the data is collected. This covers the pre-interview questionnaire analysis method, interview data analysis method and the data analysis conducted to validate the final model of this research that will ultimately address RO3 (figure 4.1). This chapter is then concluded with section 4.9, the chapter summary.

4.2 Research Philosophy

The thesis is set in the Interpretivist paradigm; the researcher's viewpoint aligns with the philosophy that delving into the complex interplay between human subjectivity, interpretive frameworks, and contextual understanding of the social world (Schwandt, 1994) will be imperative to explore the experiences and interpretations that shape marketeers' interactions with AI technology.

Conducting research within the interpretivist paradigm is highly appropriate for complex topics, especially when a conceptual framework guides the investigation (Omodan, 2022). The interpretivist paradigm is rooted in the belief that reality is socially constructed, and knowledge is subjective, influenced by individuals' experiences and interactions with their environment (Creswell & Poth, 2018). This philosophical orientation allows deeper analysis of complex topics involving human behaviour, and processes, by considering multiple perspectives and subjective interpretations (Merriam, 2009). Complex phenomena often involve intricate and interwoven variables that cannot be easily disentangled or quantified. Here, such complexity is exemplified by the PCF built on three core concepts (Type of AI, MarTech Stack and Customer Journey) giving 112 interactions, and two further concepts to explore in the primary research - Bias and People, Process and Infrastructure. Rather than seeking to generalise data, interpretivist research aims to provide rich, nuanced descriptions of specific contexts (Berger, 2015).

When building the research conceptual framework, interpretivism was particularly useful in providing a structure that guides the research without imposing rigid hypotheses - the research remains flexible and will evolve as the study progresses (Ravitch & Riggan, 2017). The researcher will use the PCF to guide their research but due to their interpretivist stance, it remains open to new understandings and interpretations that emerge from the data.

The interpretivism paradigm also aligns well with qualitative methodologies, such as case studies, which is this research's strategy. Utilising a case study strategy will allow the researchers to collect detailed, contextualised data through interviews, observations, and document analysis – this is explored further in chapter 4.5. In interpretivist research, meaning is co-constructed between the researcher and participants (Stake, 1995). Researchers do not remain detached observers but engage with participants to understand their lived experiences. This will be of great importance to test the PCF against a real-world experience to produce the final model that can be used across the industry.

For this research analysis bias propagation within the core concepts identified involves exploring the intricate relationship between human subjectivity, interpretive frameworks, and how individuals understand their social reality (Schwandt, 1994). By focusing on the importance of subjective meanings and interpretations in understanding social phenomena, the researcher can analyse the complex dynamics between individuals and their sociocultural environments (Geertz, 1973).

4.3 Research Theory Approach

The research applies inductive reasoning to provide a comprehensive understanding of such a new and complex area (Newman, 2000). Inductive research aligns with the Interpretivist stance of the researcher, to explore and interpret parallel research areas to glean insight into other studies and AI scenarios. Inductive research accurately identifies risks, opportunities, and key themes within research areas to positively impact a final research output that can be used in “real-life” scenarios (Woo et al., 2017). Inductive research methods are a key approach commonly used in marketing research for theory development (Osman et al., 2018). Inductive research starts from the data and induces theory by interpretation of the data – the adoption of an interpretivist stance by the researcher supports an inductive approach for this research.

Beginning with RO1 the researcher inductively developed a theory from the literature to create the PCF and then use empirical data to develop a new theory (Newman, 2000). This approach is valuable for the researcher to interpret existing theories and core concepts defined within the PCF in a structured way. Because the researcher is interpreting the PCF, this structure allows for a set process of data collection across respondents that leads to credibility of findings, making it well-suited for case study analysis (Osman et al., 2018). Inductive research is especially valuable for exploring new and emerging phenomena as it uses specific observations to develop theories from the bottom up (Cova et al., 1994). It supports the visibility into emerging trends to support the outcomes of the researcher (Hyde, 2000). This approach aligns with the researcher’s interpretivist philosophy to explore and interpret new information.

Inductive research is also useful at uncovering unexpected patterns or insights within data to support the final output of the research framework; it allows for the identification of novel applications, challenges, and opportunities that may not have been previously considered by the researcher. This process will be time-intensive for the researcher, and this detailed review may lack generalisability as it will be context-specific, however, the research objectives are niched to a specific industry area so any new findings will generally still apply to the broader marketing industry.

The open-ended nature of inductive research can lead to subjective interpretations by the researcher that can undermine and potentially affect the reliability of the research output (Cova et al., 1994). The researcher aims to build credibility and trustworthiness by being clear about the methods used to collect and analyse data throughout this research. The researcher will draw on previous research experience, as well as the experience of their supervisors to rigorously examine outcomes from the inductive approach taken for the final framework output. This is also supported by the researcher interpretivist philosophy that encourages reflexivity - where researchers continuously reflect on their own biases, assumptions, and the research process itself. Reflexivity is essential in complex research topics because researchers' backgrounds can influence how they interpret data and construct meaning (Berger, 2015). Through reflexivity, researchers maintain awareness of their subjectivity and strive to present a balanced interpretation of the data, acknowledging the multiple realities of participants.

4.4 Methodological Choice

The literature review (chapter 2) depicted the integration of generative AI into digital marketing as a nascent frontier primarily due to limited awareness, technical complexities, data privacy concerns, resource intensiveness, and the absence of standardised practices (Dwivedi et al., 2023). Considering the complex nature of the research goal to develop and validate a new model for revealing and mitigating bias of AI in Digital Marketing, a cross-sectional mono-method qualitative case study approach has been selected as the research method (Saunders et al., 2012). Data for this research is collected via a case study on the company CSC and this is explored further in section 4.5.

Mono-method qualitative research ensures methodological consistency by employing one approach throughout the research (Creswell & Creswell, 2017). This uniformity simplifies the processes of data collection and analysis, reducing the likelihood of confusion and increasing the reliability of the findings (Yin, 2009). This is particularly relevant in the context of AI usage in marketing, which remains in its early stages of adoption. As explored in the literature review (chapter 2) the current academic research is limited, and relying solely on quantitative data collection (such as large-scale surveys) would not allow for the exploration of the nuanced and complex nature of the research area (Saunders et al., 2012). While the systematic literature review can be used as a basis for conceptual framework development, Brunton et al. (2020) propose that in nascent research areas “stakeholders' views are employed either as participants in the research process or as the phenomenon under study” (Brunton et al., 2020, p. 16). Stakeholder involvement is essential when testing the PCF as a key stage in the development of the final model output.

The chosen qualitative research method for this thesis is one-to-one, semi-structured interviews. It is a two-part data gathering process where the interviews explore responses to a questionnaire (see section 4.7, Data Collection Strategy). These types of targeted interviews, conducted with care and purpose, enable researchers to ask insightful questions, especially when delving into complex issues (Robson, 2011; Easterby-Smith et al., 2008). Interview respondents with insider knowledge are generally more willing to participate in qualitative research as it provides an opportunity to uncover information that might otherwise remain hidden (Saunders et al., 2012). As the researcher is leveraging personal connections within CSC to interview, they gain access to valuable information (Easterby-Smith, 2008).

The participants for this qualitative research are from CSC, and the majority fit the select group of demographics of marketeers that was explored in section 2.3.2.1 of the literature review (i.e., white, and middle-class). Wöhrer (2016) argues that female perspectives are on the “periphery” of reality, as reality is a patriarchal standpoint. This includes women’s experience of work, putting female marketeers at the periphery of reality, and their marketing practices and decisions they make compared to their male colleagues; this will be relevant to explore during research collection dependent on respondent gender.

The participants are marketeers from CSC, with participants selected from the three marketing departments: Product Marketing, Corporate Marketing and Field Marketing. Product Marketing teams are responsible for effectively conveying a product's unique value to both customers and internal teams - identifying customer challenges, demonstrating how the product addresses those needs, and highlighting what differentiates it in the marketplace. These teams drive the messaging, content and value proposition strategy. Corporate Marketing are the teams responsible for the promotion of a company’s products – taking the strategy from Product Marketing to drive digital sales with a primary emphasis on establishing a strong brand identity and fostering customer relationships for brand loyalty. Field marketing is the “local” selling of the Product Marketing strategy that brings products directly to consumers in real-world settings - such as retail locations, events and corporate hospitality. These efforts typically involve activities like Account Based Marketing, product demonstrations, and direct sales promotions.

Figure 4.3 shows how these three departments go-to-market – all three are equal peers and report to the Chief Marketing Officer. Product marketing produces the marketing content that is used across the full pre- and post-sale customer journey. Corporate Marketing’s jurisdiction covers digital marketing channels and Field Marketing’s is in-person marketing. Depending on the customers’ needs both Corporate and Field Marketing could be involved in a customer’s journey. An example of this is the customer begins on digital exploration and then through digital invitation attends an in-person event and buys the product. Or just one department can be involved – an example of this is that a customer requests a digital product demo and then buys the product directly with a sales rep (this is then solely done via Corporate Marketing). An example for Field Marketing's involvement is that a customer is targeted by Account Based Marketing, attend an in-person event and buy from a local sales rep. By selecting respondents from these departments, it gives the researcher a balanced cross section of interviewees – with each marketing department represented and explored. The full MarTech Stack works across all three of these departments as CRM is the basis for all the MarTech data. Exploring participants who work in all departments that use the MarTech Stack is important so there are no data gaps for the primary research.

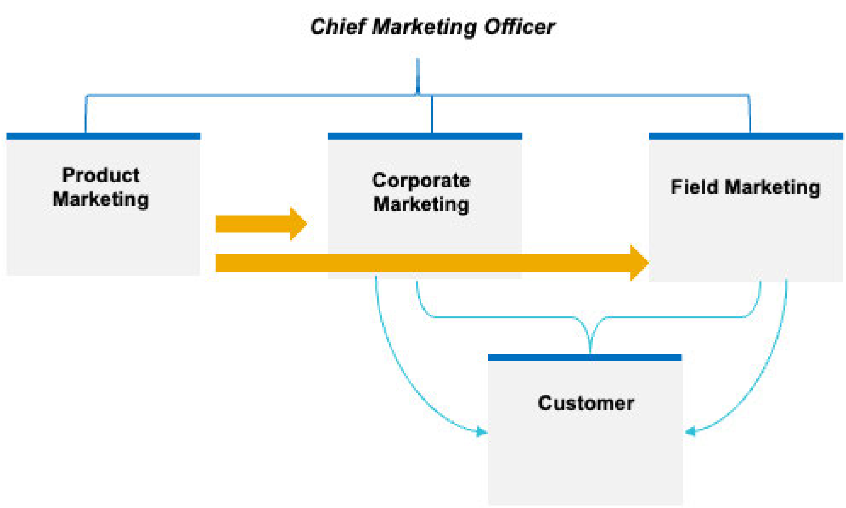


Figure 4.3: Organisational chart showing go-to-market structure for CSC marketing departments

Sourced from: Thesis Author

All interviewees have between two years to thirty years' experience within marketing to provide a cross-section of experience. Table 4.1 shows the respondents experience and current usage of AI within their role in digital marketing. Quantifying experience and time in marketing is an interesting avenue to explore for data analysis – under two years' experience is not appropriate as the marketeer would not be included in AI projects or have the experience relevant to understand a new technology implementation. As well as experience differences, participants are selected from a range of roles from individual contributor to executive management to attain a wide spectrum of data to analyse all hierarchy viewpoints. Executive management have insight into upcoming strategic decisions, budget restrictions and personnel areas – whereas an individual contributor will have a lived experience insight into how the technology is being used by marketeers. All participants must use AI either within their role or have been on a project that implemented AI into being used within CSC marketing. This allows for real-world examples and insights to test the PCF – rather than hypothetical answers from someone who doesn't fully understand the capabilities of AI. The participants will be coded for anonymity as a simple Respondent # - R01, R02, R03 – as seen in the first column of table 4.1.

Respondent Code	Job Profile	Years of Experience	Knowledge of AI
R01	Strategic Marketing Project Manager	3 Years	• Led project that implemented AI into a marketing function. • Uses AI in daily role for administration.
R02	Marketing Program Lead	13 Years	• Uses AI in daily role for administration.
R03	Content Marketing Lead	12 Years	• Contributor to projects that implemented AI into a marketing function. • Uses AI in daily role for administration.
R04	Integrated Marketing Program Management	10 Years	• Contributor to projects that use AI for content production. • Uses AI in daily role for administration.
R05	Marketing Localization Strategy Lead	15 Years	• Led project that implemented AI into a marketing function and content production / translation.
R06	Marketing Content Operations	16 Years	• Uses AI in daily role for administration.
R07	Paid Social Specialist.	2.5 Years	• Uses AI in daily role for text generation used within social media. • Uses AI in daily role for administration.
R08	Integrated Media Manager	12 Years	• Uses AI in daily role for text generation used within social media. • Uses AI in daily role for reporting and data insights. • Uses AI in daily role for administration.
R09	A/B Testing and Optimization Specialist	4 Years	• Uses AI in reporting and analytics for administration.
R10	Global Head of Field Marketing Event Management	10 Years	• Uses AI in daily role for content generation for events (text and video) • Uses AI in daily role for administration.

R11	Marketing Director	14 Years	• Uses generative AI in daily role within the MarTech stack. • Uses AI in daily role for administration. • Uses AI in daily role for project management.
R12	Integrated Media	17 Years	• Uses AI in daily role for administration. • Uses generative AI within MarTech stack for social media.
R13	Analytics and Reporting	10 Years	• Uses AI in daily role across the full MarTech stack. • Uses AI in daily role for text generation.
R14	Senior Digital Marketing Project Manager	10 Years	• Uses generative AI in daily role for content generation. • Uses AI in MarTech Stack for data analysis. • Uses AI in daily role for administration. • Uses AI in daily role for localization.
R15	Global Nurture Marketing	14 Years	• Uses AI in role for administration. • Uses AI in MarTech Stack for localization.
R16	Webinar Channel Lead	6 Years	• Uses AI in daily role for administration.
R17	Respondent removed from interview list due to not matching AI usage criteria.		
R18	Paid Social Manager	5 Years	• Uses generative AI in daily role for content generation. • Uses AI in MarTech Stack for data analysis. • Uses AI in daily role for administration.
R19	Paid Search Channel Lead	6 Years	• Uses AI in daily role for content creation used within paid media. • Uses AI in daily role for reporting and data insights. • Uses AI in daily role for administration.

Table 4.1: Respondent profiles and their knowledge and usage of AI

Prior to the interviews a questionnaire was shared with the respondents to be completed before the interviews themselves. The questions that were asked on this questionnaire are scoped and justified in section 4.7. This was to prepare the researcher to conduct the interviews and offers several benefits, enhancing both the quality and efficiency of data collection. Using a questionnaire helped to streamline the interview process by allowing the researcher to gather initial, standardised information from participants, which can inform the direction of the subsequent interviews. According to Bryman (2016), questionnaires provide structure, allowing the researcher to focus interviews on deeper, more nuanced issues that require detailed exploration; they can also help identify themes early in the research process. Gaining focus areas within this research has proved challenging with multiple focus areas giving varied topics to investigate. Utilising a questionnaire only to interviewees gives preliminary data to help the researcher develop tailored interview guides (Creswell & Creswell, 2017).

This approach supports the interpretivist paradigm of the researcher to guide them in interpreting the data in an inductive way. Having responses from questionnaires helped the researcher avoid leading questions during interviews – supporting their research knowledge and promoting more valid and reliable findings (Kvale, 2007). Using a questionnaire before an interview encourages participant engagement as interviewees are better prepared and more comfortable during the interview (Gill et al., 2008). Combined with an existing relationship with the researcher this approach facilitated a more focused discussion.

Once the questionnaire was completed and the researcher had reviewed the data to finalise the interview focus areas, the interviews commenced. The interviews were semi-structured around six to ten questions based on questionnaire topics, allowing respondents the flexibility to share their thoughts and insights (Mason, 2007). To alleviate any concerns, the interview topics were sent to participants in advance as a pre-read; however, the full list of questions was not shared beforehand to prevent participants from preparing scripted answers. While structured questions may be criticised for potentially steering the conversation into specific areas (Creswell & Creswell, 2017), they facilitate the exploration of key themes. It is crucial for the researcher to remain skilled in allowing room for additional topics to emerge (either from the questionnaire or within the interviews) and to minimise proximity bias from their prior relationship with the respondents. It is also important that the researcher creates depth through probing questions.

The use of qualitative interview methods enables the in-depth exploration of participants' perspectives, offering valuable insights into the experiences, attitudes, and perceptions of marketeers (Belk, 2006). Given the need for interviewees to possess a relevant understanding and considering the sensitive and complex nature of this research, a smaller participant group is recommended for this research (Morse, 2000). Smaller groups foster stronger rapport between researchers and participants, leading to longer interactions and higher quality insights (Marshall et al., 2013).

Data saturation is anticipated to occur in this qualitative research with approximately fifteen to twenty respondents (Hennink & Kaiser, 2022). These interviews took place via virtual teleconference on Microsoft Teams, with each call lasting one hour. The aim of the semi-structured interviews is to gather a comprehensive view of CSC’s implementation and governance of generative AI, exploring ethical considerations, bias, and personal and business perspectives - with access to insights unavailable to external researchers.

As noted by Islam and Aldaihani (2022), qualitative research does not normally include a large sample of a population because the collected data are not quantifiable. Another perspective is provided by Guest et al. (2006, p. 59), who found that, in the context of qualitative interview-based research, “saturation occurred within the first twelve interviews”. This is reinforced by research from Hennink and Kaiser (2022) that shows that qualitative studies reach saturation of data between nine and seventeen interviews. As this research has eighteen full interviews gives confidence to gaining data saturation for this topic. The heterogeneity of the respondent profiles was explored in table 4.1. The interviewees were selected because of their “particular features or characteristics which will enable detailed exploration and understanding of the central themes and puzzles which the researcher wishes to study” (Hennink & Kaiser, 2002, p. 78). The use of semi-structured interviews provides the opportunity for interviewees to provide their own perspectives on bias, possibly uncovering the less obvious aspects, giving them a “voice” in the study (Lee & Lings, 2008).

4.5 Methodological Strategy

Data for this research was collected via a series of qualitative interviews with respondents from one company, CSC. This research is positioned as a case study on CSC, due to the researchers access to the company and in-depth analysis on the specific subject of AI usage in marketing. Case studies are a valuable research method that is used across many academic fields (Hoon, 2013; Yin, 2018). Selecting a case study company is appropriate to use when examining complex phenomena being experienced in a “real-life” setting – it enhances the depth, credibility, and practical relevance of findings. Strategic management within a business setting is academically viewed as a complex research area - Hussey (2007) recommends using case studies to “untangle” complex areas. He likens strategic management to a tangled plate of spaghetti with no clear linear paths, just a complex intertwined web. Utilising the interpretivist paradigm within case study analysis allows the researcher to explore the subjective experiences of participants, offering insights into the meanings they ascribe to their actions.

The final model from this qualitative research will be applicable across the industry for companies to utilise for their marketing departments. It is important that the data captured can be used to generalise to industry, even though it comes from one case study company. The research sample in a case study differs fundamentally from a sampling unit in quantitative research, where statistical conclusions are drawn. Yin argues that “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” (Yin, 2018, p. 38). Case study research is not meant to represent entire populations but is a valuable tool to stress test research theories to design applicability in industry settings (Bloomberg & Volpe, 2019). Researchers can write statements within their thesis such as “this study was a small-scale study, and the results obtained cannot be generalized to another context” (Ting & Qian, 2010, p. 97) but this is too restrictive - some generalisation is acceptable if it is qualified.

The relevance of findings from a single case study across an industry often hinges on the concept of theoretical generalisability. Walker and Carr (2021) argue that a common misconception in case study research is that generalisations from research requires a large sample size through a quantitative study. They propose that generalisation and applicability across industry are derived from a series of replicative research – such as multiple interviews – to gather behavioural analytical generalisations. Explored in section 4.7 is the data gathering strategy, which includes both a pre-interview questionnaire and interview. The pre-interview questionnaire analysis shows behaviour generalisations that can be explored via the interviews. This detailed qualitative analysis, can identify nuanced dynamics that may be obscured in larger sample studies (Eisenhardt, 1989).

Flyvbjerg (2006) noted that case studies contribute to theory building, enabling the identification of patterns and principles that are applicable in similar contexts. This research will be applicable to companies in a similar context - with a digital marketing department using AI software. The modern customer journey is the same if you are selling software or shoes and the MarTech stack is the same interaction between marketing software no matter how many pieces of software you have in that stack. If marketing teams are using AI, they could be perpetuating bias through it and the final framework will support correct regulation – regardless of if the marketing team is made up of five or five hundred personnel.

The case study company for this qualitative research is an international enterprise software company. The company is anonymised in this study and will be referred to as the “case study company” or CSC. The CSC is an AI producer, with their own AI software, integrated into its comprehensive product suite. Employees are actively encouraged to embrace and learn about AI and use CSC’s own enterprise grade generative AI tool – this makes CSC an especially compelling case study company, as employees have direct exposure to cutting-edge AI technology. Its marketing department has approx. 3,000 people within it – this scope allowed the researcher to explore the full breadth of marketing, which can then be narrowed to the larger industry for smaller companies (Gerring, 2006).

Case studies are often linked with qualitative and inductive research and they are instrumental in theory building. By conducting an in-depth analysis of real-world examples, the researcher will map data to the PCF and refine existing literature theories (Hoon, 2013). In this study, the empirical evidence from CSC’s case serves as a valuable foundation for validating and expanding the core concepts within the PCF. However, insights gained from this case study data and qualitative research can be extended to the broader industry and utilised by different companies (Gray, 2021) - the framework output developed in this research will be relevant to the wider business to business marketing sector. Case study research on this complex topic enables the researcher to examine the interconnectedness of the core concepts and understand how they collectively impact outcomes (Bassey, 2002).

Gaining access to companies that develop and use AI is often restricted and is typically limited to researchers who are either employed by or closely connected to the organisation and its staff. Accessing these marketeers within one case study company enabled a deep contextual understanding of the applicability of the PCF. The PCF is complex and knowing that interviewees already understood the core concepts of the Marketing Customer Journey, the MarTech Stack and generative and traditional AI allowed deeper exploration of bias propagation and the concept elements of person, process and infrastructure. The researcher did not have to explain the definitions of the core concepts to the respondents or translate into a different “marketing language” for different companies. Analysis of core research areas can begin from the very beginning of the interview and will allow the researcher to examine the unique organisational culture that shape decision-making and performance (Hancock et al., 2021). It is crucial for the researcher to minimise the influence of proximity to the interviewees selected to avoid bias in data collection or interpretation (Bassey, 2002).

4.6 Methodological Time Horizon

The average research phase of a PhD thesis is between three to six years, with the duration for completing the full PhD research project taking between six to twelve years (NCSES, 2022). PhDs with extended timelines often have longitudinal research studies. However, given the emerging nature of research on AI in marketing, the primary research portion of this thesis was completed within six months and adopted a cross-sectional approach. This gives a timeframe of data collection between October 2024 and March 2025. The usage of generative AI within digital marketing remains a relatively untapped research area with significant potential (Stone et al., 2020). As AI technology is rapidly evolving and still in the early stages of adoption, longitudinal study findings risk becoming outdated. Therefore, a cross-sectional study is more suitable for this research, which aims to test the provisional contextual framework while it is relevant (Saunders et al., 2023).

Of interest to the researcher is understanding whether the adoption of AI by marketeers is at all related to the Adopter Categorisation curve seen in figure 4.4. Time horizons in technology adoption is a well-researched area with defined percentile rangers for those who are an innovator, early adopter, early majority, late majority and laggard adopters of technology (Rogers, 2003).

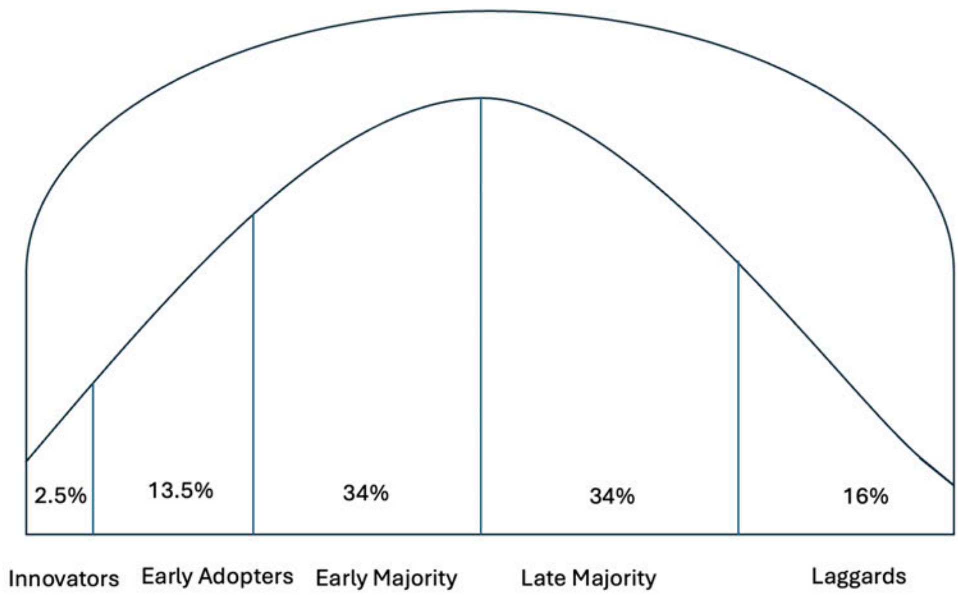


Figure 4.4: Adopter categorisation on the basis of innovativeness

Source: Thesis Author, based on Rogers (2003).

To be qualified to be interviewed for this qualitative research the respondents must all use AI within their day-to-day jobs. As explored in the literature review (section 2.3.2) females make up the larger percentage of marketeers and it will be reviewed within the data analysis if the adoption curve of usage or the marketeers' demographics have an impact on the data. While it was reported in the literature review that women are adopting AI technologies at a lower rate than men (Costa, 2023; Conick, 2018), this changes amongst early technology adopters who tend to be younger with the gender split being typically more balanced (Li et al., 2008).

Even without AI, the digital marketing landscape is vast and constantly evolving with new technologies and ways to interact with customers. Many marketing professionals are still in the process of understanding generative AI and how it works, and many will not have explored its potential applications in marketing strategies (Conick, 2018). Before the widespread release of open AI platforms in 2023, such as ChatGPT or Google Bard, marketeers utilising generative AI were primarily innovators and early adopters — individuals who often see themselves as "mavericks" (Schacht et al., 2015). Early adopters of innovative technology are typically younger, ambitious, and novelty-seeking emerging leaders (Tobbin & Adjei, 2012). However, with large companies now embracing enterprise grade generative AI and investing within AI enhanced MarTech Stacks the adoption curve has entered early majority (Singla et al., 2024). The CSC has given all employees access to an enterprise grade generative AI that utilises ChatGPT version 5 – allowing all within the company to embrace and use this technology. This is to compliment the traditional AI already in use within the MarTech Stack, such as Google SEO, Sprinklr Social Listening and website chat bots.

Company adoption of new technologies tends to mirror the individual employee's adoption curve when the appetite for use increases (Chui et al., 2023). Company CEO's play a crucial role in determining where the company and its employees fall on the adoption spectrum (Clarke, 2018). As explored in chapter 4.5, the CSC has AI technology at its core of all its strategic decisions. No reference is given to maintain the anonymity of the CSC.

Given the timeline of this research, it is likely that participants belong to the front end of the adopter categories: innovators, early adopters and early majority, and will approach technology usage differently than those in the late majority and laggards' categories (O'Leary, 2009). This gives a diverse interviewee selection within CSC which delivers data and insights on implementation requirements from those already using AI. While a longitudinal timeframe would cover the full adoption curve of AI usage in marketing to include the late majority and laggards, a cross-section study is more appropriate for this research. As explored in the Literature Review (section 2.6) there is currently no industry guidelines and governance for incorporating generative AI into marketing, and the direct output of this research is to produce a model to support mindful industry implementation. To do this requires research from the behaviour of early and early-majority adopters on how they are using AI within marketing. This can inform a robust framework that all companies can use no matter when their marketeers begin to use AI. This is especially true of laggard adopters who identify as traditionalists and require structure and guidance on how to use new technologies (Rogers, 2003).

4.7 Data Collection Strategy

As explored in section 4.4, the methodological choice for this research is qualitative, non-standard, one-to-one interviews that are semi-structured. A questionnaire was sent to respondents beforehand to support the researcher defining focus areas to be explored within the interviews and is reviewed in section 4.7.2. In nascent research areas, Brunton et al. (2020) argue that including stakeholders views into the research process, rather than just the output, will lead to better data quality as interviewees will be able to guide in new area exploration.

4.7.1 Credibility and Ethical Conduct

A Participant Information Sheet and Research Consent Form (appendix 2) was provided to all the participants. On the Participant Information Sheet their full rights were listed clearly, and all respondents were required to sign an acknowledgment of their full understanding. Only once their signed Research Consent Form was returned to the researcher they were sent the research questionnaire and their interview scheduled. Once their interview was completed, the participant was sent a Research Debrief Sheet informing them of their right to withdraw until a specified date. The researcher adhered to all responsibilities within the latest version of their University Ethics Handbook. As the researcher has connection to CSC an emic position is taken (Chenail, 2011), therefore, the researcher conducted themselves adhering to the full code of conduct; they understood that interviewees may experience a conflict of interest between personal and company viewpoints. Access to these participants has been agreed by CSC company management. None of the participants selected are direct reports to the researcher and none of the participants are direct management of the researcher. This is to maintain research integrity and limit a power relationship where a social-formative power over another could lead to incorrect research outcomes (Yin, 2018).

All communication from the researcher to the participants was honest and transparent (Driscoll, 2011). Every respondent was treated with respect, no deception and no harm came to them. Anonymity has been ensured throughout, with all data being treated confidentially, password protected on a personal laptop and will be destroyed when no longer needed.

4.7.2 Pre-Interview Questionnaire Design

Two questionnaires were utilised within this qualitative research. The first was a pre-interview questionnaire before all interviews took place, and the second was a validation questionnaire on the final model produced in Chapter 6 (reviewed in section 4.8.3). Using a questionnaire before interviews in research is a valuable strategy for the researcher. It gathers preliminary data to inform and guide the interview process to ensure that the interview questions are more relevant and focused, leading to more in-depth and meaningful data (Harris & Brown, 2019). As the interviews were up to one hour long the focus was on questions that will deliver relevant insights – rather than using that time on irrelevant questions. This questionnaire supported identifying common themes and patterns across the participants that enabled the researcher to prioritise the topics within the interviews to gain the most insight. Using a questionnaire also supports the researcher to build rapport with participants (Bell et al., 2022), giving interviewees a sense of what to expect during the interview and an opportunity to reflect on their responses beforehand. This resulted in more thoughtful and detailed answers during the actual interview, enhancing the quality of data collected.

The pre-interview questionnaire design and questions leveraged the four core concepts of the PCF (types of AI, customer journey, the MarTech Stack and PPI) and the emergent themes from the cross-tabulation analysis of the PCF core concepts PCF (Pre-Sale Customer Journey, Targeting and Testing, Analytics and Predictions and Content Generation). Exploration on bias was also included within the pre-interview questionnaire. Exploring these themes with respondents before the interviews provides a structured baseline for comparing interview findings (Harris & Brown, 2019). They serve as a reference point, helping the researcher to track changes or delve deeper into any inconsistencies, thus enriching the overall analysis and ensuring a more comprehensive understanding of the research topic.

Microsoft Forms was used to host the questionnaire as it is a cloud-based solution that is accessible for CSC employees. The design of the pre-interview questionnaire (appendix 3) is compiled of several different types of questions. Multiple choice, open text questions, ranking questions and Likert scale questions were utilised dependent on insight requirement. The ranking, Likert scale and multiple-choice questions gained structured, quantifiable data that was able to be analysed statistically as necessary throughout Chapter 6. The researcher used the ranking of topics to open an interpretive discussion with respondents. Examples of this are the Likert scale data showing the strength of agreement or disagreement on the inclusion of a core concept, and the ranking questions revealed the priority areas within an emergent theme topic.

The open text questions allowed additional qualitative insights and gave respondents the space to express opinions that the researcher explored during the interviews. This approach directly supported the RO2 by investigating the PCF core concepts and emergent themes within the interviews to validate their applicability in regulating bias issues in the use of AI in digital marketing. For additional validation and justification on why these questions were used, in appendix 4, the questionnaire questions are mapped to the PCF Core Concepts and Emergent Themes from Tables 3.1, 3.2 and 3.3. The third column in appendix 4 shows the justification on the question inclusion and what investigation the researcher wanted to achieve by including them.

Making sure that the pre-interview questionnaire was focused on the right topics was important. The second column in appendix 4 shows the link between the question and the PCF core concepts. The number of times a core concept is represented in this column has been tallied and is represented in figure 4.5. The analysis in figure 4.5 shows a simple pie chart view of the count of the PCF focus areas mapped to the questionnaire questions. The researcher has been careful about not leading the respondents into answers and therefore the number of questions with focus on Customer Journey Stage (5%) and MarTech Stack (8%) are relatively low to allow space for the respondents to explore the topics of bias (13%), People (20%), Process (22%) and Types of AI (32%). The researcher is inductively assuming that the Customer Journey and MarTech Stack play pivotal roles in answering the research objective – but by structuring the questions in this way allows space for other areas to be explored as part of the research interpretivist approach.

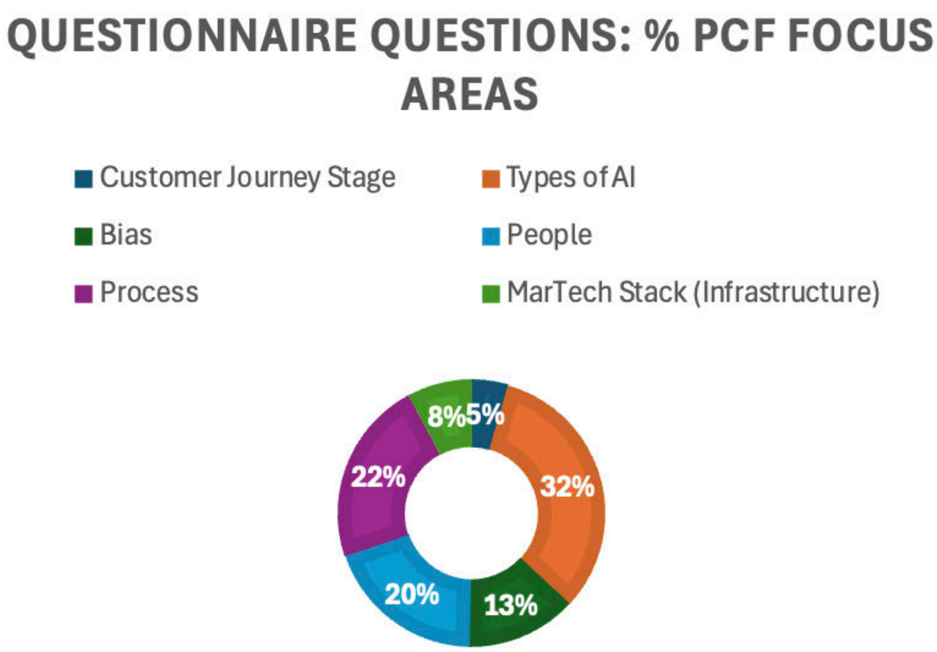


Figure 4.5: Simple pie chart showing the percentage of PCF focus areas represented in the questionnaire questions

Source: Thesis Author

4.7.3 Interview Design

Once the focus areas from the questionnaires were reviewed, the interviews were conducted. As noted in section 4.6, the timeline for the interviews to take place was between October 2024 and March 2025. The interviews conducted were up to one hour in length and were conducted via a virtual audio meeting on Microsoft Teams. They were one-to-one and semi-structured using the focus areas from the respondents' questionnaire as guiding themes to explore (Creswell & Creswell, 2017). This allowed the interviewees to know the exploratory areas before the interview to be able to provide detailed answers, and the interview allowed time to explore complex ideas.

As noted in section 4.4 eighteen respondents were selected for interview. When selecting respondents for these interviews, the researcher established a clear criterion to ensure relevant and valuable insights (table 4.1). Considering the research objective, all participants had to have direct experience and knowledge of marketing at CSC. This ensured the respondents understood the core concepts being explored and had relevant answers to interview questions. Respondents were expected to have knowledge of AI and have used it within their marketing efforts. The respondents included individuals with diverse perspectives to capture varied experiences with varying lengths of marketing tenure.

Depending on the themes derived from the pre-interview questionnaire, between 6 and 10 questions were asked to respondents during their interview. These questions focused on depth rather than breadth of insights that were applicable to the respondents answer and their job role focus. As these interviews were semi-structured, the questions asked by the researcher were open-ended to adapt to emerging themes, and probe deeper into participants' responses during the interview (Gill et al., 2008). The researcher gained rich and insightful data by keeping questions focused and flexible (Creswell & Creswell, 2017).

Through these interviews the researcher examined how participants understood and interacted with the four core concepts from the PCF and the four emergent themes from the PCF analysis (tables 3.1, 3.2 and 3.3). This knowledge is deeply analysed and justified throughout chapters 5 and 6. This method was particularly effective for the qualitative research, where understanding nuanced perspectives is essential for validating or refining theoretical models (Harris & Brown, 2019). This adaptability made it possible to gather rich, detailed data that revealed connections, contradictions, and gaps within the PCF. In chapter 5, Interview Findings, quotations from the eighteen interview transcripts are inputted into the cross-tabulations of the PCF (tables 3.1, 3.2 and 3.3) to clearly analyse the data for connection points and possible gaps. Utilising framework analysis as the analytical technique for qualitative data provides a structured and systematic approach for the researcher to manage and interpret qualitative data (Hackett & Strickland, 2018). It supports the identification of key themes while maintaining a clear and transparent design and is especially effective for handling large volumes of text from interviews. This data is then used to enhance and modify the PCF into the final model output of this research, which will address RO3.

4.8 Data Analysis Strategy

4.8.1 Pre-Interview Questionnaire Analysis

The pre-interview questionnaire (appendix 3) is comprised of tick boxes, open questions and Likert Scale questions and each was analysed in a different way. The main objective of analysing the questionnaires pre-interview was to gather data to inform the interview focus areas – it also supported validating that the respondents had experience of using AI in their job. The structured multiple-choice and Likert Scale responses were analysed for ranked data, percentage patterns, correlation analysis and comparisons of positive and negative sentiments (Creswell & Creswell, 2017). These visualisations supported the researcher in their manual data analysis - exploring emerging patterns and drawing connections between data points in both a narrative and visual representation. All questionnaires were completed and sent back to the researcher within 48 hours of the interviews so there was sufficient time for analysis. This questionnaire data analysis allowed the researcher to focus on gaps and ambiguities within the interviews which drove more meaningful dialogue (Patton, 2015). Inconsistencies with responses were also noted for follow up within specific participant interviews to attain why these had occurred (Boyatzis, 1998). The data analysis from the interviews was then more focused on answering RO3 for better overall research insights (Harris & Brown, 2019).

To analyse this questionnaire data effectively, the first step was to organise and clean the data. This involved reviewing the responses to ensure completeness, consistency, and accuracy, removing any irrelevant or duplicate entries. The data was exported into an Excel for analysis (Creswell & Creswell, 2017). The structure of the questionnaire remained the same within the Excel to maintain the core concept areas and allow for the researcher to review the answers for interesting insights, contradictions or topical areas. These areas of interest or contradictions were then explored within the audio interviews to be further analysed as part of the thematic interview analysis.

A pilot study was completed using the data of the first six interviews to give credibility to the pre-interview questionnaire and interview method (Reed et al., 2025). This pilot was published as an article, and it tested that the questions within both the pre-interview questionnaire and interviews were suitable and gleaned relevant data. This was successful and nothing methodical was changed and both the pre-interview questionnaire and the interviews remained the same.

4.8.2 Interview Analysis

The researcher interviewed participants with questions on focus areas identified from the questionnaire data analysis, as well as tailored questions from the candidates' own responses. By making space for their own experiences, the interviews were made engaging and relevant, enhancing rapport and yielding richer insights (Kvale & Brinkmann, 2015). Microsoft Teams was selected as the platform to host the interviews as it is well known by the respondents in CSC and for its automatic transcribing capabilities. Audio recordings were also taken of each interview; however, video was not recorded to maintain anonymity. Figure 4.6 shows an example of a transcript extract.

Researcher 21:01
That's excellent. And I'm assuming those alerts are within the software that you're using.

P02 21:05
Yeah, you can. You can set them up like in in some of those like model building tools, you can also set it up within the code, but yeah, it's like anomaly detection, stuff like that. So.
Yeah.

Figure 4.6: Example of a transcript extract (R02)

Interview data was thematically analysed in a manual review by the researcher from the transcripts – highlighting and colour coding themes within them. For this manual thematic analysis, the researcher utilised Terry et al.'s (2017) six-phase thematic analysis framework (figure 4.7) as the basis for their analysis method. The six phases are: 1. Familiarisation, 2. Coding, 3. Developing themes, 4. Reviewing themes, 5. Defining and naming themes and 6. Producing the report. The findings from the interviews thematically analysed in these steps are explored in chapter 5, Interview Findings.

1. Familiarisation	2. Coding	3. Developing Themes	4. Reviewing Themes	5. Defining and Naming Themes	6. Producing the Report
Immerse in the data, including transcribing, reading/re-reading, and noting initial ideas.	Systematic generation of codes; collate data relevant to each code; data reduction and pattern organisation.	Collate codes into potential themes; gather all data relevant to each potential theme; conduct analysis to refine themes.	Shape, clarify themes; further or reject; quality control of initial themes; add/subtract provisional themes.	Final list of themes; determine clarity and content for each theme; ensure clarity, cohesion, and provision of developed thematic analysis.	Connect data, analysis, and literature in a single output to answer the research questions.

Figure 4.7: Phases of thematic analysis

Source: Thesis Author, based on Terry et al. (2017)

There was the option for the researcher to also use software to support data analysis; however, manual data analysis was the only method selected. Webb (2001) recommends that researchers conducting small qualitative studies should use a manual data analysis as it supports the researcher's intuition that is not found in software analysis. Mason (2007) agreed and argued that manual review of data is preferable as it enables the researcher to explore the data to capture nuances and understand the tone of interviewees.

To cross-examine the research themes and patterns the researcher used the PCF cross-tabulations of the core concepts identified in the literature review (Tables 3.1, 3.2 and 3.3, chapter 3) and mapped in the thematic interview analysis for comparison. Manually, anonymised quotes from the participants were input into these cross-tabulations to explore relationships between the different variables and core concepts - providing insights into how responses vary across different participant groups. This comparison, explored extensively in Chapters 5 and 6, defines the final core concepts for the final model output of this research to address RO3. Using the cross-tabulations from Chapter 3 as a framework for the thematic analysis offers a clear process for conducting qualitative research (Smith & Firth, 2011). The cross-tabulation mapping of literature, researcher experience and thematic interview data to the frameworks gives transparent and trustworthy insights into the validation of the final model (Onwuegbuzie et al., 2012); especially helpful when managing and analysing large datasets and interactions - without losing sight of the original research questions (Srivastava & Hopwood, 2009).

4.8.3 Validation of Final Model

In Chapter 6, Analysis, Model Development and Model Validation, the final model is validated from the data analysis of the PCF and thematic interview data. The method employed was once again a manual data analysis method, instead of a software-supported analysis (such as by using NVivo) due to the process giving more data credibility and depth of understanding to findings (Webb, 2001; Mason, 2007). Braun and Clarke (2006) assert that thematic analysis conducted manually allows the researcher to immerse themselves intimately in the data, developing an understanding shaped by the lived experiences captured in the text.

Where algorithms seek patterns through rigid logic, human analysis embraces the ambiguity and nuance of language, culture, and context (Denzin & Lincoln, 2011). The act of manually coding data is not simply technical but interpretive; it demands that the researcher continually question their assumptions and remain sensitive to meaning-in-context. This iterative process supports theoretical insight, rather than mere pattern recognition - as diverse experiences of the interviewees give meaningfulness to this research (Saunders et al., 2023). Once the six-stage thematic data analysis was completed by the researcher and any gaps or enhancements to the PCF were noted through the cross-tabulation exercise, the researcher evolved the PCF into the proposed final model. This is explored in Chapter 6.

Analysing the data showed that the pre-interview questionnaire and interview data were similar, and that there was nothing of significance on the questionnaire replies that wasn't in the interview transcript itself. The data interpretation used within Chapters 5 and 6 was from the interview material. The questionnaires were used within this research as an initial "fact find" for the interviews and to get the respondents in the correct headspace for the interview.

To test the credibility of this final framework presented in chapter 6 an online survey was used. Microsoft Forms was used to create a simple Likert-scale questionnaire on the final framework (section 6.4). Using a Likert Scale to rank responses, supported the thesis author to treat the data as a structured prompt to elicit qualitative responses rather than as a tool for quantitative analysis. The responses ranged from strongly disagree to strongly agree on direct validation questions around bias and AI usage. A sample of eight respondents from the previous interviews were requested to participate in this questionnaire. Upon confirming their participation each respondent attended a 10-minute audio conference session on Microsoft Teams before they were sent the survey link. During this session the purpose of the survey was explained, the original PCF was revisited, and the proposed final operational model was presented. Before concluding the audio session, participants were asked to confirm they understood the requirement and any remaining questions were addressed. Respondents were then sent the survey link to complete. The questionnaire had a two-week window for completion and all requested participants responded. This survey took place two to five months after the in-depth questionnaire and interviews depending on the respondent.

4.9 Chapter Summary

This chapter provides a comprehensive and structured approach to the methodology employed by this research to ultimately address RO3 to validate a final model to mitigate bias propagation when using AI in digital marketing.

As explored in sections 4.2 – 4.6, this qualitative research is grounded in the interpretivist paradigm, emphasising the importance of understanding human subjectivity and experiences. This philosophical stance aligns with the objective to explore how marketing professionals interpret and interact with AI technologies, as these perspectives are crucial to addressing bias when prompting AI. A mono-method approach, with inductive reasoning, has been chosen to develop new insights by analysing emerging themes in a complex topic. The methodology adheres to the research onion framework (Saunders et al., 2012 – figure 4.2), ensuring a structured progression from research philosophy to data collection and analysis techniques.

The chosen time horizon is cross-sectional, enabling the research to capture real-time insights on the rapidly evolving field of generative AI in digital marketing. The researcher acknowledges that AI adoption trends vary among professionals making it essential to capture perspectives from different stages of AI adoption. This methodology chapter lays the foundation for an in-depth exploration of the research objectives - ensuring the final framework is validated, applicable, and adaptable across different industry contexts. The qualitative research emphasis on flexibility and reflexivity will ultimately contribute to a more nuanced understanding of AI usage in marketing and how bias propagation can be managed.

The data collection strategy established is that primary data was collected through a mono-method qualitative case study on CSC, where the researcher - leveraging an insider perspective – conducted eighteen one-to-one semi-structured interviews with marketing professionals. Prior to these interviews, a preliminary questionnaire was sent to each respondent to ensure focused discussions.

The data analysis strategy selected was a manual thematic six-stage analysis that focused on coding themes in the qualitative primary data to cross-reference with the data from the literature review used to validate the original PCF core concepts. The cross-referencing of this analysis is conducted in Chapter 5, Interview Findings, and it establishes gaps in the PCF and additional focus areas that are used to evolve the PCF into the final model.

This qualitative methodological and data analysis approach ensures an in-depth understanding of how marketing professionals at CSC engage with AI to contributing to the development of a robust, actionable model that addresses RO3 - to deliver a model for revealing and mitigating bias in AI deployment in digital marketing (figure 4.1).

CHAPTER 5: INTERVIEW FINDINGS

5.1 Introduction

In this chapter, findings from the eighteen questionnaires and qualitative interviews are summarised, analysed and compared. This chapter is divided into four sections. Following this introduction, section 5.2 lays out the thematic analysis of the interview data and the focus areas identified. These focus areas are justified with quotations. In section 5.3, the thematic analysis is cross-referenced with the cross-tabulations of the PCF from chapter 3 (that utilised the literature from chapter 2). This cross-referencing of the primary research and PCF core concepts is used to justify the final core themes from the interviews. In section 5.4, a summary of this chapter and a synopsis of the thematic research findings are presented.

Due to the complexity of the research topic with multiple areas of exploration, the analytical process pursued across this research is shown in figure 5.1. Figure 5.1 is brought forward from chapter 3 and has had the third column added to it. It details the core and emergent themes identified from the literature review, the PCF cross-tabulations and the interview findings within this chapter. This chapter initiates the thematic analysis of the primary questionnaire and interview data to present the interview findings. These findings are then explored through deeper analysis of the primary data in chapter 6 to evolve the PCF into the final model.

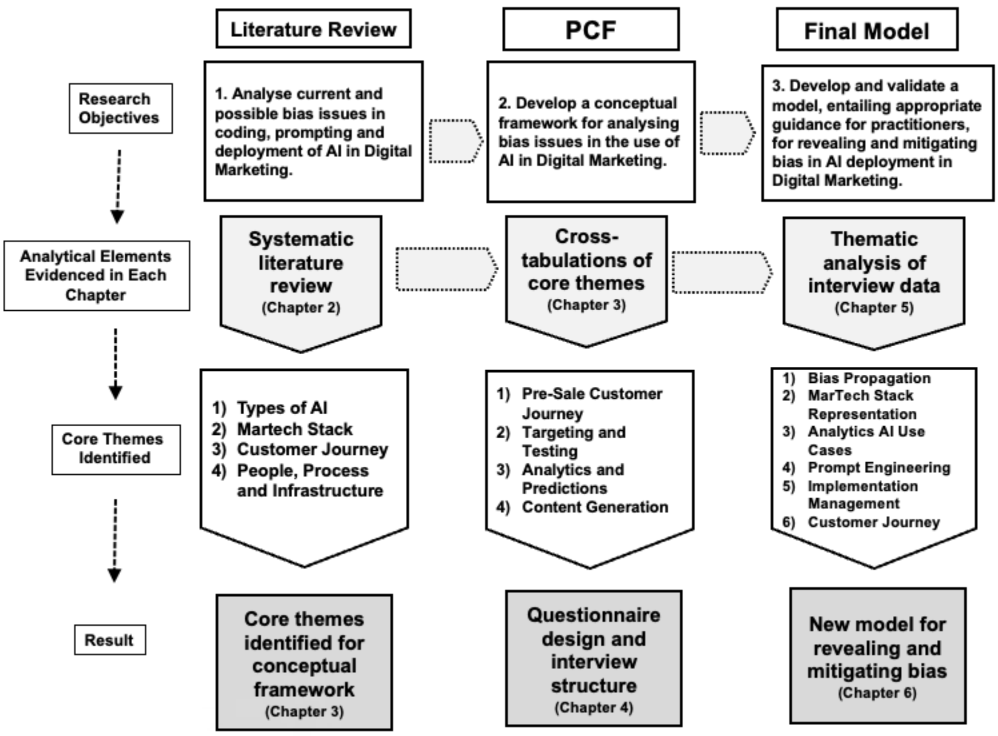


Figure 5.1: The Research Methodology Flowchart – brought forward and updated from Figure 3.2 (chapter 3)

(Source: Thesis Author)

The purpose of figure 5.1 is to show the data analysis process – it follows a structured and iterative framework built upon literature-derived concepts and primary qualitative data. From chapter 2, four core concepts - Types of AI, Martech Stack, Customer Journey, and People, Process, and Infrastructure - were extracted from the literature review to form the foundation of the PCF. These four core concepts were then validated in chapter 3 through cross-tabulations of the literature and analysis, which yielded four further emergent themes: Pre-Sale Customer Journey, Targeting and Testing, Analytics and Predictions, and Content Generation.

Informed by these PCF core concepts and emergent themes, the pre-interview questionnaire and interviews were constructed around them to ensure rigorous data collection. This was explored via the methodology in chapter 4. Thematic analysis of the questionnaire and interview transcripts begins in this chapter. Following the thematic analysis method explored in chapter 4 this chapter explores, justifies and critiques the coding and analysis of the data. In section 5.3.4 the output of the thematic analysis shows the primary data coded into six themes: Bias Propagation, Implementation Management, Prompt Engineering, Analytics AI Use Cases, Customer Journey, and Martech Stack Representation These codes are subsequently cross-referenced with the original PCF core concepts to align primary data with the literature and facilitate further gap analysis within chapter 6. This systematic approach ensures the analytical rigor and theoretical coherence of the final model.

As discussed in chapter 4, Methodology, the respondents selected for this research represent a fair cross section of marketeers at CSC, with a range of years of experience and career levels. AI adoption trends vary among professionals, making it essential to capture perspectives from different stages of AI adoption at different career levels. This also indicates the relevance of CSC as a case study company for this research – that its employees are using AI within their digital marketing jobs.

5.2 Thematic Analysis of the Interview Data

As discussed in chapter 4, Methodology, the interview data was thematically analysed from the transcripts following the analysis procedure based on Terry et al.'s (2017) six-phase thematic analysis framework: 1. familiarisation, 2. coding, 3. constructing themes, 4. reviewing themes, 5. defining and naming themes and 6. producing the report (figure 4.2).

Detailed notes and analysis of the interview transcripts initiated the familiarisation with the data from within the interview data. The notable ideas and statements within the interviews were manually sifted and mapped into a spreadsheet using the PCF core themes as a structure (appendix 5). The data was then reviewed multiple times to identify and define emergent themes which were then assigned codes (see appendix 5). This immersive exercise is necessary to create the building blocks of the findings (Terry et al., 2017).

Only once coding was completed throughout the full respondent data of the eighteen interviews, was the final development of themes reviewed. This was an essential step to ensure credibility within the findings and limit any researcher bias in analysis of the data and the findings output (Braun & Clarke, 2023). The development of these themes was an initial assessment. Another review of the interview data (the fourth stage) was conducted to uncover any missing or inaccurate data.

Following this fourth stage of thematic analysis, the coded data was mapped to the data from the cross-tabulations from chapter 3, PCF (tables 5.2, 5.3 and 5.4). This comparison, reviewed in section 5.3, uncovered gaps within the PCF original core concepts and suggested new elements that should be incorporated within the PCF to evolve it to the final model. Using cross-tabulation as a framework analysis tool offers a clear process for conducting qualitative research (Smith & Firth, 2011). By comparing the PCF cross-tabulations to cross-tabulations of the primary data gives transparent and trustworthy insights into the validation of the final analytical framework (Onwuegbuzie et al., 2012). The sixth stage of the thematic analysis is to produce the "final report", which is the final model of this research – shared in chapter 6, Model Development and Validation.

5.2.1 Interview Thematic Analysis

Thematic analysis was conducted for each respondent, with key points and quotations inputted into a cross-tabulation within Excel (appendix 5). This cross-tabulation allowed for the data to be structured during analysis against the PCF core concepts – this was done to structure the interview data appropriately to the study objectives. While most of the emergent themes from the thematic analysis matched the PCF core concepts, additional emergent themes were identified beyond the PCF areas, which are explored in section 5.3 of this chapter and in chapter 6 when validating the final model. Once the data had been structured into Excel, and the quotations analysed, coding was added to assign the emergent themes (also represented in appendix 5). In table 5.1, the coding of the thematic analysis and their meanings are listed. In section 5.3 these codes and emergent themes are explained and discussed, and the themes are given final names for deeper analysis in chapter 6.

Code	Code Meaning
Bias	Where the respondent believed bias to be propagated.
Pyramid	Pyramid hierarchy of the PCF MarTech Stack.
Analytics	Defining the many analytics applications for AI.
Prompting	Further education required for prompting.
Management	Management of AI implementation is reactive, rather than proactive.
Customer Journey	Pre- and post-sale use AI differently.

Table 5.1: Stage 2 of the Thematic Analysis of the Primary Data - coding the data and labelling the meaning

When reviewing appendix 5, note that no coding was applied to any data that explored the use cases on how AI is used in marketing – while interesting, that analysis would not answer the outcome required of RO3. We know AI is used for a range of applications in marketing, but this research is focused on how it can be managed to limit bias propagation. A reminder that respondent 17 was removed from the respondent list due to not matching the usage criteria of AI in their role. Therefore, there is no R17 mentioned within chapters 5 and 6, but the quotations do show respondent numbers ranging from R01 to R19, despite there being only 18 respondents.

The interviews were kept focused on respondents' roles and experiences to limit data captured from respondents on marketing areas they did not understand, which could impact the authenticity of the data. These marketing professionals provided valuable insights that address RO3 and help progress the PCF into an analytical framework (as discussed in chapter 6). In an emotive field such as bias, which is dependent on personal perceptions and attitudes amongst the participants, there are unavoidable interpretive ambiguities in their engagement with the topic. Bias was intentionally kept towards the latter half of both the questionnaire and the interview - this was intentional by the researcher as it can be perceived as a sensitive subject. Leaving to the latter half of the interview the respondents were comfortable from the first half and so trusted the researcher – making them feel more comfortable opening up on the subject of bias.

5.3 Cross-Reference of Thematic Data to the PCF Cross-Tabulations for Interview Findings

Following the first two stages of the thematic analysis (analysis and coding), the third and fourth stages of analysis concentrated on constructing and reviewing the credibility of the emergent themes: bias, pyramid, analytics, prompting, management, and customer journey (table 5.1).

The cross-tabulations from chapter 3, PCF, are of importance to rigorously test the literature review core concepts against the primary data, and vice versa. From the literature review four core concepts were outlined to structure the PCF: types of AI, the technology of the Martech Stack, and the stages of the Marketing Customer Journey amounted to 112 individual interactions that were explored by mapping the literature to each interaction. This was overlayed by colour coding of the elements of People, Process and Infrastructure (pink, orange, and blue) to show the correlation and importance of that theory to each interaction. The 112 cross-tabulation interactions have been mapped to the thematic analysis of the primary data within this section.

Using the interview data analysed and coded, it was cross-referenced against the data from the PCF cross-tabulations (tables 5.2, 5.3 and 5.4). This was done by creating the tables and inputting key analysis from the first two stages of the thematic analysis (appendix 5). Then the data from the PCF (tables 3.1 – 3.3) was mapped into each corresponding theme or area, allowing for the data to be critiqued and analysed for gaps in sections 5.3.1 to 5.3.4. All six thematically identified focus areas from the interviews were able to be cross-referenced with the PCF core concepts (table 5.5). The mapping of these coded areas is explored in this section - this reinforces that the PCF elements were the correct focus areas for the final model and gives expansion areas to develop a richer picture of the issues in AI usage.

The next section shows the analysis of the focus areas ascertained from the interviews against the PCF cross-tabulation data. For ease there has been coding added within the tables (e.g. C1) so this analysis can be easily referred to in this section.

5.3.1 Coded Themes: Bias, Prompting and Management

Unsurprisingly bias was a dominant theme throughout the thematic data analysis. In table 5.2, respondents interview analysis is imported from the thematic analysis in appendix 5 and grouped with the PCF analysis (table 3.4) to justify the identification of the coded themes: Bias, Prompting and Management. Within table 5.2 each portion of interview data or literature has a letter and number assigned (e.g. D1) and these are used throughout the section when referencing the data. This analysis mapping was initially unstructured until it was structured against the three AI bias areas from RO1: to analyse current and possible bias issues in coding, prompting and deployment of AI in Digital Marketing. Prompting was a coded theme that emerged from the thematic data analysis and grouping like this gives structure to not only answer the research objectives but also enables clear areas where biases permeate. Another code that emerged was Management, and that appears to link very closely to Deployment (table 5.2). This will be explored further in chapter 6.

Respondents with a background knowledge of coding traditional and generative AI spoke on the biases that come within an AI. R08 stated “the bigger the data the AI is fed on, the more skewed outcomes you will have. Knowledge of how large the data is can help the marketeer understand the level of bias risk” (C8). This reinforces the literature mapped into the PCF cross-tabulations - that transparency and accountability are limited due to the proprietary nature of these algorithms, raising ethical concerns (Lipton, 2016 - C1). R07 and R13 built upon this view that it can be hard to get accurate data from AI within the MarTech Stack as marketeers are not sure what the AI has done to the data to read and analyse it: “There is an over emphasis [in CSC] on install base customer in the data and large enterprise companies. The demographics of these customers can drive biased outcomes” (C4). This reinforces and aligns directly to the literature from the PCF on machine learning heuristics that drive AI speed and scalability, but often at the expense of accuracy and fairness (C1).

However, before these AI are even trained, they can become corrupted. In chapters 2 and 3, AI production location and law bias were explored - there are no global regulatory rules for AI; different countries, continents and political and economic unions are employing different approaches (Schwartz et al., 2022; Diakopoulos, 2026 – C6). However, an additional bias element emerged from the thematic analysis – political bias. R07 spoke passionately on how AI models are biased politically: “the model itself already has some, even politically motivated bias within…if you look at what Open AI puts out versus Deep Seek for instance” (C7). The example given was asking what democracy is when using OpenAI in the USA and using Deep Seek in China – you will get completely different answers from the AI – that starts to reveal political bias embedded in the AI.

The final coding bias noted by respondents was the gender of the coders, which aligns with the literature mapped into the PCF cross-tabulations - that only 8-10% of software developers are female, and this imbalance can encode biases into algorithms, often unintentionally (Kaminksi, 2023; Vailshery, 2022; C2). R18 noted “coders of AI are mainly male – input data that is biased by this, will have biased outcomes” (C3). There is confidence in these findings for bias in coding as the respondent data reinforces the literature mapped into the PCF cross-tabulations data.

Prompting of an AI, while a focus area for RO1, was not considered a core focus area of the PCF itself after the literature mapped into the PCF cross-tabulations were analysed – however, from the interview data, it is one of the most important identified themes of this research. Seventeen respondents noted a lack of understanding and knowledge for correctly prompting an AI by marketeers. “The art of prompting” is not something currently taught and so marketeers are having to use their own knowledge or research to learn how to prompt. To be aware of bias propagation they must currently use their own “moral compass” (P3). The term Prompt Engineering was used by R03, R07, R09 and R18 - “Prompt Engineering is very important”. This is the teaching of how to create a prompt correctly to get the best outcome. It appears to be complex and something that needs to be taught, which will be explored in chapter 6. It closely aligns with the emergent theme of Management – as education of Prompt Engineering is “very powerful and teaches technique for better outputs. Training should be mandatory as otherwise it is left open to interpretation and bias” (R18).

R18 noted that in CSC itself, “Bias isn’t overly considered in analytics usage day to day as the data sources for CSC traditional AI are trusted. However, there can be bias for gen-AI prompting" (P8). Three main biases within prompting were identified from the thematic analysis: confirmation bias, Eurocentric bias, and persona bias. R09 noted "yes, bias is 100% present in marketing campaigns. The main types of bias are confirmation bias, selection bias, algorithmic bias, and cultural bias" (P5).

R09, R15 and R16 noted confirmation bias as specifically being an issue, "there is a lot of confirmation bias propagated through digital marketing at CSC where people will decide campaign strategies based off of things they think the audience will like, not based off what the data is indicating" (P6). If marketeers are assuming they know what their customers are like, then the persona data they use (the customer groups) should be a reliable source of data. This is not the case, as data analysis showed there is bias within the data when targeting personas. Seven respondents noted that persona data is often incorrect which is unhelpful to inform marketeers who are trying to use the data to make decisions - "often aligned to biases of targeting groups. Main categories would be left-leaning liberal vs. right-leaning conservative" (P4). These incomplete persona profiles also fuel Eurocentric marketing practices. R02 and R09 noted "persona research may just be done on one or two markets, adding bias into findings" (D4). Eurocentric bias in marketing will be explored fully in chapter 6, as there was a considerable amount of data for this bias. R14 reported having to regularly change images and Eurocentric wording within social media posts from marketing colleagues from the USA when posting to local language social media channels. This raises exploration around the marketeer experience, location and review cycles to identify and manage Eurocentric practices.

These identified biases when prompted into an AI algorithm can corrupt the original coding and model. This was noted by R10 that "marketeers need to be trained to be aware of inputting bias and anomalies as it will skew the learning data". This reinforces the literature mapped into the PCF cross-tabulations - that marketers themselves can unintentionally corrupt AI models through adversarial attacks, altering input data such as text or images to mislead algorithms. These subtle manipulations compromise machine learning models for all users (P2).

The column labelled as Deployment (table 5.2) is similar to the thematic code of Management that was identified in the stage one thematic data analysis. The focus area of Management also links to the PCF identified Process element of "People, Process and Infrastructure”. Inclusion of Process was highlighted using colour coding in the PCF cross-tabulations (tables 3.1, 3.2 and 3.3). When analysing data on Deployment / Management respondent data showed unanimous feedback from all eighteen respondents that more training is required on using and prompting AI, but particularly that it should show use cases on how to use AI specifically in Marketing. R14 noted: “basic training is available to use AI, however, training on how to use in daily marketing roles is missing”. R15 went further to note “training is currently not prevalent for marketeers. There should be pilot areas to test and prove out the use cases to show accurate outputs. Marketeers should then develop training, roadmaps and implementation plans”.

Coding	Prompting	Deployment
C1. Machine learning heuristics—quick, approximate solutions—drive AI speed and scalability, but often at the expense of accuracy and fairness (Karimi-Mamaghan et al., 2022). Transparency and accountability are limited due to the proprietary nature of these algorithms, raising ethical concerns (Lipton, 2016). C2. Only 8-10% of software developers are female, and this imbalance can encode biases into algorithms, often unintentionally (Kaminksi, 2023; Vailshery, 2022). C3. Coders of AI are mainly male – input data that is biased by this, will have biased outcomes [R18]. C4. Hard to get accurate data from AI within the MarTech Stack as you are not sure what the AI has done to the data to read it. “There is an over emphasis on install base customer in the data and large enterprise companies. The demographics of these customers can drive biased outcomes” [R07, R13].	P1. Generative AI learning from the users’ preferences. This can include any bias from the prompter who does not understand a culture but is generating content for their market; or any bias from the prompter who assumes their target audience characteristics – gender, age, location etc [R01, R02, R04]. P2. Marketers themselves can unintentionally corrupt AI models through adversarial attacks, altering input data such as text or images to mislead algorithms. These subtle manipulations compromise machine learning models for all users (Palmer, 2023). “Marketeers need to be trained to be aware of inputting bias and anomalies as it will skew the learning data” [R10]. P3. Lack of understanding and knowledge for correctly prompting an AI. “The art of prompting” is not something currently taught and so marketeers are having to use their own knowledge or research to learn how to prompt. To be aware of bias propagation they must currently use their own “moral compass” [R01, R02, R04, R05, R07, R08, R09, R10,	D1. No identified failsafe in generative AI usage to flag biased prompts or inputs [R01, R02 R03, R04, R05, R06]. D2. Further training is required that is focused specifically on marketing use cases and projects. This includes prompting guidance or training and should be a continuous learning experience [R01, R02 R03, R04, R05, R06, R07, R08, R09, R10, R11, R12, R13, R14, R15, R16, R18, R19]. D3. Inconsistency of laws regarding AI and its usage allows Eurocentric marketing practices to occur. Those who are not culturally or language fluent work on localized projects [R04, R05, R08, R09, R14, R16]. Eurocentric marketing practices are prevalent within large companies - where decisions are made on behalf of other markets by people who may not be aware of cultural norms and differences (Henning, 2022; Yalkin & Özbilgin, 2022). D4. Further Eurocentric focus can result from incomplete data integrity for research profiles. Persona research

C5. Assumptions made by predominantly male developers can lead to unfair outcomes, particularly in culturally sensitive applications where debiasing efforts remain insufficient (Sun et al., 2024). The European Union's AI Act mandates debiasing, but loopholes allow companies to circumvent regulations based on production location, perpetuating inequalities and sustaining market dominance by former colonial powers (Yalkin & Özbilgin, 2022). C6. There are no global regulatory rules for AI; different countries, continents and political and economic unions are employing different approaches (Schwartz et al., 2022; Diakopoulos, 2026). C7. AI models are biased "The model itself already has some, even politically motivated bias within…If you look at what open AI puts out versus Deep Seek for instance" [R07]. C8. The bigger the data the AI is fed on, the more skewed outcomes you will have. Knowledge of how large the data is can help the marketeer understand the level of bias risk" [R08].	R11, R12, R13, R14, R15, R16, R18, R19]. P4. Targeting bias with segmentation criteria for personas. "Often aligned to biases of targeting groups. Main categories would be left-leaning liberal vs. right-leaning conservative" [R07, R08, R12, R13, R14, R15, R19]. P5. "Yes, bias is 100% present in marketing campaigns. The main types of bias are confirmation bias, selection bias, algorithmic bias, and cultural bias" [R09, R10]. P6. "There is a lot of confirmation bias propagated through digital marketing at CSC where people will decide campaign strategies based off of things they think the audience will like, not based off of what the data is indicating" [R09, R15, R16]. P7. "ALT text (image text for blind or visually impaired using voiceover support to use smartphones and computers) has become better with AI than with a human doing it. There is better description used and all images now have ALT text (showing scalability)" [R11]. P8. "Bias isn't overly considered in analytics usage day to day as the data sources for CSC traditional AI are trusted. However there can be bias for gen-AI prompting" [R13, R18, R19].	may just be done on one or two markets, adding bias into findings [R02. R09]. D5. Usage of historical data for current data driven decision making - such data for software buyers can be skewed by gender, age, demographics etc., and then used for current marketing where purchaser profiles are evolving to new demographics [R01, R03, R12, R13]. D6. Barriers to adoption AI is GDPR and data privacy implementation. Large language models has proven bias within it – uses up to 9 data sets and 7 of these data sets are from the USA [R09, R13]. D7. Marketeers require experience to identify bias and proactively manage diversity. "It was important to the respondent to use diverse representation within the images. To know this requires marketing experience" [R08 R10, R11, R14, R16].

Table 5.2: Cross reference of the extant literature in the PCF cross-tabulations and interview thematic analysis on bias issues for coding, prompting and deployment of AI in digital marketing (coded R01 – R19)

5.3.2 Coded Theme: Customer Journey

This section uses data from table 5.3 (which is respondents interview analysis imported from the thematic analysis in appendix 5) grouped with the PCF analysis data (table 3.4) to justify the identification of the coded theme: Customer Journey. Within table 5.3 each portion of interview data or literature has a letter and number assigned (e.g., PO1) and these are used throughout the section when referencing the data.

In sections 3.4 and 3.5 of chapter 3 – the discussion and analysis of the pre- and post-sale literature showed that the marketing applications were similar and that the AI usage across both stages would be similar. This was not the findings from the thematic analysis and the respondents explored the vital differences between them – this will be explored further in chapter 6, Model Development and Validation. In the PCF the customer journey stages are broken down into eight stages and there was no feedback from any respondents to say this was inaccurate. The respondents were asked to feedback on the eight stages, but it was accepted across them it is a common depiction. However, the interview analysis showed that respondents only focused on the pre- and post-sale journeys are wholes rather than stages (table 5.3).

The difference on AI application for pre- and post-sale marketing came down to "buying committees", these are the different persona groups of customers who make the decision to purchase. For pre-sale R01 and R12 both noted there are "more influencers in the process" (PR1). R07 agreed and argued that the "stakes are higher with using AI in pre-sales, you have to make sure the targeting is correct to the personas with the correct content applicable. The marketing goes to a broader audience, it is out in the world". The idea that pre-sale marketing is persona dependent was shared by five respondents and R09 noted: "we can use AI to create hyper-personalized content for every segment of customer that comes to the website in order to increase conversion rates" (PR2). This reinforces the literature mapped into the PCF cross-tabulations findings that AI can create personalised generated content at scale (Haleem et al., 2022; Rabby et al., 2021).

This application of AI changes when moving to post-sale – the targeting becomes more detailed and efficient as the company will know who has purchased the data and their demographics so you can target a lot more efficiently. Respondents R03, R08, R14 and R16 noted that post-sale is about customer adoption and using the product, this could mean chat bot support, optimizing product UI (user interface) with guidance and product-related nurture based on interaction of product – R14 "in post-sales, AI is leveraged to enhance customer retention" (PO2, PO6). This aligns with the literature mapped into the PCF cross-tabulations - that companies can use Target Account Lists to target certain companies and personas (Flavin & Heller, 2019; Earley, 2022; Meda, 2023 – PO1). This could reduce bias in AI targeting as the personas of the customers are already known.

Respondents R13 and R16 did caution that "there is a risk of churn as you can target existing customers too much with their data" (PO3). R02 agreed with this and noted there is data privacy to consider when targeting customer data - "considerations for data privacy and proprietary company information related to CSC solutions, user licenses, etc" …this will impact data segmentation and persona targeting for post-sale marketing (PO5).

The clear differences between pre- and post-sale AI usage in marketing and the majority of respondents citing differences between them, mean it was a clear coded theme that deserves more discussion and validation in the PCF within chapter 6.

Pre-Sale Customer Journey	**Post-Sale Customer Journey**
PR1. Difference in the buying committee in pre-sale, more influencers in the process [R01, R12]. PR2. Use case for AI changes between pre and post-sale marketing. Personalised generated content at scale. Content produced for differing stages: images, videos, text and audio (Haleem et al., 2022; Rabby et al., 2021). "We can use AI to create hyper-personalized content for every segment of customer that comes to the website in order to increase conversion rates" [R09]. PR3. Online events (i.e. webinars) – full content production, tailoring content (Buczek et al., 2023). A/B testing on email and content wording and structure (Nair & Gupta, 2021). "Current A/B testing is done on the CSC website is top of funnel for marketing" [R09]. PR4. Presales will focus on qualifying and giving the customer the most relevant information for that persona / interaction with types of assets and content they most need. The goal in pre-sales is to inform the customer as quickly as	PO1. Using Target Account Lists to target certain companies and personas (Flavin & Heller, 2019; Earley, 2022; Meda, 2023). PO2. Data difference for post-sale. You already have your customers data (persona, company, gender, etc) so you can target a lot more efficiently [R01, R04, R07, R12, R15]. PO3. There is a risk of churn as you can target existing customers too much with their usage data [R13, R16]. PO4. Webinars - segmenting event audiences, geofencing (Buczek et al., 2023). Nurture emails and webcast routing rules (Nygard, 2019; Roetzer & Kaput, 2022). "We can use AI to create a customer support tool that uses agentic design to answer any specific question related to the product" [R09]. PO5. "Considerations for data privacy and proprietary company information related to CSC solutions, user licenses, etc"…will impact data segmentation and persona targeting for post-sale marketing [R02].

possible to move them to a [sale] [R02, R03, R05, R08, R15]. PR5. Stakes are higher with using AI in pre-sales, you have to make sure the targeting is correct to the personas with the correct content applicable. The marketing goes to a broader audience, it is out in the world [R07].	PO6. Post sales it is about customer adoption and actually using the product, this could mean chat bot support, optimizing product UI (user interface) with guidance and product related nurture based on interaction of product [R03, R08, R14, R16].

Table 5.3: Cross reference of the extant literature in the PCF cross-tabulations and thematic analysis on the importance of the customer journey using AI in digital marketing (coded R01 – R19).

5.3.3 Coded Themes: Analytics and Pyramid

This section uses data from table 5.4 (which is the respondents interview analysis imported from the thematic analysis in appendix 5) grouped with the PCF analysis data (table 3.4) to justify the identification of the coded themes: Analytics and Pyramid. Within table 5.4 each portion of interview data or literature has a letter and number assigned (e.g. A1) and these are used throughout the section when referencing the data. While reviewing the MarTech Stack within interviews, the topic of Analytics became a recurrent theme for respondents and was noted within the thematic analysis - R03 argued that analytics within the MarTech Stack is so important that the different use cases for it must be examined individually. R03 "Analytics is too broad a term. When reviewing the training required you should also focus on data modelling and predictive analytics as separate analytics use cases – especially as they use algorithmic traditional AI" (A5). This demonstrates that the different types of analytics use AI in a different way to drive marketing success as analytics is mostly applicable to strategy - covering scoring, AB testing, trends reporting, data modelling and predictive analytics.

Six other respondents agreed with R03 that analytic applications are different - Google Analytics, Adobe Analytics, and A/B testing platforms are often used in the MarTech stack to review and validate AI-driven outputs. "[I like] using AI to generate insights, automate reporting, and identify trends for data-driven decision-making" (A3). Only R13 and R15 noted the importance of scoring, and their justification was compelling based on customers marketing journey (whether good or bad) is dependent on the scores they receive when interacting with marketing content - “scoring systems (contacts being scored on interactions) are enhanced by AI. The machine learning algorithm and data aggregates into a score” (A6) – this will be reviewed deeper in chapter 6 as it is an important analytical viewpoint for further analysis.

The code of Analytics also links to the codes of Bias and Prompting through persona rules being driven by analytics. R12 and R18 agreed that “incomplete or old data can skew data used to create personas – creating incorrect persona rules and groups” (A2). This is bias propagation – beyond the scope of a marketeer prompting in a biased way – that informs marketeers incorrectly on their data on personas and data maturity that will drive biased marketing outcomes.

Because Respondents were focused on Analytics within the MarTech Stack, they also noted the presentation structure of the MarTech Stack as a pyramid in the PCF. It was confirmed by all interviewees that the MarTech Stack (which directly links to Infrastructure) is of great relevance when using AI in digital marketing – it is the conduit through which the AI is used – and must be part of the final operational model. R05 noted the MarTech Stack “ensures quality of marketing output”. However, there were some conflicting perceptions on how the PCF structured it as a hierarchy. R07 noted that showing the MarTech Stack as a hierarchy in the PCF is appropriate, however, “concrete examples of how AI is used within it are needed to show the application of them”. On the contrary other respondents did not agree it was appropriate. R04 observed “[when you] put it in a pyramid, people immediately think of level of importance…this is a hierarchy”. R02 agreed and stated, “a pyramid structure implies a foundation or a level of importance, or a volume implication”. R02 also noted their view in the PCF that looks like a bias cascade through the MarTech Stack “[when you] start at the analytics and then because there's something that's set up with a bias there, it cascades into the next level, which would be then like the SEO and then further to the social media and then on to the web itself”. The MarTech Stack is a core component of the framework, but interview feedback suggests the presentation of these technologies in a pyramid and the AI cascade warrant review in chapter 6.

Analytics and Pyramid
A1. Dependent on data maturity – a large database is required. First-party & third-party data targeting. Generating forecasts (Welsch, 2024; Lee, 2023; Wilson, 2023). “Provide data and insights to improve strategy and achieve sales objectives” [R14].
A2. Persona rules. Analysis of customer data (Flavin & Heller, 2019). Dependent on data maturity – large database required (Lee, 2023). “Incomplete or old data can skew data used to create personas – creating incorrect persona rules and groups” [R12, R18].
A3. Google Analytics, Adobe Analytics, and A/B testing platforms are often used in the MarTech stack to review and validate AI-driven outputs. “Using AI to generate insights, automate reporting, and identify trends for data-driven decision-making” [R01, R08, R09, R10, R11, R13].
A4. Reviewing the PCF the MarTech Stack looks like it is represented hierarchical with the bias cascading from analytics, this is an inaccurate view as the MarTech stack is linear and feeds each other [R02, R04, R09, R11, R16, R19].
A5. Analytics is too broad a term. When reviewing the training required the researcher should also focus on data modelling and predictive analytics as separate analytics use cases – especially as it uses algorithmic traditional AI. Using AI in “Analytics for reporting and content optimization” [R03, R14, R18].
A6. Scoring is particularly important within analytics and AI. “Scoring systems (contacts being scored on interactions) are enhanced by AI. ML algorithm and data aggregates into a score” [R13, R15].

Table 5.4: Cross-reference of the extant literature in the PCF cross-tabulations and thematic analysis on the importance of analytics (part of MarTech Stack) using AI in digital marketing (coded R01 – R19)

5.3.4 Final Cross-Reference between PCF Focus Areas and Thematic Coded Themes

The justification for the six thematic coded areas has been presented from the thematic analysis of the primary research and cross-referenced and justified using the PCF cross-tabulations. The final cross-referencing of these coded areas is done against the PCF emergent themes. These were explored in chapter 3 (section 3.7) and were the emergent themes that were drawn from the literature and the researcher’s experience. The questionnaire and interview design and structure were designed from the PCF emergent themes – so it would be expected these themes and codes would match – however, a final review on if they do and any areas that are new is justified.

Table 5.5 shows the final PCF emergent themes from section 3.7 matched the thematic analysis coded areas. Two coded themes were not identified by the original PCF themes: Bias and Management. As explored in chapter 3, bias was intentionally not reviewed as part of the PCF due to the literature already showing bias to be present in multiple forms and the research would assume it was prevalent throughout AI usage. However, Management is a new theme area that has been coded through the thematic analysis. As explored in section 5.3.1 Management and Deployment are similar, and linked to the Process part of People, Process and Infrastructure. The fact it is a coded stand-alone theme shows the importance of the topic to explore within the PCF and chapter 6, Model Development and Validation.

PCF Emergent Themes	Thematic Analysis Coded Themes
n/a	Bias Management
Pre-Sale Customer Journey Targeting and Testing	Customer Journey
Analytics and Predictions	Analytics Pyramid
Content Generation	Prompting

Table 5.5: PCF Emergent Themes matched to Thematic Analysis Coded Themes

The other coded themes match the PCF emergent themes (table 5.5) and offer additional rigour to the direction of this research in addressing RO3. Customer Journey matches to Pre-Sale Customer Journey and Targeting and Testing. Analytics and Pyramid align to Analytics and Predictions and Prompting aligns to Content Generation (of note prompting of an AI includes content generation but also incorporates prompting of traditional AI as well). The data from the literature has been confirmed through thematic analysis and justified, giving credence and credibility to these thematically coded areas.

Entering the final stages of the thematic analysis is Phase 5 – defining and naming themes. Having justified the coding, final theme names have been produced and aligned to the codes (table 5.6). These theme names will be used within chapter 6, Model Development and Validation, to analyse and validate the data collected to achieve the RO3 of a final operational model that will include appropriate guidance for marketeers.

Code	Code Meaning	Theme Name
Bias	Where the respondent believed bias to be propagated.	Bias Propagation
Pyramid	Pyramid hierarchy of the PCF MarTech Stack.	MarTech Stack Representation
Analytics	Defining the many analytics applications for AI.	Analytics AI Use Cases
Prompting	Further education required for prompting.	Prompt Engineering
Management	Management of AI implementation is reactive, rather than proactive.	Implementation Management
Cust Journey	Pre- and post-sale use AI differently.	Customer Journey

Table 5.6: Thematic Analysis Stage 5 – naming the themes after justification and aligning them to the thematic data coding

5.4 Chapter Summary

This chapter laid out the process and stages of the thematic analysis of the eighteen questionnaires and interview transcripts of the qualitative data. To maintain rigour on the data and have confidence in its output, the research utilised the structure of a six-stage thematic analysis to rigorously review the primary data captured to give meaningful output.

Section 5.2 laid out this thematic analysis as a step-by-step approach. The primary data from the pre-interview questionnaires and interview transcripts were analysed within Excel. These were mapped out using the original PCF core concept areas for consistent structure (appendix 5). The data was then coded based on the recurring themes identified by the researcher. Doing a manual data analysis was justified in this research as it allowed for a depth of understanding of findings that software analysis struggles to ascertain. The nascent and complex topic of AI usage justified the researcher's manually capture of nuances from the tone and context of the interviews.

Section 5.3 then analysed the data from the initial Excel thematic analysis and cross-referenced it against the PCF cross-tabulations that used the initial literature review data. This analysis was explored throughout section 5.3 and justified through exploring this cross-analysis. This produced six final themes from the data that will be carried on into chapter 6, Model Development and Validation, where a deeper analysis of the primary data and how it is used to evolve the PCF into the final model is explored. The final thematic themes to be explored in chapter 6 are: Bias Propagation, MarTech Stack Representation, Analytics AI Use Cases, Prompt Engineering, Implementation Management and Customer Journey.

CHAPTER 6: MODEL DEVELOPMENT AND VALIDATION

6.1 Chapter Introduction

This chapter directly addresses RO3 to develop and validate a model, entailing appropriate guidance for practitioners, for revealing and mitigating bias in AI deployment in Digital Marketing. A final summary discussion on the outcome of addressing all three ROs is also included in chapter 8, Conclusion.

Within chapter 5, Interview Findings, research themes were explored and justified using the findings from the thematic analysis method of the questionnaires and interviews. In this chapter, chapter 6, the findings are explored through a deeper analysis - comparing and contrasting respondent views and supporting them with further quotes from the interview transcripts and questionnaire forms. This deeper analysis is then taken to inform the evolution of the PCF into a proposed final model to be validated through an online survey of a small group of returning respondents.

This chapter is divided into five sections. Following this introduction, section 6.2 analyses further viewpoints of respondents to critique the original literature and PCF and define areas for evolution within the thematic analysis. Section 6.3 proposes the specific development areas of the PCF into the proposed final model, detailing the thematic data that drove the changes from the interviews. Section 6.4 presents the results of an online survey conducted with a selection of the original respondents on the new proposed final model. This validation aims to confirm the frameworks applicability to industry and how it can be used by businesses. Final conclusions of this chapter are outlined in Section 6.5.

6.2 Further Analysis of the Thematic Data Findings

Six coded themes emerged from the thematic analysis in chapter 5, Interview Findings. These themes were justified using the thematic analysis of the interview data and cross-tabulation of the PCF literature data. Stage five of the six-stage thematic analysis was to give the themes a name, these were: Bias Propagation, MarTech Stack Representation, Analytics AI Use Cases, Prompt Engineering, Implementation Management and Customer Journey. This chapter will analyse the interview data further in these six theme areas with respondent quotes being used throughout to reinforce viewpoints, contradictions and any gaps identified.

6.2.1 Bias Propagation

Within section 5.3.1 the thematic analysis of bias was formatted against the categories of coding, prompting and deployment (table 5.2). This section analyses the biases (both conscious and unconscious) identified by respondents within CSC marketing and the viewpoints of respondents. The analysis throughout section 6.2 aligns these biases with the topics of Prompt Engineering and Implementation Management that will be explored in section 6.2.4 as vehicles to mitigate bias propagation as part of the final model.

Throughout the research, bias was viewed as implied and present when using AI. From chapter 2, Literature Review, the themes of bias in the literature focused on gender and Eurocentric biases (Tatman, 2017; Tang et al., 2021; Haleem et al., 2022). The bias themes identified within the interview data reinforced both gender and Eurocentric bias, as well as focusing on additional biases of confirmation, culture, accessibility, persona, political and geographical. R09 argued that “yes, bias is 100% present in marketing campaigns. The main types of bias are confirmation bias, selection bias, algorithmic bias, and cultural bias”. R01 clearly notes that “marketers may focus only on data that supports their pre-existing assumptions, overlooking data that contradicts their views”. R19 agreed and stated “digital marketing campaigns are developed based on persona's and how the strategist of the campaign sees these personas, so they cannot be unbiased”.

R01 defined marketing bias as “CSC marketing leverages Gen-AI to identify target accounts, translate content, deliver content to the right personas, and optimise campaign programs effectively…AI-driven algorithms may reinforce stereotypes by targeting ads based on biased data, such as focusing on certain demographics or interests while excluding others”. R15 agreed noting that “bias is of the winning campaign, bias of who will purchase products” – meaning those campaigns with more money or ROI will have more data to target. The identified biases are also not siloed but interwoven with each other and this is noted throughout this chapter which compares, contrasts and add context from the respondent interviews.

6.2.1.1 Generative AI is more at risk of bias than Traditional AI

The bias issues for AI coding are well documented in the existing literature within chapter 2. The literature on traditional AI (such as data modelling or large language models) positioned algorithmic AI rules as more inherently biased (Gerhard, 2008; Roetzer & Kaput, 2022; Schwartz et al., 2022). However, bias issues within the prompting and deployment of AI are less researched. This focus area within the primary research showed respondents view generative AI as being more at risk of bias than traditional AI. From the questionnaire returns, 16 out of 18 respondents agreed that marketeers bring their own biases into marketing campaigns. When reviewing the split between the two, 10% more of the respondents thought bias propagation could occur more when using generative AI. This was explored further in the interviews and generative AI was perceived to be the risker for bias propagation over traditional AI. R01 stated “I talk to ChatGPT on a daily basis, now it understands my preference and current work…sometimes it works faster than my own brain”. R03 agreed and noted “every time you prompt (Open AI) and the memory is updated you're training the model on something”. Traditional AI was perceived as less at risk for bias prompting as there are review processes within IT at CSC for any traditional AI projects. 100% of the respondents trusted that the data used for traditional AI within CSC came from a reputable source. R18 agreed that in CSC itself, “Bias isn’t overly considered in analytics [traditional AI] usage day to day as the data sources for CSC traditional AI are trusted. However, there can be bias for gen-AI prompting”. There was an assumption by respondents that IT would have followed due diligence in selecting the appropriate people to create AI algorithms and processing of balanced data for the large language models. R05 noted that when marketeers use traditional AI that “industry standard tools take on the due diligence”. R08 agreed and stated they know they may have their “own biases in daily work so I take special care when prompting an AI”. Prompting can corrupt the original AI coding and model. This was noted by R10 that “marketeers need to be trained to be aware of inputting bias and anomalies as it will skew the learning data”. Therefore, not just relying on IT or industry tools to do their due diligence. This reinforces the literature that marketers themselves can alter input data such as text or images to mislead algorithms (Palmer, 2023). The respondent focuses on bias when prompting a generative AI will be further explored in section 6.2.4.

However, the automation of generative AI has been reducing bias in marketing in some areas. R11 noted that accessibility for blind or visually impaired people has improved with generative AI. ALT text (a short description added to images) not only can be used to optimise websites but allows people to use voiceover on smartphones and computers to read out what they cannot see. “You can generate ALT text for images so it will read the image and then suggest some text. It can generate AI options for preview text which is the first snippet of copy that you see when you're in your inbox before you open the e-mail”. This automatic production of image text has improved with AI, rather than with a human doing it. R11 noted that AI identifies better descriptions, “when a human did it the description was short and sometimes incomplete”. R11 was the only respondent to identify ALT text as an accessibility tool that shows AI can reduce ableist bias. It does not show an AI has empathy, but it does show that AI automated processes can be inclusive, as well as scalable.

6.2.1.2 Gender Bias

From the literature we know that the average split of genders working within marketing is 62% female, to 38% male – with female roles being predominantly mid-management and junior roles, with most leadership positions being male (EMR, 2023). The split of genders for this research was 12 female respondents and 6 male respondents (66% to 33%) – this was unintentional – but aligns closely to the average split. Within the literature review the data showed that only 30.5% of female marketeers are using AI as they consider it “cheating”. However, the respondent sample for this research all use AI as prolifically as they could within their jobs and personal lives. R14 stated “for me using AI has enhanced my life” in relation to increasing productivity and creating content for webinars in a local language quickly. This could be an outcome of working for a software company (where adoption of new technology is encouraged) regardless of gender.

A further gender bias noted by respondents was the gender of the coders of AI models, noting R18 “coders of AI are mainly male – input data that is biased by this, will have biased outcomes”. This reinforces marketeers’ awareness that only 8-10% of software developers are female, and this imbalance can encode biases into algorithms, often unintentionally (Kaminksi, 2023; Vailshery, 2022). R09 agreed, noting “large language models have proven bias within them – generative AI uses up to nine data sets and seven of these data sets are from the USA. This causes bias for ethnic groups and promotes Eurocentricity. USA data is also weighted to males which can cause bias”.

Gender bias was well documented in the literature for AI usage. Generative AI’s showed gender bias across multiple uses, such as in their imagery generation (Sun et al., 2024), or through YouTube algorithms (Bishop, 2018) - with mis-gendering being an issue (Tang et al., 2021). It was well documented by Cunningham and Roberts (2021) that genders are being misinterpreted in current marketing practices. R10 reinforced this “I think that marketing tries hard to maintain an unbiased view at CSC. Gender bias, culture bias, religious bias are sometimes seen, but not intentional”. R11 agreed, they raised that “gender bias is present in email building AI tools when the imagery is chosen”. It was important to the respondent to use diverse representation within the images but stated this only came through experience. When using traditional AI within image generation the bias is regulated, R18 “reporting AI for social media supports analysis of creative performance such as Click-Through-Rate or Analyse Creative and will determine what performs better - if a person in an image or not”. You can code diversification; it is generating images personally as a marketeer, which appears to have room for bias. This can be regulated by prompt engineering which is explored in section 6.2.4.

The theme of the experience of a marketeer to limit the main biases (confirmation, gender, persona, political, cultural and Eurocentric) was raised by 60% of the respondents. R08 noted that "experience as a marketeer working in different locations can help mitigate this (bias)" – meaning the recommended way of overcoming biases is to have experience of working in different cultures. R14 agreed, stating they "use experience to keep own biases in control". R16 further reinforced this by arguing that if marketeers are multicultural then they will be more balanced "you don't know what you don't know". The ambiguous nature of measuring a marketeers life experience is not a reliable fail-safe for bias output. Again, prompt engineering and education can support a marketeer's experience, or lack thereof, and will be further explored in section 6.2.4.

6.2.1.3 Eurocentric Bias

In exploring types of bias with respondents, Eurocentric biases were especially noted and the Eurocentricity of marketing was explored, which was also considered in the literature review. Imagery for "white collar" occupations exhibited Eurocentric aesthetic qualities on Google (Henning, 2022) – and Google is one of the large language models feeding generative AI. R14 reported having to regularly change images and Eurocentric wording within social media posts from marketing colleagues (particularly from the USA) when posting to local language social media channels – articulated as "[I am] conserving local brandings direction". This relates to centralised content being sent to Latin America, R14 added "we have as in Europe, Spanish, but there is Central American Spanish, Mexican Spanish and Argentinian Spanish. They talk differently and the way to reduce that spending (on localisation) is to use AI. For example, we receive images from Asia Pacific, and the images with people that are physically is different – so local people think, no, this content is not for us…it's for other people". Reinforcing the 2019 Adobe Cloud Report that 53% of Latino/Hispanic Americas are dissatisfied with how they are portrayed in advertising (Adobe CMO Team, 2019). R04 also gave an example of bias where social media banners were produced using generative AI– "in a team review it was noted the imagery was not culturally diverse, or gender diverse". This manual review by the marketeers allowed the images to be edited before the content was used externally.

This understanding on language and imagery differences aligns to marketeer experience and knowledge to know the appropriate approach to generating content that is sent to other countries to use. Prompt engineering could help to identify and manage Eurocentric practices – this will be explored in section 6.2.4.

Advertisements frequently adhere to Eurocentric standards, prioritising specific aesthetics, languages, and lifestyles, which marginalises non-Western cultures (Gunaratne, 2009). In CSC AI is used for “translation of copy through AI, usage of AI service to generate voice-over in language for video localisation…AI for translating the website across the globe” (R05). When localising centrally created content, R04 noted “there's so much, not just languages, but you have to think about dialects”. Essentially, literarily translated content may not land well in a local language, and reviewers should understand that culture, as well as being able to speak the language, to ensure correct wording, known as transcreation. R14 uses AI to localise content “it saves me time and money as there is no budget for very small countries and their local languages”. However, R05 did not agree, stating “using Gen-AI content is a brand image risk especially due to AI output not being quality. AI produced content isn’t always correct, especially if it has been directly translated into another language”. This demonstrated the importance of having a local reviewer, who speaks the language, reviewing the AI output. This is an important part of implementation management and will be explored in section 6.2.5.

Closely linked to Eurocentric bias, the cultural biases that were explored through the interviews were focused on the homogenizing of culture and thoughts from centralised marketing campaigns. As noted in the literature review visual creative and content in marketing, such as images and symbols, can carry different meanings in diverse cultures (Usuneir et al., 2005). R04 stated for marketeers “you have to think about the culture”. R14 agreed, “we receive the emails that we need to send - we received all the material, but sometimes we need to give that local flavour to the Global initiative”. R10 gave an example where a recent video was used on social media at CSC that was culturally appropriate for its market (and created by that market) but was extremely sexist within other cultures. It should never have been published, but with only a local review in place it was approved for use. R10 observed: “I think that marketing tries hard to maintain an unbiased view at CSC. Gender bias, culture bias, religious bias are sometime seen, but not intentional”. This is an important example of both prompt engineering and implementation management of AI and will be explored further.

6.2.1.4 Confirmation Bias

Gender, Eurocentric and cultural biases can be reinforced by the marketeer themselves through confirmation bias. When reviewing the literature, confirmation bias was defined as individual experiences and interactions creating confirmation bias where we seek information that aligns with preconceptions (Lo Iacono, 2023).

R09, R15 and R16 noted confirmation bias as specifically being an issue at CSC. R09 concluded: “there is a lot of confirmation bias propagated through digital marketing at CSC where people will decide campaign strategies based off of things they think the audience will like, not based off what the data is indicating”. R15 agreed noting “going into different launching of campaigns people have a hypothesis. So, they're usually biasedly thinking certain things will play out a certain way”. R16 also agreed with this but also linked the experience to Eurocentric marketing practices to give further insights to local marketing – “when I see (US Marketing) as a European I get an initial - Oh Is it for me? Would I fit in that space? - that's my question”. R16 goes further to give an example of this Eurocentric confirmation bias when selecting a time zone for centrally run webcasts with the usual selection for US friendly time zones without reviewing the data to select better performing times - “the communication needs to be clear that this webinar is targeting to certain customers in a certain time zone. We need to think what our offering could be to other regions, and it might not be ideal. But what do we do for other regions is a question we should ask, otherwise it becomes bias in my mind”.

Adoption of AI by the workforce at CSC is crucial to begin making data driven decisions to reduce confirmation bias. To complement the implementation management of AI usage there should be enablement and learning for all marketeers to be empowered to use it. This will be further explored in section 6.2.5.

6.2.1.5 Persona Bias

Within the literature it was well documented that marketing uses sales agreed “Target Account Lists” to target certain companies and personas, however there is bias in persona rules (Lee, 2023). Many companies lack data maturity and will supplement data gaps with third-party data lists that can be “unclean” and not correctly validated. Seven of the eighteen respondents noted that persona data is often incorrect which is unhelpful to inform marketeers who are trying to use the data to make decisions – R07 stated “[it is] often aligned to biases of targeting groups. Main categories would be left-leaning liberal vs. right-leaning conservative”. R08 agreed and gave a further opinion that “the bigger the data the AI is fed on, the more skewed outcomes you will have. Knowledge of how large the data is can help the marketeer understand the level of bias risk”. This reinforces the literature that transparency and accountability are limited due to the proprietary nature of these algorithms, raising ethical concerns (Lipton, 2016). R07 and R13 agreed and built upon this view that it can be hard to get accurate data from AI within the MarTech Stack as marketeers are not sure what the AI has done to the data to read and analyse it: “There is an over emphasis [in CSC] on install base customer in the data and large enterprise companies. R12 and R18 further noted that “incomplete or old data can skew data used to create personas – creating incorrect persona rules and groups”. The demographics of these customers can drive biased outcomes.

Through analysing customer data and their persona preferences, AI algorithms can generate content that resonates with individuals on a deeper level, increasing engagement and conversion rates (Haleem et al., 2022). R02 expanded on this noting the bias within buyer personas as Eurocentric “for research profiles, we survey 600ish people. But it still usually skews heavily into one market, making up a lot of the responses for the survey…that adds a bias into findings, even though we're using the data as opposed to just opinion”. R09 reinforced this by stating “persona research may just be done on one or two markets, adding bias into findings”. This is unintentional selection bias, skewing the data that are used to craft personas.

Persona data can also be biased in other ways with R14 stating “the segmentation is biased always by industry, for example, or the size of a company. We are looking for big companies - we need to have that strategy clear for the different companies, now for small companies, medium and big companies”. Any data used that isn’t validated can drive bias and favour some groups over others; missing key audience preferences which can lead to product misalignment and customer attrition (Wilson, 2023). R03 agreed with this in terms of hyper-personalisation - “hyper-personalisation based on anonymised customer IDs and behaviour patterns…we're definitely missing a good monitoring system (at CSC)”. This can lead to performance disparity across individuals or groups.

Once the personas have been established, the marketeers can select imagery based on their consumers persona profile, select the creative design theme, and create images (Nair & Gupta, 2021). This begins to link to confirmation bias where a marketeer believes they know the persona (age, gender, demographic) of the customers they are targeting – selecting images based on who they think their customers are. However, from the respondent’s data analysis on the persona bias it appears to be driven by data instead of the marketeers themselves. If the marketeer is using the persona data to inform their decision-making then they will trust that persona. R08 noted that “bias is present in marketing campaigns, often influencing targeting, messaging, and content personalisation. Over-representing or under-representing specific audiences in campaigns”. Leading to any generated output of AI being at risk of false content generation.

It is clear from the respondent data analysis that persona bias in CSC is driven by data inadequacy or incompleteness, and this links to the theme of Analytics Use Cases and Prompting – as persona segmentation rules are driven by specific analytics. Prompt Engineering could help marketeers understand the balance of the persona data provided to them (by size of company, industry or location of the data) to give visibility and inform them on moving forward with targeting those personas.

6.2.1.6 Political and Legal Bias

The literature gives insight into the lack of effective failsafe’s and laws regarding AI and all respondents noted that to their knowledge no failsafe’s are in place in CSC for generative AI output. Currently there are no global regulatory rules for AI; different countries, continents and political and economic unions are employing different approaches (Schwartz et al., 2022; Saito, 2024). R13 reported that training on using AI at CSC is available as self-service and the respondent took their own initiative to learn about AI. The only failsafe on generated AI output currently is described as “curiosity…trial-and-error mentality”.

As explored in the literature review the only law currently in place for AI regulation is the European Union's AI Act (European Parliament, 2023). The rest of the world has the UNESCO guidelines known as "Recommendation on the Ethics of Artificial Intelligence" for guidance. Within Europe, GDPR is also an active law to regulate companies for data privacy and security**.** GDPR was only mentioned by R13, but it was an important insight into the biases that this regulation can drive - "complexity of compliance and legal governance. Better do nothing than doing something wrong". GDPR requires companies only keep encrypted data (non-identifiable data). This can be difficult to gain true persona insight as the data is homogenized and does not include identifying persona traits. R09 agreed, stating that "the barriers to adoption of AI are GDPR and data privacy implementation".

The topic of the geographical location of the "Big Tech" companies being able to subvert regulatory biases was explored in the literature. As explored in chapter 6, Findings, R09 noted that some of the large language models use up to 9 data sets and 7 of these data sets are from the USA. This opened up into an additional area of analysis from the respondents, as within each country you not only find law, but also political philosophies. R07 noted that AI models are biased politically: "the model itself already has some, even politically motivated bias within…if you look at what open AI puts out versus Deep Seek for instance". The respondent's point was that you will be given very different answers on democracy from each AI. This was echoed by R09 who gave the almost exact same example, "you ask (a generative AI) in China – "what does democracy means?" - and it gives you basically the complete opposite answer (to the USA created AI) - so you know it, it can be very, very fickle".

This may be an issue for driving further Eurocentric qualities within marketing. Prompting one demographically produced AI to produce content for another market that has radically different political or legal ideology could drive Eurocentric values. R16 agreed, stating "our bias develops because we don't necessarily agree with what we see around us and then that triggers so many decisions, right, where it's political". This education for the prompters will be required within Prompt Engineering, as well as Implementation Management.

6.2.2 MarTech Stack Representation

In chapter 5, Interview Findings, a recurring theme was noted by respondents on the structure of the MarTech Stack as a pyramid in the PCF. As defined in chapter 5, all eighteen respondents viewed the MarTech Stack as essential to utilising AI in marketing. This view by the respondents aligns with the literature that the MarTech Stack is of great importance to manage, execute, measure, and improve marketing planning, strategy, and execution (Earley, 2021). R05 stated that the Martech Stack “ensures quality of marketing output”. This aligns with the respondents’ views explored in section 6.2.1.1, where R05 noted that when marketeers use traditional AI that “industry standard tools take on the due diligence”. The majority of the MarTech Stack utilised industry tools that are viewed as having quality outputs.

There were disagreements on how the MarTech Stack should be represented in the PCF by the respondents. R04 observed “[when you] put it in a pyramid, people immediately think of level of importance…this is a hierarchy”. R02 agreed and stated, “a pyramid structure implies a foundation or a level of importance, or a volume implication”. R15 and R19 while not directly agreeing with the presentation of a pyramid, gave further insight into why it would be necessary to evolve it so it is not in pyramid structure. R15 stated “the triangle is misleading” as it appears to show people mapped to the pre-sale and process mapped to the post-sale journey. R19 further requested that if it is structured then the MarTech should be reordered to match the customer journey steps: Analytics, Social Media, SEO, Website, Nurture, DAM and CRM. The Martech Stack having multiple technologies within it that interact with each other, means that bias within it can be imputed at multiple stages (Flavin & Heller, 2019; Roetzer & Kaput, 2022). Aligning with R19 views, R04 stressed the importance of an “organised Martech Stack”, whereby companies using this PCF should make sure their Martech Stack technologies interact with each other correctly, and pass information coherently to each other to maintain data integrity.

However, none of the other respondents viewed it as hierarchical with R08 and R11 noting that presenting the MarTech Stack as a hierarchy was fine. R08 stated “for me, this view, it's completely accurate”. R11 agreed, noting “I think it makes sense”. R07 was vaguer on the structure – “you could definitely do that” – but had more of an opinion on making the PCF structure meaningful “concrete examples of how AI is used within it is needed to show the application of them”. These concerns on the hierarchy structure promoting some MarTech software as more important than the other, cascading, bias and a lack of meaning show a requirement to restructure the PCF presentation of the MarTech Stack. This will be explored in section 6.3.2.

All other respondents, when asked about the structure of the PCF in their interviews had no discernible feedback directly on the MarTech Stack pyramid structure. As the respondents have fixed roles in specific areas of marketing, they do not cover the full MarTech Stack. This review shows that not all departments are AI-enabled. R09 stated “I don't think AI is very well integrated into CSC’s marketing technology landscape yet. It is the very early stages of it, and many employees still don't have access to any AI tool. But I do think it will be very well integrated within the next year or two”. R04 agreed with this view that AI in the MarTech Stack is “still fairly new and not completely implemented”. This links to implementation management that is explored further in section 6.2.5.

6.2.3 Analytics AI Use Cases

As discussed in chapter 5, Interview Findings, the collective respondent feedback suggested that unlike the other software listed within the MarTech Stack, analytics should not be viewed as a monolith - it is a complex ecosystem of tools, use cases, and interpretations that should be built out within the final model. R19 exclaimed that “analytics is data” and it is being central to strategic marketing. This does align with some of the literature from chapter 3, where Flavin and Heller (2019) noted that within analytics AI enhances a MarTech Stack through algorithmic improvements, guided decision making and modelling predictive outcomes. However, the majority of the literature viewed the MarTech Stack as including all software systems that enable marketing content to go-to-market via marketing channels; none were positioned as more independent than the others (Purcarea, 2018; Roetzer & Kaput, 2022; Earley, 2022). R14 remarked, “our system can provide data and insights to improve strategy and achieve sales objectives,” emphasising the value of analytics with significant focus on predictive analytics, scoring models, and automation. In figure 6.1, analytics is the dominant software that respondents used in the MarTech Stack, enhanced with AI. This is closely followed by social media, but the two are intertwined and this is discussed further within this section.

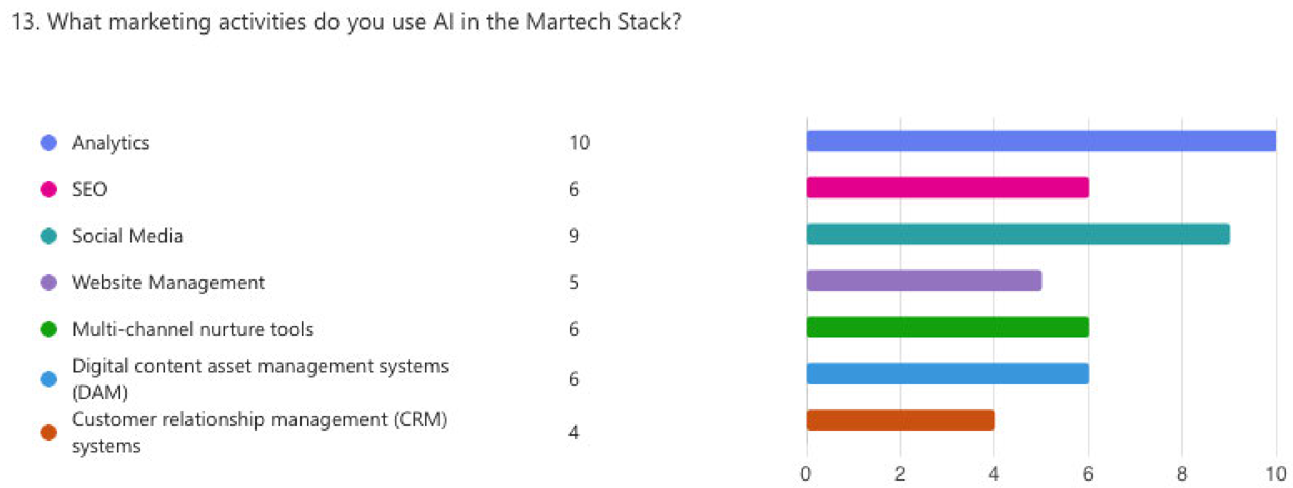


Figure 6.1: Analysis from Questionnaire on the usage of AI in the MarTech Stack software

The significance of analytics—especially in how it integrates with AI-driven processes—was emphasised by multiple respondents and is reflected prominently in the thematic analysis. R03 led the discussion by arguing that analytics in the MarTech Stack is too complex to be treated as a single, unified concept. They stated, “Analytics is too broad a term. When reviewing the training required, you should also focus on data modelling and predictive analytics as separate analytics use cases – especially as it uses algorithmic traditional AI”. R03’s position was reinforced by six other respondents, who also saw analytics as multi-dimensional and dependent on its application. For instance, R01 noted the role of platforms “Google Analytics, Adobe Analytics, and A/B testing platforms are often used in the MarTech stack to review and validate AI-driven outputs”. R13 agreed, noting analytics across multiple use-cases: “Adobe Analytics, flexible analysis in our Marketing Data, Adobe Experience Management, Marketo, CRM, Marketing Cloud”. Similarly, R08 captured the operational role of analytics in “using AI to generate insights, automate reporting, and identify trends for data-driven decision-making”. R11 insisted that “[a hard skill for marketeers is] how to interpret results in analytics that use AI". These examples highlight how analytics tools are not just evaluative but are embedded in the execution and optimisation layers of marketing campaigns.

As well as general analytics tools, scoring systems stood out as a distinctive use case with deeper customer journey implications. R13 and R15 placed particular emphasis on scoring models, with R13 offering a detailed explanation: "scoring systems (contacts being scored on interactions) are enhanced by AI. The machine learning algorithm and data aggregates into a score". Further, they introduced a group-level analytical approach by stating, "let's understand how many signals of interest we do see from a group of contacts and then score the group, rather than the individual contact". R15 aligned with this, succinctly stating, "scoring models are important for AI enhancement". These scoring models are seen not only as retrospective evaluation tools but also as predictive indicators of marketing impact, forming the foundation of propensity models.

Additionally, CRM emerged as a focal point within analytics discourse, with R10 advocating for the integration of AI in CRM. Happily, R13 confirming it is actively in use in CSC's CRM system. However, R13 noted that due to CRM's incomplete data isn't without bias and this is reinforced by R07 who expressed scepticism about the reliability of AI-driven analytics, saying, "you are not sure what the AI has done to the data to read it". R13 gave two examples where bias in CRM exists as an incomplete data capture – the first was "[at CSC we have] Experience Centres…[we] invite customers to close deals, but these visits are not captured in CRM as a touchpoint". Therefore, CSC can not include this data in propensity to buy models. The second example was on web-based trial versions of products "customer usage within the trial is not captured, so you get no test drive data". This drives bias within scoring models where interactions for trials would be scored highly. These two examples of incomplete data capture align to persona bias from section 6.2.1.5, where un-balanced data sets drive inaccurate personas that marketeers use to target certain customer groups.

Analytics was not viewed just as a standalone entity, but the core technology that underpinned the rest of the MarTech Stack, and therefore it's applicability through the Customer Journey. R03, R08, R10, R12, R13 and R18 contextualised the value and different application of analytics across the marketing lifecycle. R03 noted using AI in "Analytics for reporting and content optimisation". R08 differentiated pre-sale and post-sale analytics, "yes, AI use cases differ between pre-sale and post-sale marketing. Pre-sale AI focuses on lead generation, advert optimisation, SEO, and predictive analytics". R10 agreed with the applicability based on Customer Journey stage – "[Analytics] are used pre campaign to analyse the data and ensure the right customers are targeted, all the way to post campaign analysis and demand generation conversions". R09 took the applicability further describing AI-supported A/B testing: "[I] use AI to create A/B test analyses by giving it the raw data…and ask it to give three bullet points insights". R13 also noted that "generative AI is great to create visualisations of data into easy-to-read charts and visuals". R12 described a complete suite of AI-enhanced analytics applications "[analytics covers] analyse customer behaviour, predict outcomes, automate marketing tasks, create and personalise marketing content and optimisations". These categorisations of analytics are utilised within section 6.4 to evolve the PCF into a new framework. R08, agreed with these views noting that they are "using AI to generate insights, automate reporting, and identify trends for data-driven decision-making". R18 provided further operational insight, discussing the integration of analytics with social media reporting, "AI is embedded which auto generates paid social campaign insights based on the data which helps us make optimisations decisions," and noted that AI "saves me hours of work" when generating tools like Excel formulas. This reflects the automation and efficiency gains analytics can deliver, especially when embedded directly into the MarTech Stack software. R18 gave an example, stating "we're introducing a sophisticated audience matching tool".

As a result of these insights the PCF will be developed to show the different applications of analytics across the MarTech Stack and the Customer Journey. This will show both technical sophistication and critical oversight for marketing departments - ensuring that AI enhances, rather than obscures, the analytical processes underpinning digital marketing. This evolution will be explored further in section 6.3.

6.2.4 Prompt Engineering

The skill of prompting AI emerged as a dominant and unifying theme across all eighteen interviews. All respondents noted the vital importance of correct prompting of generative AI – R06 called it “the art of prompting”. R03, R07, R09 and R18 all used the term “Prompt Engineering” as a way to educate marketeers on structuring and crafting an instruction to a generative AI to produce the best possible output. Structuring is learning the correct structure of prompts, the words and tone to use. Crafting is the personal awareness of how to produce a prompt that will provide the optimal output. R07 stated that marketeers using AI need to have “basic understanding of AI technology and prompt engineering”. R09 agreed and further added “it is important to have proper prompt engineering when using an AI to get the best possible outputs”. R18 was more definitive, equating prompt engineering directly with critical marketing competencies: “Hard skills? That is prompt engineering”. Every participant acknowledged that crafting effective prompts is not just a peripheral skill but the core competency in leveraging generative AI for marketing.

While R19 raised concern that “prompt learning can be challenging”, R04 conveyed the issue that there is currently no prompting training at CSC. R02 noted their current unease with the lack of prompting education and training: “I would feel a lot more confident about what I could and couldn't put into a prompt [with training]”. R02 also notes that these concerns “holds them back from using AI for anything other than administrative tasks”. R06 agreed, “saying it was not a question of “one-off training”, but rather “it’s really the art of how I do that [prompt]”, adding that “I personally don't feel comfortable yet [to do it]”.

In the absence of formal instruction, many of the respondents have taken it upon themselves to self-educate. R14 is self-taught and taught themselves industry prompting guidelines to prompt “in the correct way”. They propose that “using AI has made me 20 to 30% more productive”. R16 is also self-taught and became curious to try AI when it was not rolled out centrally by management. They did this by “reading online content on how to target questions correctly”. R08 and R11 also developed personal prompting guidelines, including A/B testing strategies, ethical frameworks, and the use of supporting documentation to improve their AI comprehension. R08 “I have a set of prompts already written out that I use to optimise the way that I used Gen AI to make changes or to create the content that I need”. Interestingly, R11 found that improving one's prompting skillset also allows individuals to detect AI-generated content more easily — a form of self-reinforcing digital literacy – "getting a better sense of being able to tell when something is AI generated".

Respondents' exploration of prompting guidelines were not for generic prompt engineering, but specific prompt training for marketing use cases. R12 stated that there is "currently a grey area [in CSC]" in training on how to prompt. Current training shows use cases for AI in other departments (such as procurement or HR), but none are currently for marketing specifically. R14 agreed stating that "there is currently no prompting training at CSC. Basic training is available to use AI; however, training on how to use it in daily marketing roles is missing". R16 gave an example where employees at CSC are encouraged to use an embedded administrative AI in their work but there is no prompting training to accompany it. R07 gave insight that "training is not standard…pushed out and for the user to work out how to use it correctly". R09 finished by stating that "current trainings weren't effecting or memorable". 60% of all respondents strongly agreed and 20% agreed (with 20% neutral) that more training is needed to use AI responsibly in their job, and 50% reported the current training at CSC was inadequate. Respondents reported that current training was hard to apply to their day-to-day jobs. R03 notes "we're trusting people to use their own critical thinking which isn't enough". R02 stated that they are using their own "moral compass" to use AI ethically and check their own bias when using it.

There was strong consensus that prompt engineering must become central to AI education and governance at CSC and respondents gave a variety of ideas and insights on what prompt engineering guidelines should entail. R18 advocated for prompt engineering to be mandatory, "training should be mandatory as otherwise it is left open to interpretation and bias". An educational program on how to prompt an AI for digital marketing use was raised by multiple respondents. R03 recommended that a training model could be used by employees to test their prompting skills in a training scenario based on their job role and interests. They noted that companies should define the bias parameters themselves and a list of acceptable promptings for marketing use cases should be provided. R02 noted that publishing prompting "guidelines on how to do so" would be beneficial. R05 envisioned an "AI guidebook" and "AI ambassadors" within the workforce to provide real-time support.

R07 recommended showing marketeers "best practices on how to create and use prompting should be available showing unbiased, clear prompts would be a good start". R04 agreed with prompting education "being clear and concise". R08 spoke on the need for training, especially on how to craft complex prompts - "use clear, neutral, and inclusive language to avoid leading or skewed responses…structure prompts to encourage diverse perspectives, and where possible, request AI to consider multiple viewpoints or verify information…additionally, fact-check outputs, refine prompts for fairness, and apply human reviews to ensure ethical, balanced results". R09 agreed and gave additional information that the prompt training "includes using neutral and fair language, providing very specific context and examples, requesting multiple outputs in a certain form (bullet points, charts, etcetera), and to add refine content by adding feedback and certain requests".

Of note, R19 noted that CSC employees are mandated to use an Enterprise AI (due to having additional security for CSC for the large language model and the data prompted into it) and it is not as good as a public gen-AI and requires simplified prompts – "the public AI's can consume complex prompts but the Enterprise AI one is not trained on as much real-time data". A facet that will be explored in the implementation management section is that the Enterprise AI is available to all marketeers in CSC, but there is currently no widespread adoption with only four respondents citing that they use it.

R11 gave great insight into how to get an AI to perform better with better prompting – "give the prompt background, such as attaching an email or chat history to give it a data source to pull from". This is treating a generative AI almost like a traditional AI, by giving it a data source to work from (as well as its original large language model data) to make sure the output is as focused as possible. While R03 recommended a training simulator and R05 an AI guidebook, R11 recommended hosting a "Promp-A-Thon" training course for marketeers where digital medals and prizes supported motivating marketeers to prompt correctly. The output of prompting training was nicely summarised by R18, "I think people will be encouraged to use prompts on AI tools as part of their work, driven by the expectation to be more efficient".

Another facet of prompt engineering that was noted by R09, R11, R12, and R18 is the differentiation between personal and professional prompting. R12 and R11 likened ChatGPT to a “friend” in personal use but maintained formality with AI in the workplace. R09 suggested that while personal AI use may be conversational, workplace AI interactions should remain structured and formal, with carefully framed parameters and tone – “the prompter should never swear or use offensive language”. R11 agreed with this view, stating their personal usage is more friendly with more interaction, whereas professional is “direct, less friendly and my prompting is shorter”. This was also reinforced by R12 who noted that “ChatGPT is a friend, however [business AI] for work is more formal interactions”. This is not just anecdotal interactions from the interviews; the AIs have been coded this way. R11 is a business AI trainer (this is further explored in the Implementation Management section) and interestingly shared that “business AI does respond positively to being friendly…it's part of its training. So [in my training] they did actually suggest saying please and things like that in our prompts…being polite and friendly gets a better response”. This behavioural split emphasises a need for contextual prompt training—to help employees switch effectively between personal familiarity and professional accuracy in AI interactions.

A strong concern expressed by R01, R02, R06, R07, and R08 is the potential for bias in prompting without training. R02 underscored the necessity for prompts to be “neutral and inclusive”, noting that “humans will add in bias when prompting an AI”. R01 agreed with this and suggested “crafting prompts that are neutral and inclusive, avoiding language that may unintentionally lead to biased responses”. This aligns with the views of R09, R07, and R18 who saw correct prompt engineering as synonymous with implementation management - tying it directly to productivity, consistency, and brand governance. R04, R02, and R06 warned that without standardisation, AI outputs will vary, undermining brand consistency and quality control. R18 reinforced how this training should be mandatory as otherwise it is left open to interpretation and bias – “perhaps if there was a stage between AI developing the prompt, and the prompt being delivered. Or, where the prompt is delivered have a scale to identify the level of biases present in the answer”.

Crucially, cultural bias was raised by R04 and R08, who warned about the Eurocentric outputs that can emerge from homogenized prompting. R04 noted “one of the main challenges is that we all use AI differently, so I could use a prompt in a different way [to others] …because we all have different experiences, languages and so on". This links to the literature that cites this difference in prompting could lead to Eurocentric aesthetic bias that excludes diverse cultural representations (Tang et al., 2021; Henning, 2022; Yalkin &Özbilgin, 2022). R08 agreed with this view, noting that generative AI outputs can be too Eurocentric – "I use local experts to review my outputs when used in local countries to make it culturally appropriate".

R19 extended this prompting bias risk into a risk of adversarial attacks, suggesting that unconscious prompting biases may corrupt AI models, compromising output integrity. This reinforces the documented literature that prompts from marketeers can change the input data, such as images or text, which in turn corrupts the machine learning model for everyone who uses it (Palmer, 2023). R04 pointed out that "in the end the outputs also change" but that for his/her company "in terms of branding, in terms of messaging, we want it to be more consistent. The risk is that …the AI output won't be the same". R06 agreed, stating "I don't think there is a whole standard yet, everybody's using it…but how do I even prompt AI to get out what I need". R02 noted that "[currently employees are] learning through errors of how to appropriately craft a prompt". AI algorithms are instructed to learn from their prompter to give a more tailored service and are therefore vulnerable to small, imperceptible changes to input data – this is known as prompt injecting (Palmer, 2024). R04 and R06 noted that companies should be limiting AI's learning from employees (especially in large companies that want to maintain the same brand integrity) and offer generic prompts for marketeers to use – similar to Microsoft Co-Pilot that offers standard prompts to all users. R06 "[employees] need specific approvals or quality checks, which are not included in today's processes". This will require initiatives across implementation management for the elements of people, process and infrastructure if it is to be successfully implemented. R08 captured it well, stating "AI quality assurance and governance is establishing formal review and validation frameworks for AI-generated content, ensuring compliance with brand guidelines and ethical standards". This is directly aligned to the theme of Implementation Management – as education of Prompt Engineering is "very powerful and teaches technique for better outputs. Training should be mandatory as otherwise it is left open to interpretation and bias" (R18). This is explored in the next section.

6.2.5 Implementation Management

Implementation management became an equally dominant theme, on par with Prompt Engineering, from the respondent's thematic analysis. The two seemed to be synonymously discussed, as prompt engineering requires education implementation through processes and people support, as well as the infrastructure to deliver the training. It appears to complement the emerging research area of AI where human empathy and creativity are coded within parameters of the AI to build public confidence in AI governance and usage (Margetis et al., 2021; Hernández et al., 2023). The respondents felt responsible for using AI correctly with R01 describing a modern marketeer as "someone skilled in AI, with the ability to create the right prompts and leverage AI tools effectively for the role". This directly aligns to Liu et al. (2021), who recommend a human training schedule for employees using AI, to minimise biased outputs.

Creating a plan for Implementation Management of new technology is important and directly aligns with the literature school of thought where any new deployment of technology within a company requires organisational changes for its successful integration, usually referred to as organisational complements (Brynjolfsson et al., 2019). By successfully implementing AI it encourages fast competency and usage within the workforce. R18 noted that by using AI "perhaps people don't need to lean on the expertise of others as much as they have needed to before, as they can simply prompt for an answer".

Some of the current literature (Gartner, 2023; Buczek, 2023) maintains that increased ROI and employee output is to be expected from increased AI deployment. This was generally supported by interview feedback. R05 noted that, "latest campaign content being created with help from AI [makes] for quicker production timeline". When asked to rank the perceived value of using AI against 10 criteria, "reduced workload" and "increased output" were ranked first and second overall (table 6.1). This points to the value of centrally supporting CSC's workforce when the potential of new technology in increasing productivity is understood, and staff are engaged in applying new technology to enhance their own performance and output.

Overall ranking of the respondent data: 1 = Reduced Workload; 2 = Increased Output; 3 = Work on Higher Value Activities; 4 = Increased Conversion Rates; 5 =

Improved Brand Adherence; 6 = Increased Control; 7 = Reduced Risk; 8 = Increased Visibility of Data; 9 = Higher Quality Output; 10 = Improved Supplier Performance

Please now rank the value of using AI in Digital Marketing (1 = highest ranked, 10 = lowest ranked)

Respondent	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th
R01	Work on Higher Value Activities	Improved Supplier Performance	Reduced Workload	Increased Output	Increased Conversion Rates	Higher Quality Output	Reduced Risk	Increased Control	Increased Visibility of Data	Improved Brand Adherence
R02	Increased Conversion Rates	Increased Output	Work on Higher Value Activities	Improved Supplier Performance	Increased Visibility of Data	Higher Quality Output	Reduced Workload	Reduced Risk	Improved Brand Adherence	Increased Control
R03	Increased Output	Work on Higher Value Activities	Improved Supplier Performance	Reduced Workload	Higher Quality Output	Increased Conversion Rates	Increased Visibility of Data	Reduced Risk	Increased Control	Improved Brand Adherence
R04	Reduced Workload	Increased Output	Improved Brand Adherence	Work on Higher Value Activities	Improved Supplier Performance	Increased Control	Higher Quality Output	Increased Visibility of Data	Increased Conversion Rates	Reduced Risk
R05	Work on Higher Value Activities	Increased Visibility of Data	Reduced Workload	Increased Conversion Rates	Improved Brand Adherence	Increased Control	Higher Quality Output	Increased Output	Reduced Risk	Improved Supplier Performance
R06	Increased Output	Increased Conversion Rates	Work on Higher Value Activities	Reduced Workload	Increased Visibility of Data	Increased Control	Higher Quality Output	Improved Brand Adherence	Improved Supplier Performance	Reduced Risk
R07	Increased Output	Work on Higher Value Activities	Reduced Workload	Increased Conversion Rates	Higher Quality Output	Improved Supplier Performance	Improved Brand Adherence	Increased Control	Reduced Risk	Increased Visibility of Data
R08	Increased Conversion Rates	Higher Quality Output	Work on Higher Value Activities	Reduced Risk	Increased Output	Reduced Workload	Increased Visibility of Data	Improved Brand Adherence	Increased Control	Improved Supplier Performance
R09	Reduced Workload	Increased Output	Work on Higher Value Activities	Improved Brand Adherence	Increased Visibility of Data	Increased Control	Reduced Risk	Increased Conversion Rates	Higher Quality Output	Improved Supplier Performance
R10	Reduced Workload	Increased Output	Higher Quality Output	Work on Higher Value Activities	Increased Visibility of Data	Increased Control	Reduced Risk	Increased Conversion Rates	Improved Brand Adherence	Improved Supplier Performance
R11	Higher Quality Output	Work on Higher Value Activities	Increased Output	Reduced Workload	Increased Conversion Rates	Improved Brand Adherence	Increased Control	Increased Visibility of Data	Improved Supplier Performance	Reduced Risk
R12	Reduced Workload	Higher Quality Output	Increased Conversion Rates	Increased Output	Improved Supplier Performance	Increased Visibility of Data	Work on Higher Value Activities	Reduced Risk	Increased Control	Improved Brand Adherence
R13	Reduced Workload	Work on Higher Value Activities	Increased Output	Increased Conversion Rates	Higher Quality Output	Increased Visibility of Data	Reduced Risk	Improved Supplier Performance	Increased Control	Improved Brand Adherence
R14	Reduced Workload	Increased Output	Higher Quality Output	Increased Conversion Rates	Reduced Risk	Work on Higher Value Activities	Improved Supplier Performance	Increased Control	Increased Visibility of Data	Improved Brand Adherence
R15	Reduced Workload	Work on Higher Value Activities	Increased Output	Increased Conversion Rates	Improved Brand Adherence	Higher Quality Output	Improved Supplier Performance	Increased Visibility of Data	Increased Control	Reduced Risk
R16	Work on Higher Value Activities	Reduced Workload	Increased Control	Increased Visibility of Data	Improved Brand Adherence	Increased Conversion Rates	Increased Output	Improved Supplier Performance	Reduced Risk	Higher Quality Output
R18	Work on Higher Value Activities	Higher Quality Output	Reduced Workload	Increased Output	Increased Control	Increased Visibility of Data	Increased Conversion Rates	Improved Supplier Performance	Improved Brand Adherence	Reduced Risk
R19	Increased Output	Reduced Workload	Higher Quality Output	Work on Higher Value Activities	Increased Conversion Rates	Reduced Risk	Increased Control	Increased Visibility of Data	Improved Brand Adherence	Improved Supplier Performance

Table 6.1: Results from respondents' pre-interview question on their perceived value of using AI in Digital Marketing

This data insight in table 6.1 shows a willing workforce which aligns with Jarrahi et al.'s (2023) views that successful implementation of AI lies in the infrastructure of its adoption not the technology itself. To get to this critical adoption level, the three elements of people, infrastructure, and process are required to successfully integrate AI (Jarrahi et al., 2023). Indeed, empowering employees to use new technology fosters a culture of innovation and efficiency; similar to software developers that are encouraged to create AI at speed (Karimi-Mamaghan et al., 2022). When employees identify tools that enhance their productivity, it is often based on a first-hand understanding of their tasks and pain points. Supporting such initiatives demonstrates trust, boosts morale, and encourages ownership of work outcomes. It positions the company as adaptable, leveraging modern tools to maintain a competitive edge. Ignoring these requests risks disengagement and inefficiencies, while embracing them can drive better collaboration, streamlined workflows, and higher job satisfaction. Ultimately, actively supporting employees in their use of new technologies creates a win-win for workforce motivation and organisational performance. In section 6.2.4 we learnt that R16 self-taught themselves how to prompt when it was not “rolled-out centrally by management”. R05 argued that while marketeers are encouraged to use generative AI, “we get guidelines but no risk management”.

It was noted by R02 that companies usually are “reactive to new technology” – rather than embracing a proactive approach to technology usage and implementation. In this context, R03 drew a parallel with the evolution of the Internet: “if you go back to the early days of the Internet - people didn't really use the Internet very much because the operating system was really, really terrible. It was not until they fixed the operating system that the adoption of it became really interesting”. The respondents’ viewpoints were consistent in that rather than allowing users to explore AI and allowing something “bad” to happen, companies should provide proactive guidance, education and adoption assistance in advance. R02 noted that more control around new technology provides comfort for cautious users, and therefore proactive management is in employees’ best interests to encourage more usage. This underscores the value of a proactive approach to supporting users through an adoption transition, in which the analytical framework discussed above may act as a useful action checklist.

R01 suggested that those resistant to using AI and incorporating it into their work are "legacy thinkers and laggard adopters" and noted "incremental adoption [of new technology] requires support". All respondents rated themselves as data-driven marketeers and all use AI in their jobs, marking themselves as "early adopters" within CSC (R01). The average score of where they saw AI usage to be at CSC by their peers was 2 out of 5 (1 being not used and 5 being used prolifically). R04 noted that while this score is low, CSC is nevertheless ahead of the current industry standard and rate of adoption. R08 agreed with this view, noting "[CSC] leverages generative AI to accelerate time to market and enhance data analysis".

Within the Prompt Engineering section, it was clear that prompting training should be mandatory for marketeers: learning how to prompt in a concise, unbiased way, feeding correct data for the prompt, writing politely, using the provided Enterprise AI and having the training done specifically for marketing use cases. However, there were other educational ideas from respondents beyond prompt engineering. R10 recommended using disclaimers when using AI in any work, however R05 only agreed halfway, "once a certain % of content is AI generated it should only be used with a disclaimer to say it is AI". R10 added that brand guidelines were an important element of training and understanding brand guidelines can support the removal of bias – "[marketeers at CSC] need to stop off brand content, research on prompting words, how to use the AI and what data it is trained on".

A recurring theme from respondents is the lack of practical, role-specific AI training for marketers. While foundational tools and knowledge exist, they fall short in preparing marketing professionals for real-world applications. R14 highlighted that "basic training is available to use AI; however, training on how to use it in daily marketing roles is missing". R15 reinforced this with a call for operational integration - "training is currently not prevalent for marketeers. There should be pilot areas to test and prove out the use cases to show accurate outputs. Marketeers should then develop training, roadmaps and implementation plans".

This gap in formal, structured learning is compounded by a fractured and inconsistent training ecosystem, where knowledge and access differ by team, geography, or individual initiative. Multiple respondents report disparate, stand-alone training programs that other respondents were not aware of. Only R08 mentioned a training space called Experience Garage, “in terms of experience garage, I used it to understand how to properly use generative AI within the company. What are the do's and don'ts within CSC”. R11 was the only respondent to be invited to join an initiative called the Copilot Champions Network, where employees become an evangelist for generative AI – “it's adoption for those who have it, because not everybody is allowed to have it yet”. Both R09 and R12 had used training through LinkedIn Learning; however, this was still self-initiated learning – R12 “if learning to prompt, marketeers can use LinkedIn Learning to learn through doing”.

As discussed above in section 6.2.4, CSC has its own Enterprise AI for employees to use if wishing to generate content. However, only four respondents (R09, R14, R18 and R19) knew that it was mandated for use for CSC’s workforce. R19 raised the issue that “Enterprise AI is available to all marketeers but there is no widespread adoption”. R14 uses the Enterprise AI “for text generation to craft questions and insights that facilitate interaction with our audience”. Table 4.5 from chapter 4, Methodology, showed that 15 respondents use AI for administrative tasks within their daily role which is embedded into the software they use – this is not a compliance concern. However, in figure 6.2 which is analysis of questionnaire data, it shows all 18 respondents use generative AI within their daily role to generate text; this leads to the assumption that the Enterprise AI is not used for all generated content and the widespread adoption of it would reduce a compliance risk for CSC.

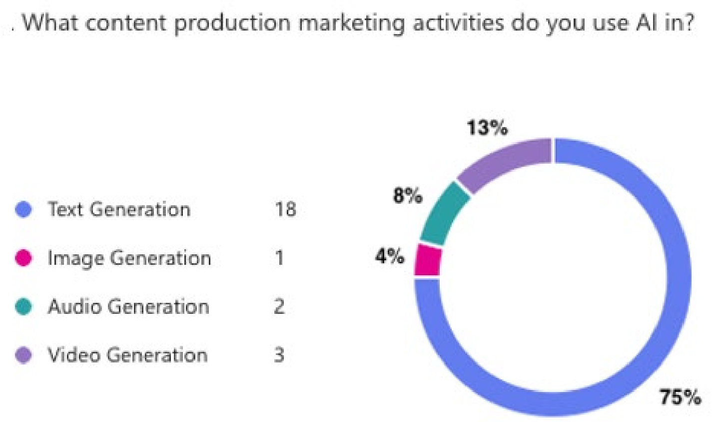


Figure 6.2: Analysis from the Questionnaire on what respondents use AI to generate

As well as a lack of awareness on Enterprise AI, only R13 mentioned a platform called AI Sandbox. R13, “AI sandbox for CSC employees…we can leverage not just generative AI products, but we have large language models from other vendors and it's often quite interesting to compare the different tools to each other and see how well they perform on different tasks”. Employees at CSC have access to both traditional and generative AIs – all with enterprise-grade security to support their usage of AI; however, these insights point to the absence of a centralised training strategy or communication plan. As noted above this fractured training education system leads to unequal enablement across marketing teams.

When reviewing a proposed training process, respondents broadly agreed that human oversight must remain central to the production process when using AI. There were differing opinions on what a review cycle would entail; however, all included at least a double review with a human making the final decision. R02 likened AI involvement to existing agency review cycles, “much like we proof/review/sign off on materials from an agency, we should work with AI to support our work but not to complete and publish autonomously. The process truly depends on the sensitivity and visibility of the work and its intention - much like our internal and vendor review-approval cycles look like”. R07 fully supported a dual approach with an AI Agent within the Enterprise AI to review any marketeer prompts and a “human review before publishing”. R04 also highlighted usage of AI Agents to support regulation and a hybrid approach, “once or twice by humans for most critical outputs should be enough. If reliable AI reviewing software would come along that could also be implemented. Possibly with AI agents that streamline the process to basically just prompt, create and check at once, final go by human”. R08 detailed a formalised two-step review process – with the first being an initial review by the user (to look for obvious bias, inaccuracies, or misaligned messaging) and the second being a peer review by an AI specialist (to check for subtler biases, ensuring inclusivity, ethical compliance, and alignment with brand guidelines). R12 agreed with the other respondents, “once AI is implemented, it's important that processes are adjusted to include 'human' review throughout, particularly when AI is first integrated, particularly as the LLM needs training to enhance its outputs”. Only R13 disagreed with a requirement for training, believing that “learning to prompt is 80% trial and error” and therefore it is better to have a lived experience, than trying to learn from a training session. The disagreement between respondents show that prompting is both a structure and an art to achieve the best outputs.

Implementing a two-step review process was a theme the respondents all shared independently; however, this was not a one and done approach. Respondents emphasised ongoing risk monitoring was essential – R12 stated that “I think that risk is an area of AI that will need constant review and monitoring of the outputs to ensure that there is no bias, that the correct prompts were used to generate the outputs, that the sources of the content are clearly indicated, that there are no confidentiality issues”. This was reinforced by R04’s example of using AI for generating social media copy, “there are multiple (human) review cycles… these multiple reviews caught bias in generated social images that showed only white individuals”. The risk of cultural and racial bias in AI generated content is not hypothetical but it has already materialised, and respondents advised practical mitigations. R14 suggested employing local reviewers to avoid Eurocentric norms, and R07 encouraged CSC to supply generative AIs with local large language models to account for legal, cultural, and political nuances. These recommendations help to support mitigation for the Eurocentric biases that were explored in section 6.2.1.3 by R04, R10, and R14 – where each respondent currently works with a local marketing colleague to double check their AI outputs. R16 went further to request from CSC that any AI used by marketeers should have “[a] validated algorithm by multicultural individuals”.

There were disagreements between the respondents on making AI training mandatory. Within the Prompt Engineering section, it was established that 60% of all respondents strongly agreed and 20% agreed (with 20% neutral) that more training is needed to use AI responsibly in their job, and 50% reported the current training at CSC was inadequate. However, not all wanted that training to be mandatory. R13 noted that Prompt Engineering or further AI training was unlikely to become mandatory as CSC only chooses mandatory trainings for legal and compliance issues only. There is one mandatory AI training at CSC, this is “AI Ethics Training” (R13) (formed from the UNESCO recommendations) however it is not marketing specific, nor does it cover Prompt Engineering.

6.2.6 Customer Journey

As discussed in chapter 5, the existing literature presents a largely uniform perspective on the application of AI across the pre- and post-sale stages of the customer journey, suggesting minimal differentiation in terms of channel use, content creation, or strategic execution (Lemon & Verhoef, 2016; Dowling et al., 2020; Haleem et al., 2022). However, insights from the respondent interviews challenge this assertion by presenting a nuanced view that highlights distinct variations in AI application across these two phases.

All eighteen respondents validated the use of the customer journey in the PCF and considered it essential to the modern go-to-market for digital marketing. R03 reinforced that marketing has changed significantly with the four stages of the customer journey becoming eight stages - affirming the evolution from traditional models (such as Dowling et al., 2020). R04 reinforced its value, calling the journey “crucial” to modern marketing, yet observed that “a single customer journey for a single customer…does not really work anymore,” emphasising the need for individual personalised paths. R09 agreed, and gave an example for how this is achieved - “we can use AI to create hyper-personalised content for every segment of customer that comes to the website in order to increase conversion rates”. This aligns with literature on content scalability being possible with AI (Haleem et al., 2022; Rabby et al., 2021). Despite the comprehensive eight stage customer journey model being used in the PCF, the thematic analysis revealed that respondents spoke primarily of the pre-sale and post-sale stages as broad categories rather than dissecting each of the eight stages individually.

Respondents consistently identified pre-sale AI usage as more vulnerable to bias due to its reliance on historical data and broader audience targeting. R01 raised an analytical concern, “if we use the AI for content generation…the AI can only train itself based on the historical data,” potentially skewing content, particularly “towards men”. This links to respondents concerns on persona and analytical bias through incomplete or unbalanced datasets in CRM. R03 affirmed this perspective: “the white man in business is everywhere,” reflecting implicit bias in data sources. This was echoed by R14, who identified segmentation imbalances as “demographic, size of the company…when CSC should be targeting all interacting companies”. This reinforces the notion that segmentation of the pre-sale customer journey is important as it feeds into scoring which affects a customer's interaction with the company.

The complexity of targeting was a key theme that arose from the thematic analysis. R07 stated that in pre-sale marketing, "stakes are higher…the targeting has to be correct to the personas". This is due to the marketing being visible to a broader audience - "it is out in the world" (R07). This reinforces the broader and riskier nature of this phase. R01 notes that this is due to there being a difference in the buying committee in pre-sale, with "more influencers in the process". With broader targeting, comes the risk of audience fatigue. R13 cautioned that for pre-sale customer "there is a risk of churn as you can target existing customers too much with their data". This was reinforced by R16 who noted that targeted customers can suffer from audience fatigue – where they are constantly inundated with marketing and their attention span is lessened. R02 agreed with this and noted there are "considerations for data privacy" within the pre-sale phase. Correct targeting is important, as noted by R03 "presales will focus on qualifying and giving the customer the most relevant information for that persona / interaction with types of assets and content they most need. The goal in pre-sales is to inform the customer as quickly as possible to move them [to a sale]". R14 agreed and noted the importance of targeting correctly, "in pre-sales, AI is often used to identify potential leads and personalise marketing outreach".

A/B testing was another pre-sale AI strategy, with R09 describing AI's utility in testing messaging: "we use AI to create A/B test analyses… and asking it to give three bullet points insights". These practices were situated within top-of-funnel activities designed to drive initial engagement. This aligns to the literature where it was asserted that A/B testing is an important facet for digital marketeers (Nair & Gupta, 2021). R08 noted the applicability of AI when supporting A/B testing, "pre-sale AI focuses on lead generation, ad optimisation, SEO, and predictive analytics".

In contrast, AI usage within the post-sale journey was described as more focused, efficient, and grounded in actual customer data. R01 highlighted that once the purchase is made, the company already possesses key customer information, allowing for more refined targeting - "for the post-sales, it's not as skewed as the pre-sales". R04 pointed out that "we have more insights and can come up with better results,” implying an advantage in personalisation and journey planning. R16 agreed and explained how post-sale customers are easier to target, they have already purchased the software so you should have less audience fatigue as you can tailor your communications with them to “offer them just what they want”. R15 captured it well, stating through post-sale data you can “understand propensity of accounts to purchase”.

R03 and R14 noted that post-sale marketing shifts focus to adoption and retention, with R03 stating, “post-sales it is about customer adoption and actually using the product, this could mean chat bot support, optimising product UI (user interface) with guidance and product related nurture based on interaction of product”. R09 also had ideas on how post-sale data can impact customer offerings, “for post-sale we can use AI to create a customer support tool that uses agentic design to answer any specific question related to the product”. R16 linked this to personalisation of all this customers data – “post sales needs to be a lot more customised”. This was agreed with by R07 who argued “post-sale needs to be even more conscious about personalisation”. R08 also aligned with this thinking, stating “post-sale AI enhances customer support, personalisation, sentiment analysis, and retention strategies”.

R02 supported this, stating that “post purchase is where it [the customers journey] scatters into very different directions, so there would be much less overlap [than pre-sale]” compared to the pre-sale stage. This aligns with AI's ability to handle fragmentation through efficient targeting. R04 similarly emphasised the strategic advantage: “we don't really have to spend more money on creating awareness…we have so much more input…to create the perfect customer journey”. R05 agreed with this, stating “[marketing] evolving as technology evolves and as quality of the output increases”. R12 captured it well stating “post-sale activities can analyse sales data, look at past customer behaviours and transactional patterns to identify commonalities and build best-fit customer profiles”.

Despite these differences, a few respondents noted overlap. R10 and R18 described AI use as “quite similar” across stages for content generation and analysis, with R12 acknowledging “cross-over usage”. R06 mentioned the same broader uses across both pre- and post-sale customer journey, including “localisation, SEO, content audits and in customer journey planning”. R15 envisioned AI’s evolution from a content enabler to a sales aid: “a tool… to understand propensity of accounts to purchase”. R10 agreed, noting that “both [stages] will use it for content and as well as creative asset creation, the context may change, but the usage will be similar”. It appears that R18 defined it best as a similarity for the following: “they are quite similar in regard to content creation, grammar checks, data analysis and idea generation”.

While the literature suggests uniformity in AI’s role across the customer journey, thematic analysis of respondent’s interviews presented a contrasting picture. There is a clear divergence between pre-sale and post-sale applications of AI – with pre-sale marked by bias, persona complexity, and broader targeting, and post-sale characterised by control, efficiency, and retention strategies. This difference between pre- and post-sale stages and how this will be formatted in the final model will be further explored in section 6.3.3.

6.3 Model Development

In this section, the feedback from respondents on the PCF is combined with perspectives discussed above in section 6.2 to develop the final model. From the thematic analysis and cross-reference of literature in previous sections, there are clear areas of feedback on the PCF and how it should be evolved and further developed. This model will be validated by respondents in the next section, section 6.4.

During the interviews, respondents were asked to review the PCF (figure 6.3). The pre-interview questionnaire structure and interview script were entirely consistent with the PCF focus areas: types of AI, stages of the Customer Journey, technologies of the MarTech Stack, the elements of People, Process, Infrastructure and Bias (section 4.7.2). This was to ensure consistency throughout the study and to gain as much insight into the focus areas as possible during the interviews.

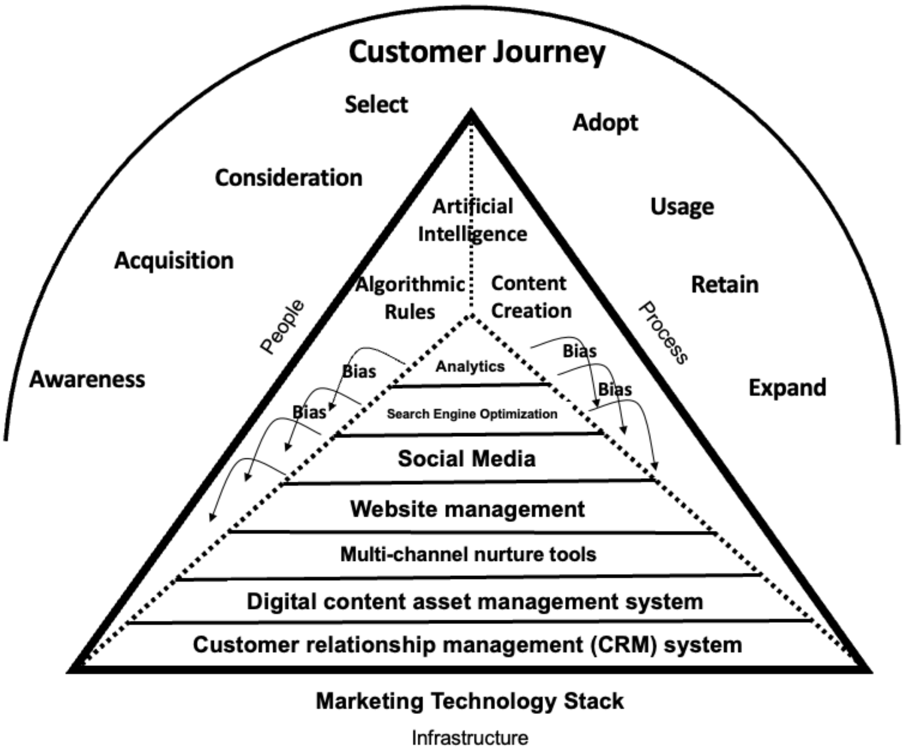


Figure 6.3: Provisional Conceptual Framework – brought forward from chapter 3 for reference.

6.3.1 Bias: Arrow Cascade Representation Incorrect

It was clear from both the literature and thematic analysis that bias is propagated through AI when using it within marketing. This was regardless of the type of bias, and there were multiple elements identified in section 6.2, from Eurocentric to Persona biases. This is due to: 1) the coding of it (this includes the location of the developing company, political ideologies in markets, and data imbalances within the large language models); 2) The deployment of AI (which is a lack of standard education, implemented by management and that is available for marketing use cases); and 3) prompting (due to the lack of prompt engineering training). This clearly shows that the inclusion of bias within the model is appropriate, however, the PCF representation of arrows made some respondents think of a cascade of bias. This was confusing to them and requires reformatting. R02 articulated the viewpoint of the arrows representing a bias cascade: “[When you] start at the analytics and then because there's something that's set up with a bias there, it cascades into the next level, which would be then like the SEO and then further to the social media and then on to the web itself”. Both R09 and R11 agreed with R02’s view, stating “the bias arrows are confusing” and “the bias arrows are unclear” respectively. R11 went further to ask, “can you explain the bias things [arrows] and why are they at the top? Or are you insinuating that they go all the way down to the bottom?”

In the PCF, bias is visible as arrows that show its existence in both generative and traditional AI and can be propagated through it. This overall was accepted by respondents, who noted the vulnerability of bias propagation through generative AI, but also acknowledged the data inconsistencies at CSC for traditional AI biases. There was feedback from R11 on this AI split and the biased representation on the PCF - “the AI split looks like it applies to different sides of the customer journey…which I don’t think you’re intending”. This was not the intention. Therefore, to evolve the PCF into a final model, the bias arrows are removed and the propagation represented as through both AI (traditional and generative), with the addition of bias being propagated through Coding, Deployment and Prompting.

6.3.2 MarTech Stack (Infrastructure): Relevant but Visually Problematic

The MarTech Stack was unanimously recognised as the critical infrastructure within the PCF within the analysis. As R05 put it, the stack "ensures quality of marketing output". R04 reinforced the importance of interconnectivity: "organised Martech Stack" technologies must "interact with each other correctly" to maintain data integrity. However, the visual representation of the stack — particularly the pyramid format — received mixed reactions from respondents.

R04 noted, "[When you] put it in a pyramid, people immediately think of level of importance…this is a hierarchy". R02 echoed this concern, stating, "A pyramid structure implies a foundation or a level of importance, or a volume implication". The Martech Stack is not a hierarchy; multiple technologies within it interact with each other, and any bias within it can be imputed at multiple stages. R04 stressed the importance of an "organised Martech Stack", whereby companies using this PCF should make sure their Martech Stack technologies interact with each other correctly, and pass information coherently to each other to maintain data integrity. R09 confirmed that linking MarTech Stack to Infrastructure in PCF was good – "I understand the infrastructure side of the MarTech Stack".

Contrastingly, R11 found the pyramid structure acceptable and R09 also agreed, "I like this triangle [representation] of this three-pronged or three-sided concept". The representation of the elements of People, Process and Infrastructure as a triangle with the MarTech Stack within it, while neatly presented, drove more confusion with respondents than not and therefore the representation of this will be evolved from a pyramid view in the final model.

Alongside this, R19 suggested that any representation of the MarTech Stack should be ordered to align more directly with customer journey stages for ease of visualisation of the marketeer using it: "Analytics, Social Media, SEO, Website, Nurture, DAM, and CRM". There were other requests from respondents to change labels of software within the MarTech Stack, again this was to support a marketeer view of the framework understand all the elements correctly. R02 proposed renaming "Social Media" to "Organic and Integrated Social Media" to distinguish between paid and non-paid activities. As analysed in section 6.2.3 analytics is far more than one line visualised in a MarTech Stack - R03 and R04 found Analytics too broad a term, suggesting a shift to “algorithmic analytics and data modelling”. These request for changes is accepted for this research.

Request for additions to the MarTech Stack also came from a few respondents. R16 requested adding a new MarTech component for Webinar Management, possibly labelled “Additional Platforms”. This would then cover any software that is added to the MarTech Stack in the future but not represented in this research – giving this research more longevity. Project management also surfaced as a request in several of the early interviews and there were differing respondent viewpoints on this. R01 was in favour of adding Project Management within the Martech Stack, whereas R02, R03 and R04 saw Project Management sitting under the Process umbrella within the PCF reflecting its role in workflow coordination and governance.

With multiple changes requested within the MarTech Stack representation, from the hierarchy to the software labelling within it a completely new approach has been employed to evolve the PCF to the final model. The MarTech Stack technologies are removed as individual labels to give the framework a longer applicability in the industry. It is also taking the guidance from the analysis section 6.2.3 on showing use case value. This is achieved by mapping out the use cases for the MarTech Stack applicability so that there is a better understanding of the framework on how the MarTech Stack technologies are applied in marketing and it can then also be used across industry and applied to other marketing departments.

6.3.3 Customer Journey: Consensus on Relevance and Placement

There was consensus from all respondents that the customer journey was of value and relevance within the PCF – it was understandable to them, and its visualisation across the framework was acceptable. R09 stated, “I like how the customer journey goes along with [what marketeers] know from pre-sale to post-sale on the other side”. R07 agreed, noting “[the] customer journey I would say is end-to-end. That really brings it to life”.

All respondents understood the eight phases of the customer journey; this was of no surprise due to it being a mandated strategy and execution planning guide within CSC. As explored in section 6.2.6, this was underpinned by the literature, where, from sections 2.5.1 to 2.5.8 the literature supported a journey broken into specific points that have different AI applicability and use cases. This was not the analysed feedback from respondents; they viewed the split for AI usage and room for bias propagation as for pre- and post-sale only.

There was no feedback from respondents that the eight stages of the customer journey should be renamed or formatted into a simplified view of pre- and post-sale. R03's statement that marketing has changed significantly with the four stages of the customer journey becoming eight stages, means that completely rehauling the view in the PCF for the customer journey would be inappropriate. As such, the eight stages remain in the evolved model; however, labelling of pre- and post-sale has been applied for easier visibility and consumption for the reader. A labelling of "Impacts vary at different stages of the customer journey" has been inputted as a link to bias propagation visualisation. This is due to the literature reinforcing there are variable usages of AI in the Customer Journey and bias will impact it in different ways.

6.3.4 Terminology and Structure Enhancements

Both elements of People and Process were widely accepted as essential umbrella concepts in the PCF, and this aligns with the analysis within section 6.2.5 that People and Process are essential to correct Implementation Management and Prompt Engineering. Though some respondents offered detailed views on improving their alignment to enhance clarity and usability. R09 noted that the way people and processes are currently mapped does not work, "[I am] confused about [the representation of People and Process] just because there's not really anything about the people or the processes on those sides [of the triangle]". This was a view agreed with by R15 who noted that the triangle is misleading as it appears to show people mapped to the pre-sale and process mapped to the post-sale journey which is inaccurate. This is due to how the framework visually associates these themes with different journey stages.

R02 noted, for example, that "People" would align better to "Content Generation" and "Process" aligned better to "Algorithmic Rules" in the PCF with people generating the content, and traditional rule-based AI being aligned with an established process. R06 agreed that “[it’s required to have the] right processes and reviews and governance in place”. All respondents agreed that multiple human reviews of AI output in marketing should take place and that it should be a set process. This was reinforced by R11 who noted that the AI split looks like it is applies to different sides of the customer journey which is not a correct view. “The algorithmic rules are applying to the customer, journey on the left side and the content creation is applying to the customer journey on the right side, which I don't think you're intending”. This concern was also raised by R14, who expressed concern over perceived misalignments: “AI still needs to be evaluated and reviewed before being incorporated into an automatic process. There should indeed be additional measurement and control processes”.

This feedback delineates the equal importance and different applicability of both elements of People and Process within the framework. The current mapping of them in triangle format to one side of the customer journey and one typology of AI is confusing to respondents and inaccurate. Within the evolved framework they are split out into outcomes from the AI applications to show how People and Process can be used to regulate bias propagation through AI usage through the MarTech Stack.

6.3.5 Applicability and Use Cases: A Gap Identified

Despite general support for the PCF's core concepts of bias, types of AI, the MarTech Stack (Infrastructure), People, Process and the Customer Journey – R09 stated “overall, I think it's really good” – several respondents highlighted a lack of practical application guidance for marketeers. R18 succinctly noted, “the PCF is great, but it needs to visualise and raise awareness on how this could be implemented by companies”. R07 agreed and requested to see “examples…that would really bring it to life”. R04 agreed with this and went further to define their concerns “about the people and process. I think they're involved in every single stage, I'm a bit unclear about what is really [the] process here”. This feedback emphasises the need for actionable examples to improve framework applicability in real-world settings.

To manifest this, the evolution of the applicability in the proposed final model is two-fold. The first is showing the different applications of AI across the MarTech Stack split by generative and traditional AI - such as A/B testing, scoring, customer journey analysis and targeting. The second is adding in how companies can implement through People and Processes. Both elements of People and Process align with Implementation Management and Prompt Engineering. This will support a marketeer reviewing this framework to see real-world marketing examples, application guidelines and perhaps even role-specific relevance. Listing out the use-case applicability of AI within marketing for both traditional and generative will also allay R08 concerns. R08 fed back that AI should be represented more positively in the PCF as they viewed that including bias in the same view as AI drove a negative connotation – “showing the bias detracts from the value of AI within marketing”. By formatting the proposed final model in this new way, with applicable uses, shows its value to the digital marketeer.

6.3.6 The Proposed Final Model

Following the process of this research from initial literature perspectives in chapter 2, cross-tabulations of the literature and emerging concepts in chapter 3, and thematic analysis of the respondent interview data in chapters 5 and 6 a new framework for revealing and mitigating bias in AI deployment in marketing is developed (figure 6.4).

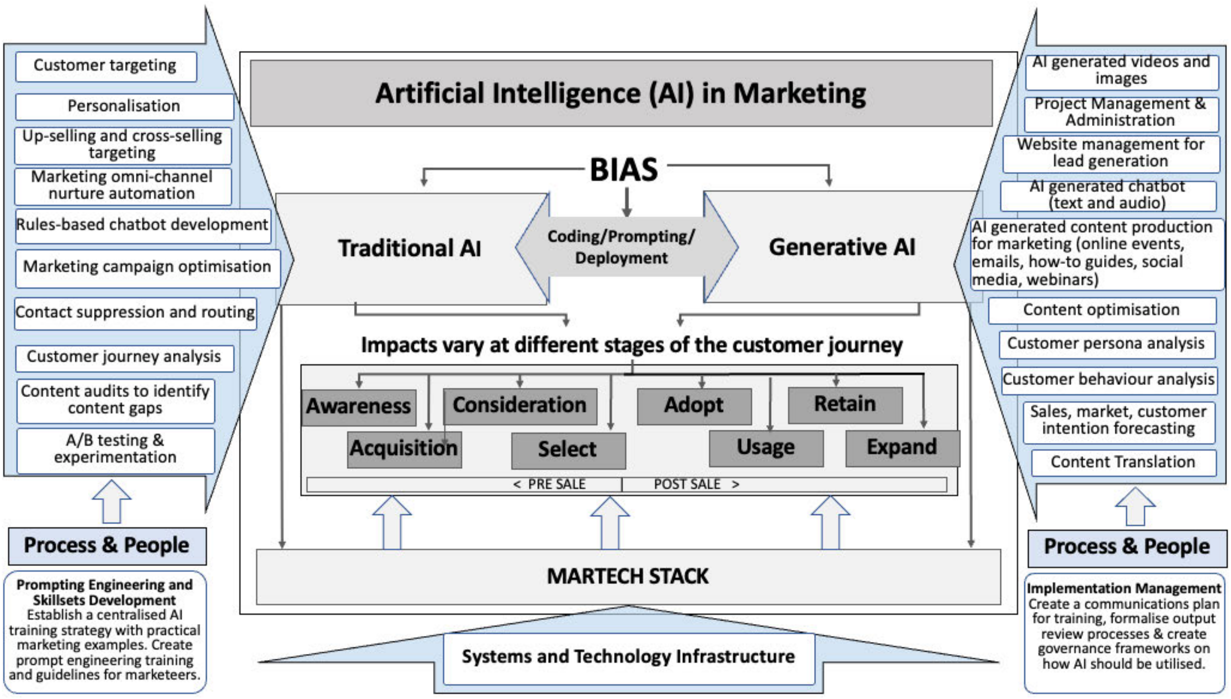


Figure 6.4: Model for Identifying and Mitigating Bias when using AI in Digital Marketing

This proposed model is a progression from the PCF, incorporating the interview feedback analysed in sections 6.3.1 to 6.3.6 (figure 6.5). Figure 6.5 shows the original PCF next to the proposed model. The yellow rings on the PCF show the concepts that were retained for the model, and the pink rings on the model show additional areas that were added from the findings.

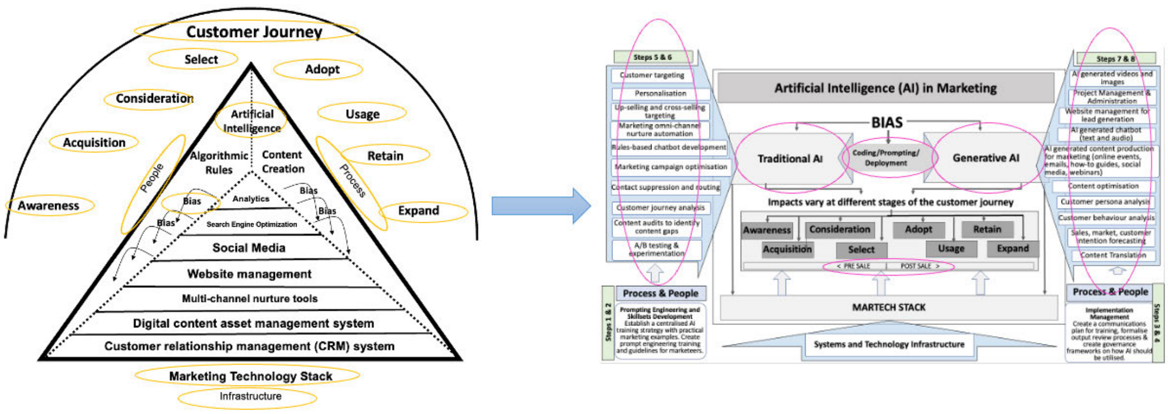


Figure 6.5: Side-by-side view on how the PCF differs from the Model

The main box in the middle of the model retains the original PCF core concepts of types of AI, the MarTech Stack and the Customer Journey – it shows how AI is deployed through marketing activities and the structure of the marketing environment. Types of AI retains its split between traditional and generative AI, however, the delineation of coding, prompting and deployment have been added between them to show where the bias can be propagated through their use. The Customer Journey retains its eight-stage representation with the additions of noting the pre- and post-sale areas, as well as the label “impacts vary at different stages of the customer journey”. This is appropriate as the uses for AI differ between the pre- and post-sale applications of it. The concept of the MarTech Stack has been condensed. In the PCF the technologies within it were shown, however, due to feedback on the hierarchy and the lack of use cases for the technologies it is now shown as one element. Infrastructure is still aligned to the MarTech Stack – as it was in the PCF – as this is the technology that infrastructures digital marketing.

The main additions to this model from the thematic analysis are the traditional and generative AI use cases and the People and Process elements. The use cases on how traditional and generative AI can be used within digital marketing activities are within the blue arrows to the left and right of the framework. These have come from the thematic analysis of the literature and primary data across sections 6.2 and 6.3 and have emerged to furnish the model with use cases on where to use AI within digital marketing. These use case activities are directly linked from the people and process outputs that support their implementation and governance – these are Prompt Engineering and Implementation Management.

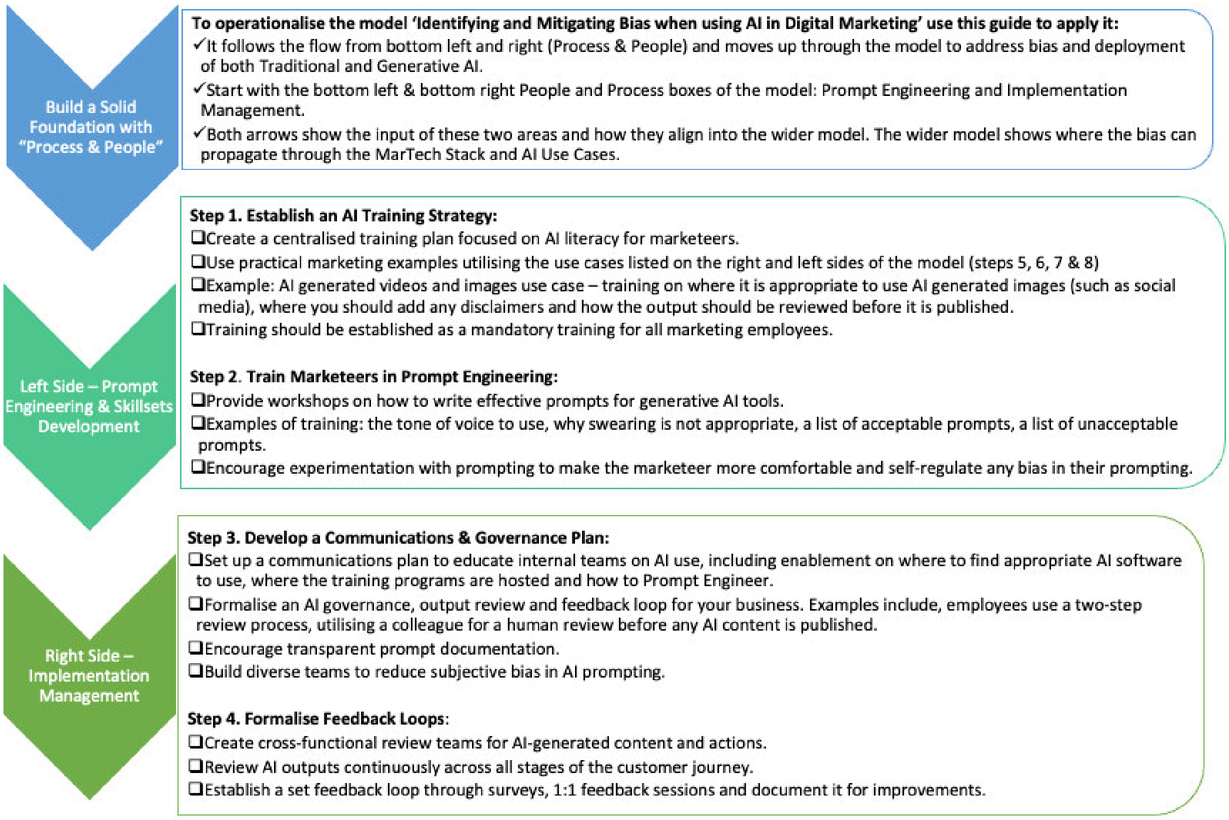
These two key management issues emerged from the data analysis were highlighted as being of particular significance for the development and deployment of AI in today's marketing technology environment. Both sections for prompt engineering and implementation management have suggestions on what needs to be delivered for marketeers to operationalise mitigation strategies to bias propagation.

From analysis within sections 6.2.4 Prompt Engineering and 6.2.5 Implementation Management the recommended actions to achieve identification and mitigation of bias when using AI are to:

1. **Establish a centralised AI training strategy** for marketing roles, including practical examples and prompts by channels. Add in use cases, using Enterprise AI for security and where to find AI tools.
2. **Prompt Engineering Training** make mandatory where possible.
3. **Formalise review processes** with multi-level human-in-the-loop checkpoints, using a local expert to the country the marketing will be in-market in.
4. **Create a communications plan** to improve visibility of existing tools and training.
5. **Strengthen governance frameworks** with clear risk management and bias mitigation steps.

The above five recommended actions have been added to the bottom left and bottom right boxes of the model to inform the inputs required by businesses to achieve bias identification and mitigation. The model is a multi-factor model that is derived from both the theory and interviews and graphically from the PCF. Its contribution to business is to help companies install correct practices for their marketing departments and marketeers to use AI while supporting identifying and mitigating bias.

To operationalise this model within any business to enable marketing departments to utilise AI while identifying and mitigating bias the model should be used in tandem with the guide to apply the model (figure 6.6). This guide will enable any marketing or business leader to implement the model for their company.



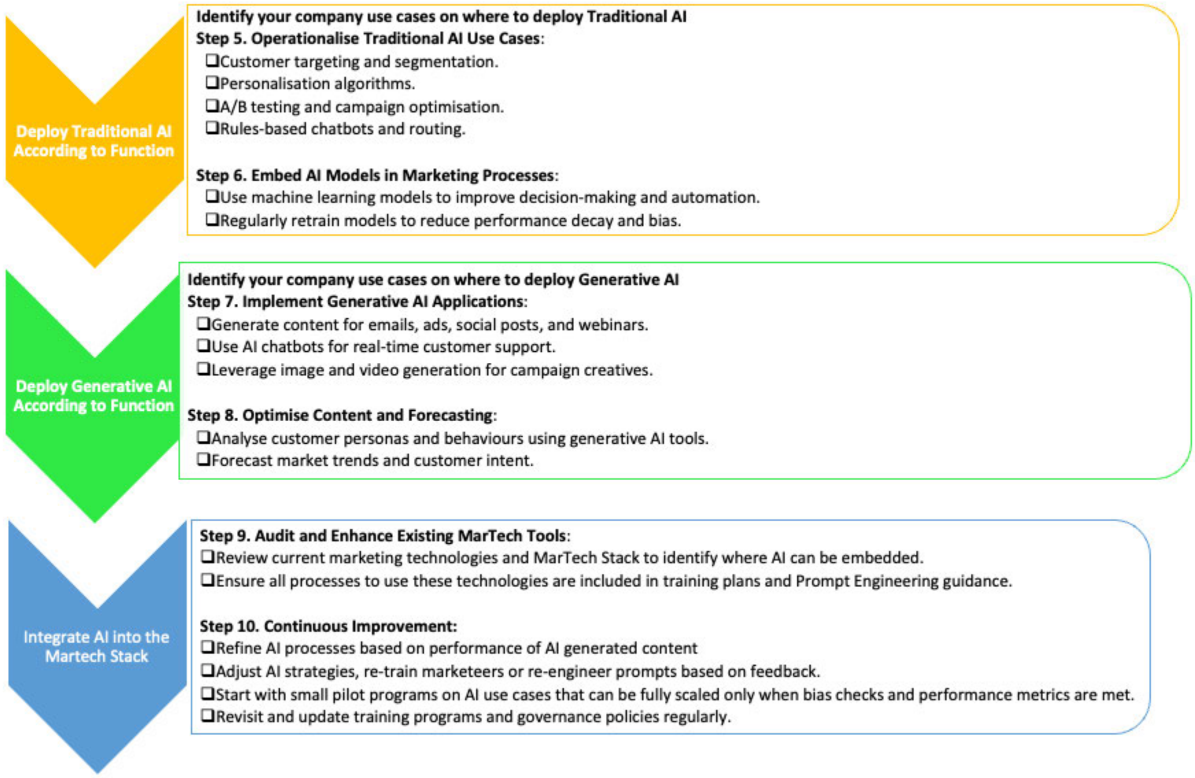


Figure 6.6: Recommended Guide to Apply the Model in Industry

The two most important elements to use the model in practice are People and Process, with the element of People focused on Prompt Engineering and the element of Process focused on Implementation Management. Within the model these have arrows signifying how they are the inputs to identify and limit the bias propagation. Using the guide to apply the model (figure 6.6) for step 1 and 2 the user is recommended to begin on the bottom left box for Prompt Engineering and Skillset Development with a checklist on what to create and implement to achieve sufficient skillset development. Step 3 and 4 guidance is to move to the bottom right box for Implementation Management and use the checklist on what to do to achieve a governance plan.

Entering steps 5 to 8, the user can then identify the use cases they have within their company where they can deploy Traditional and Generative AI. These are the use cases listed on the left and right long boxes in the model. These are helpfully segmented into their uses within the checklist. Step 9 within the checklist encourages the user to audit their MarTech Stack to make sure technologies and processes are included within the training materials. The guide ends with step 10, which encourages continuous improvement from monitoring the processes and performance of the model. The validation of this proposed final model will be reviewed in the next section.

6.4 Model Validation

To assess the proposed model's value and practical relevance, an online survey was conducted with six participants who had previously taken part in the in-depth interviews. Preparation of the survey was achieved by detailing questions that related to the final model, the inclusion of the core concepts and findings from the thematic analysis – with the goal to validate the proposed model. These participants were randomly selected. The survey included six Likert-scale statements (labelled 1–13) rated on a five-point scale: strongly disagree, disagree, neutral, agree or strongly agree (table 6.2). Participants who disagreed or strongly disagreed with any statement were asked to provide a brief explanation for their answer. Using a Likert Scale to rank responses, supported the thesis author to treat the data as a structured prompt to elicit qualitative responses rather than as a tool for quantitative analysis.

	Statement
1.	Overall, the operational model supports the areas of realistic bias propagation of AI implementation and usage within digital marketing
2.	Overall, the operational model supports identifying the areas of bias and bias propagation, when using and implementing AI within digital marketing
3.	The dimensions of the operational model - **MarTech Stack, Infrastructure, People, Process and Customer Journey** - are appropriate for the model and allow for a comprehensive assessment of how AI is implemented within digital marketing
4.	The descriptors for the use-cases proposed for **Traditional and Generative AI** (left and right long arrows) are appropriate and applicable
5.	The way bias propagation is displayed is correct: coding, deployment and prompting.
6.	The representation of the pre- and post-sale marketing customer journey is appropriately used
7.	The **Prompting Engineering and Skillsets Development** section (bottom left) is appropriate guidance for companies to implement for their marketing workforce to mitigate bias.
8.	The **Implementation Management** section (bottom right) is appropriate guidance for companies to implement for their marketing workforce to mitigate bias.
9.	The flow of the diagram (arrows) is appropriate and conveys the correct representation of how the dimensions of the model work together

10.	The operational model supports ideas on correct implementation for companies and marketing management.
11.	The operational model can be used in practice as a guide to deploy the usage of AI in marketing to reveal bias and limit its propagation.
12.	The operational model has longevity within the marketing industry
13.	If you chose ‘disagree’ or ‘strongly disagree’ for any of the questions, please explain why in this section.

Table 6.2: Proposed Final Model Survey sent to Respondents

This survey took place two to five months after the in-depth questionnaire and interviews depending on the respondent. The online survey was conducted using Microsoft Forms as a cloud-based solution that is accessible to CSC employees.

As reviewed in chapter 4, Methodology, a random selection of six previous interview respondents were contacted and invited to take part in the online survey. Upon confirming their participation each respondent attended a 15-minute audio conference session before they were sent the survey link. During this session the purpose of the survey was explained, the original PCF revisited, the proposed final model was presented and the approach on how it should be implemented was discussed. Before concluding the audio session, participants were asked to confirm they understood the requirement and any remaining questions were addressed. Respondents were then sent the survey link to complete.

6.4.1 Respondent Feedback from Audio Conference

When asked for feedback within the audio conferences all respondents noted the complexity of the model, but none voiced any concerns about this – agreeing that such a complex topic would require a complex model as a structure. R01 stated it was “complex to begin with…but well designed and well displayed”. R07 described it as “clear, even though it is complicated at first”. R10 went further to say, “everything I am seeing [in the model] is essential and has a purpose”. Respondents were taken through the guide on how to apply the model (figure 6.6) and this received positive feedback from all the respondents. R01 stated, “[the model] isn’t overly complex when it is explained”. R04 agreed, noting “while the diagram is complex, the explanation of it makes sense”.

There was consensus on the model beginning with the elements of People and Process in the bottom left and right corners of the model. R16 exclaimed that “[I am] so glad to see humans at the core…this is perfect”. R10 reinforced this by noting “people and process go hand in hand”. There was also consensus on the applicability and incorporation of the use cases in the model to truly operationalise it via people and processes within marketing. R01 stated “I love the addition of the use cases…and the separation of these to generative and traditional AI”. R19 agreed with the use cases split, stating “I think the split is acceptable”. R19 gave the example that A/B testing could sit in both generative and traditional AI, however, displaying A/B testing as traditional because of its algorithmic nature but using the generated content as the test makes sense. R07 agreed, reinforcing “[these are] good use cases”. R10 went further to feedback that the use case inclusion allowed companies implementing the model to “follow their own journey” to select what use cases they want to use based on company size, AI usage or budget allowance. An example R10 gave is that companies using this model could choose only generative AI use cases to focus on if they wanted to – a truly customisable experience. This customisable theme was also incorporated by R04 who noted that they liked the way the model is “both generic and specific…it can apply to big and small [companies] they can choose what they want”.

There was also consensus on simplifying the MarTech Stack and making it one concept within the operating model. R07 stated, “[it is] good that the MarTech Stack is simplified”. R19 agreed, noting “less focus on the digital channels [within the MarTech Stack] and more on the use cases makes more sense”.

There was feedback on minor enhancements to the model that were incorporated and explored in section 6.4.3. There was also additional feedback on limitations that are explored in chapter 7, Discussion, on how this model can be evolved in the future.

6.4.2 Respondent Feedback from Survey

Survey results are shown per question and respondent answer in table 6.3. There were no statements that respondents replied to as “strongly disagree” or “disagree”. All questions received almost 100% “strongly agree” or “agree” to their statements. There were only a couple of neutral answers, and the respondents gave insights as to why below.

Survey Question	**R01**	**R04**	**R07**	**R10**	**R16**	**R19**
Overall, the operational model supports the areas of realistic bias propagation of AI implementation and usage within digital marketing	Strongly Agree	Agree	Strongly Agree	Strongly Agree	Strongly Agree	Agree
Overall, the operational model supports identifying the areas of bias and bias propagation, when using and implementing AI within digital marketing	Strongly Agree	Agree	Agree	Strongly Agree	Strongly Agree	Agree
The dimensions of the operational model - MarTech Stack, Infrastructure, People, Process and Customer Journey - are appropriate for the model and allow for a comprehensive assessment of how AI is implemented within digital marketing	Strongly Agree	Agree	Strongly Agree	Strongly Agree	Strongly Agree	Agree
The descriptors for the use-cases proposed for Traditional and Generative AI (left and right long arrows) are appropriate and applicable	Strongly Agree	Agree	Agree	Strongly Agree	Agree	Agree
The way bias propagation is displayed is correct: coding, deployment and prompting	Strongly Agree	Agree	Agree	Strongly Agree	Strongly Agree	Agree
The representation of the pre- and post-sale marketing customer journey is appropriately used	Strongly Agree	Agree	Strongly Agree	Agree	Strongly Agree	Agree
The Prompting Engineering and Skillsets Development section (bottom left) is appropriate guidance for companies to implement for their	Strongly Agree	Agree	Strongly Agree	Strongly Agree	Strongly Agree	Agree

marketing workforce to identify and mitigate bias						
The Implementation Management section (bottom right) is appropriate guidance for companies to implement for their marketing workforce to identify and mitigate bias	Strongly Agree	Agree	Strongly Agree	Strongly Agree	Strongly Agree	Strongly Agree
The flow of the diagram (arrows) is appropriate and conveys the correct representation on how the dimensions of how the model work together	Agree	Agree	Agree	Strongly Agree	Neutral	Agree
The operational model supports ideas on correct implementation for companies and marketing management	Strongly Agree	Agree	Strongly Agree	Agree	Strongly Agree	Agree
The operational model can be used in practice as a guide to deploy the usage of AI in marketing to reveal bias and limit its propagation	Strongly Agree	Agree	Strongly Agree	Strongly Agree	Strongly Agree	Agree
The operational model has longevity within the marketing industry	Strongly Agree	Agree	Neutral	Strongly Agree	Agree	Agree
If you chose 'disagree' or 'strongly disagree' for any of the questions, please explain why in this section	N/A	N/A	N/A	N/A	Neutral: It would help to help readers understand where to start reading the slide to better digest the content.	N/A

Table 6.3: Results from Respondent Survey on the Final Model

These survey results show that 100% of the respondents strongly agree or agree that the model is applicable to identify and mitigate bias propagation when using AI in digital marketing. Two respondents strongly agreed, and three agreed that it also has long term applicability within the marketing industry to be used by all companies. One respondent replied as neutral but with no further information on the reasoning for this selection. A total of 100% of the respondents agreed that the core concepts of the MarTech Stack, Infrastructure, People, Process and Customer Journey were all appropriately used within the model and was represented correctly. About 40% strongly agreed and 60% agreed that the addition of the marketing use cases are all applicable and labelled correctly within the model. This is compounded by 50% of the respondents strongly agreeing and 50% agreeing that the way bias propagation is displayed is correctly as coding, deployment and prompting. The flow of the model also was appropriate and beginning with the elements of People and Process was agreed with by 100% of the respondents.

The flow of the model received 34% neutrality and 34% agreement and 34% strong agreement. The respondent feedback was anonymously given, stating "[I] wanted to comment my neutral selection. It would help to help readers understand where to start reading the model to better digest the content". This is addressed in the final model in section 6.4.3 to incorporate additional guidance on model usage.

6.4.3 Final Model

The final model for this thesis is in figure 6.7. Multiple respondents requested that numbers be added to the model that correspond with the guide for applying the model (figure 6.6) for ease of use. R01 asked, "to follow the flow can you add numbers?". R16 agreed, noting "if I didn't have your voiceover, I would be a bit lost. Add step 1, step 2 on the model...you also need to add where to start". These additions have been incorporated into the final model as labels of "start here" and "step #". Steps 9 and 10 are omitted from the model as these are additional enhancements that can be done on an ongoing basis by the company but are not essential to the implementation of the model. There was no feedback on changing the guide on how to apply the model (figure 6.6) so this remains unchanged and should be used to operationalise and implement the final model.

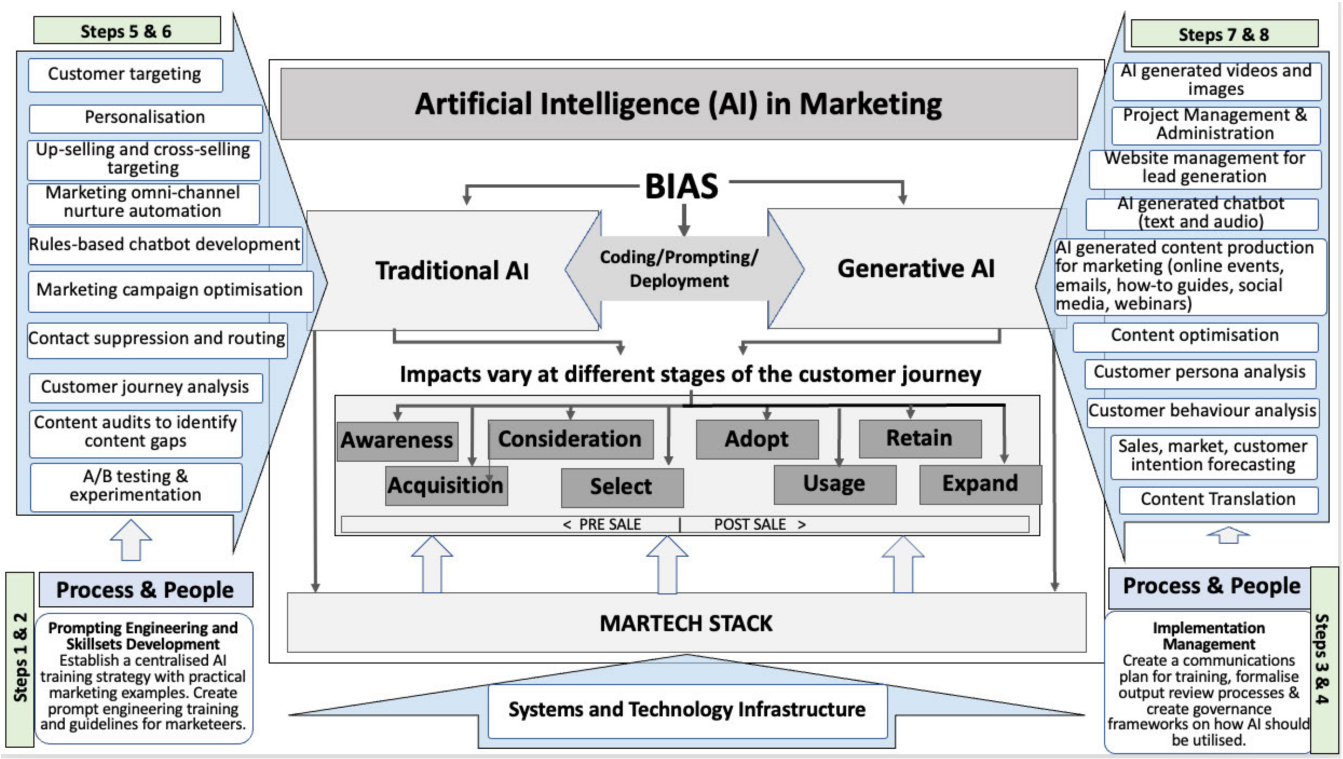


Figure 6.7: Final Model for Identifying and Mitigating Bias when using AI in Digital Marketing

6.5 Chapter Summary

This chapter took the initial thematic findings within chapter 5, and deeply analysed them for academic rigour and to develop the PCF into a final model.

The analysis conducted in section 6.2 of the eighteen questionnaire and interviews makes it clear that the elements of People and Process are essential to successful AI integration. Respondents were unanimous that implementation management was essential to governance and identifying any biased activities. While self-learning is currently compensating for a lack of formal education, this is neither scalable nor equitable. Companies must invest in a structured, context-specific prompt training program, incorporating simulation, bias education, and formal review systems to support marketing staff and ensure responsible, consistent, and effective AI use. All respondents agreed that prompt engineering is foundational to mitigating the bias - from ethics and governance to branding and productivity, prompting emerged as the most crucial skill gap.

In section 6.3 the thematic analysis of the data revealed broad validation of the PCFs core concepts but also significant suggestions for its evolution. The key areas requiring change included revising the pyramid format to avoid implying hierarchy, clarifying the role of bias arrows and updating ambiguous terms like “Analytics” and “Social Media” for precision. Additional feedback on adding implementation management and marketing use cases was incorporated to provide real-world examples and applicability but showed positivity of using AI to counterbalance the focus on bias. There was also analysis on changing the categorisation of the MarTech Stack as well as where the elements of process, people and infrastructure were structured in the model.

In section 6.4 the evolved model and guide to apply the model were well received by the respondents invited to critique it. Unanimous agreement on the model gave it longevity of use but also agreement that it fulfils its purpose of identifying and mitigating bias when using AI in digital marketing. There were some small neutral feedback areas that were incorporated into the final model in figure 6.7. This model answers RO3 in its entirety and fulfils the objective of this thesis to produce an “operational model for identifying and mitigating bias when using AI in digital marketing”.

CHAPTER 7: DISCUSSION

7.1 Chapter Introduction

This chapter focuses on the discussion around the final model proposed in chapter 6, Model Development and Validation. The model was created to address RO3 to develop and validate a model, entailing appropriate guidance for practitioners, for revealing and mitigating bias in AI deployment in Digital Marketing. This chapter summarises the major findings and discusses them to uncover issues that merit further consideration.

The chapter is structured as follows: section 7.2 explores the emergent issues that arose from participant interviews and surveys on the final operational model and explores the issues raised by respondents that should be considered for future evolution of the model. Section 7.3 discusses the operational model's current relevance to existing theory that was explored within chapter 2, Literature Review. It discusses where it has built upon and enhanced existing theory.

Section 7.4 discusses the implications for the wider marketing industry from the research conducted. The research identified that marketing workforces will bring and perpetuate biases when using AI within marketing campaigns and companies must embrace this knowledge to provide suitable mitigation strategies. Section 7.5 utilised the discussion from sections 7.2, 7.3 and 7.4 to discuss and define future evolutions of the model. The chapter finishes on section 7.6, chapter summary, that summarises the identified topics, focus areas and evolution within the chapter.

7.2 Emergent Issues from Participant Interviews

A key concern raised by interviewees relates to the variation in terminology and operational structures across marketing sectors. As R04 pointed out, “terminology differs between industries for marketing”, suggesting that foundational language within the model may not resonate universally. This issue is compounded by their further observation that “customer journey terminology may not be the same for all of the marketing industry…post-sale may not have four stages for all companies”. This reduction of a post-sale customer journey would be product and company dependent (Purmonen et al., 2023). While the applicability of the model can just apply to a simplified two stage pre- and post-sale customer journey these remarks underscore the need for further models to account for industry-specific practices and language. If core terms or phases in the model (such as MarTech Stack) do not align with how different sectors operate, its practical utility could be compromised.

Scalability across different organisational sizes also emerged as a significant issue. R10 noted that “steps for each company [on how they incorporate AI] will differ”. As regards the potential future evolution of the model, essential steps could be outlined separately for large versus small companies. This approach acknowledges the operational disparities between organisations with abundant resources and those with leaner structures. Supporting this, R07 noted that “bigger companies can API [application programme interface]”, implying that larger organisations may have more sophisticated integration capabilities for their MarTech Stack that smaller companies might lack. The guidance for the usage of the model is that users can pick and choose the use cases relevant to their company to implement. However, without explicit customisation guidance and options, smaller entities could struggle to implement the model effectively or derive equal value from it.

Additionally, an implementation timeline was flagged as a requisite for any future evolution of the model. R16 stated “an addition of a timeline approach on how to implement would be great”. However, the difficulty in creating such guidance without knowing key variables like budget, amount of personnel and marketing experience makes the applicability of an implementation timeline borderline redundant. This could be a future research area on structuring a full implementation plan on AI in marketing that builds on this model. This qualification highlights a gap between conceptual design and real-world execution. The lack of a standardised but flexible implementation timeline may leave some users uncertain about how to begin or sustain the process, particularly when internal capacities vary widely.

Another issue that surfaced in discussion regarding the final model validation with respondents was the additional guidance on implementing change management, a crucial element when introducing new systems or models to employees. As R16 pointed out, “change management guidance is missing for whoever is implementing this”. This research assumes that the user will be utilising the governance of implementation management to implement the model. However, the concept of change management techniques being imbedded within the model guidance to encourage all users of AI – from early adopters to laggard adopters – is of note. Without such support, even well-designed models risk poor adoption, as its success may be down to the implementors skills in business transformation (Jarrahi et al., 2023). Business stakeholders may resist or misunderstand these proposed changes, particularly when bias mitigation practices challenge existing workflows or assumptions.

7.3 Relevance to Existing Theory

Several frameworks in the literature review, chapter 2, explored how bias can emerge when using AI in marketing. Dowling et al. (2020) developed a conceptual framework that categorised bias into three types—nonstandard preferences, nonstandard beliefs, and nonstandard decision-making—mapped across the four stages of the marketing customer journey: need recognition, pre-purchase, purchase, and post-purchase. Huang and Rust (2021) proposed a framework illustrating the application of AI in marketing strategy and operations - categorising AI as mechanical, thinking, or feeling. Haleem et al. (2022) offered a framework identifying 23 ways marketers can use generative AI in marketing. However, these frameworks remain divulged – focusing on either AI use in marketing or bias in marketing. None of the frameworks provided guidance on how businesses can deploy AI in marketing in ways that actively reduce the perpetuation of bias. The most relevant attempt came from Dwivedi et al. (2023), who identified three key areas for mitigating bias in generative AI: (1) knowledge, transparency, and ethics; (2) digital transformation of organisations and societies; and (3) teaching, learning, and scholarly research. While the framework highlighted important focus points, the framework lacked practical guidance for implementation, particularly within industry contexts.

Utilising framework analysis as the analytical technique for the thematic data analysis provided a structured and systematic approach for the researcher to manage and interpret qualitative data into the final model and guide (Hackett & Strickland, 2018). It supported the identification of key themes while maintaining a clear and transparent design from the large volumes of text from interviews. The model put forward in this study is a significant contribution as it builds upon these frameworks to produce a model that shows the use case applicability of AI in marketing and the types of AI, structured with the operational guidance of People, Process and Infrastructure elements. The structure of the People, Process and Infrastructure framework from Jarrahi et al. (2023) was created to be applicable to new technology in general and applies to the successful implementation for any new technology in a business. The three elements of People, Process and Infrastructure were applied in this study successfully.

The model also aligns with and builds upon the concept of Human Centred Design that was explored in section 2.4.2. Human Centred Design is based upon the concept that human empathy and creativity should complement each other when using AI (Margetis et al., 2021). As explored in section 6.4.1, when R16 observed, in reference to the new model “[I am] so glad to see humans at the core…this is perfect” this model aligns with Hernández et al.’s (2023) view that putting humans at the core of AI design is essential to build public confidence in AI governance and usage. The human elements of Prompt Engineering training and robust Implementation Management were final themes of the thematic analysis and were evident in steps 1-4 of the step-by-step action plan that complimented the operational model.

The model presented here also exhibits two further aspects worthy of comment: the inclusion of the MarTech Stack as the infrastructure to AI in marketing, and the importance of including traditional AI within the analysis. For the first aspect, the model retains the core focus from Dowling et al. (2020) that bias is propagated throughout each stage of the customer journey but newly identifies the importance of the MarTech Stack in the usage of AI. The MarTech Stack software has AI embedded and added from a range of software vendors, it facilitates data flow between technologies to personalise and target at scale and allows marketeers to use AI in a range of areas. There is currently no other literature that shows the MarTech Stack as an important element in the identification and mitigation of bias.

For the second aspect, earlier frameworks appeared to focus solely on generative AI (Haleem et al., 2022; Dwivedi et al., 2023). However, this study has identified the relevance of managing traditional AI usage by marketeers as well as generative AI. While traditional AI is at a greater perceived risk of coding bias than generative AI, it is not impervious to prompting and deployment issues that can perpetuate bias. This study confirmed the relevance of focusing on both traditional and generative AI within the digital marketing landscape and segmenting bias propagation identification by the coding, prompting and deployment of it.

The use cases identified as part of the thematic analysis for both traditional and generative AI allows for the model to be operationalised and mapped to any companies marketing efforts. Selection can be made based on budget, resourcing and personnel. These use cases align with the work of Haleem et al. (2022) who showed 23 use cases that can be applied to generative AI in marketing. The model built upon these clustering the generative use cases as applicable and adding in the entirely new section of traditional AI use cases. These were agreed to be an appropriate representation by 100% of the respondents who reviewed the final operational model.

7.4 Implications for the Wider Marketing Industry

This research has wider implications for the marketing industry as it suggests that companies need to begin acknowledging that their marketing workforce will bring and perpetuate biases through the use of AI within marketing campaigns (Rogers, 2022). Companies like CSC are adopting the use of AI in marketing due to its ability to personalise content at scale, reduce workloads and redefine the value of predictive analytics. Yet, the lack of literature on the subject implies that many have failed to critically examine a core issue: the inherent biases that marketing teams bring to the prompting and deployment of AI tools. These biases—conscious or unconscious—can significantly shape not only the generative outputs but also the data selected for them through traditional algorithms (Haleem et al., 2022). The thematic analysis of the data from respondents at CSC revealed that training enablement was irregular and the understanding of how to use AI appropriately was lacking. A reliance on the marketeers themselves appeared to dominate, where they were educating themselves on prompt engineering and regulating their own perceived biases in lieu of official company guidance (section 6.2.4). The lack of acknowledgment around this issue reveals a systemic blind spot in corporate AI strategy, one that has implications for both ethical integrity and long-term brand trust.

There could be a reluctance to confront the implications of bias in marketing because doing so can expose uncomfortable truths about brand positioning and customer profiling (Buczek et al., 2023). Marketing has long been about targeting the "right" customer, and the analysis of respondent data showed the data profiling at CSC was weighted to specific customer groups and personas (section 6.2.1.5). While of use to marketeers to target correctly, this same targeting can become exclusionary or discriminatory when based on biased training data or heuristics derived from homogenous teams (Dwivedi et al., 2023).

7.5 Future Evolution of the Model

While the limitations in section 7.4 do not impact the credibility and applicability of the model to marketing departments across all businesses, there are certainly additional avenues to evolve the model in the future.

The operational model, while initially tailored for marketing, offers a scalable and transferable framework to help mitigate bias across all business functions including sales, HR and finance. At its core, the model emphasises structured training, ethical governance, system integration, and continuous monitoring - all of which are universally applicable in any department where AI is prompted and deployed. In sales, AI is increasingly used for lead scoring, sales forecasting, and customer communication. By embedding the same principles of this research model - prompt engineering training, diverse data usage, and formal output review processes - bias can be reduced in how prospects are scored or prioritised, ensuring no demographic or behavioural profiles are unfairly excluded. In HR, AI is playing a critical role in recruitment, talent analysis, and employee engagement. This research model emphasises “ethical” AI use to minimise bias propagation. This regulation and the implementation of governance frameworks helps prevent discriminatory practices in resume screening, interview scheduling bots, or employee performance assessments. In finance, AI use cases such as credit scoring, fraud detection, and financial forecasting carry significant bias risks if models and prompts are not properly monitored (Dwivedi et al., 2022). Applying the same model of continuous feedback loops and governance ensures these systems are not only technically sound but ethically aligned. The implementation of cross-functional review teams also adds human oversight where decisions can have material impacts.

There is also scope to evolve the model in the future with newer use cases as AI production is increased and further uses for it are utilised. Further use cases across traditional and generative AI will be created through agentic AI’s and increasingly advanced coding and this may require an evolution of the model’s applicability.

This research highlighted the evolution of the customer journey from four stage to eight stages (Dowling et al., 2020; Purmonen et al., 2023) and was tested against an eight stage pre- and post-sale methodology. The customer journey itself will evolve however, and in the future the linear eight stage may become either obsolete or change. When this occurs, this research model will require evolution against a new customer journey landscape to test its applicability.

7.6 Chapter Summary

This chapter focused on the discussion around the final operational model from chapter 6, Model Analysis and Validation. This model was created to address RO3 to develop and validate a model, entailing appropriate guidance for practitioners, for revealing and mitigating bias in AI deployment in Digital Marketing. The discussion areas of this chapter were focused on the emergent issues that arose from participant interviews, its current relevance to existing theory, implications for the wider marketing industry and future evolution of the model.

There was unanimous agreement by respondents that the model can be used within the marketing industry to identify and mitigate bias propagation, but the study nevertheless has its limitations. Respondents who reviewed the final model had some additional feedback on its limitations. For example, it was emphasised that while the model's intent is valuable and relevant, its current applicability may lack the flexibility and contextual nuance needed for truly broad application.

The respondent feedback suggests the model could evolve further to meet users where they are in their businesses - across industries, organisational sizes, and internal capacities – it shouldn't just be limited to marketing. Further researching modular elements, additional segmentation by company size, and further change management guidance could enhance the usability of the model too. This operational model and step-by-step plan lays a strong foundation, but its effectiveness could be enhanced through ongoing research and adaptation to future developments in AI. This could then produce future use cases within marketing or an evolved customer journey overview.

By further researching and developing the model around centralised training and AI literacy across all departments, businesses can embrace fostering a culture of accountability. Bias mitigation becomes a shared responsibility, not a siloed marketing concern. Ultimately, this cross-business approach increases trust, fairness, and effectiveness in AI adoption, ensuring organisations harness the benefits of AI without compromising equity or integrity.

CHAPTER 8: CONCLUSION

8.1 Chapter Introduction

The principal aim of this research study was to produce an operational model, entailing appropriate guidance for practitioners, for revealing and mitigating bias in AI deployment in Digital Marketing.

AI is increasingly playing a critical role in digital marketing by enabling smarter, more personalised customer interactions. Through data analysis and machine learning, AI – both traditional and generative - helps marketers understand consumer behaviour, predict trends, and optimise campaigns. AI tools such as chatbots, predictive analytics targeting, and automated content creation improve engagement and efficiency. With evolving algorithms and natural language processing, AI is streamlining customer journeys and maximising ROI for companies. As technology advances, AI's role in digital marketing continues to grow, becoming indispensable for businesses aiming to stay competitive in a data-driven world.

Bias identification and mitigation are essential in AI when used within digital marketing to ensure fairness, accuracy, and inclusivity. AI systems learn from data, which may reflect historical or societal biases. If unchecked, these biases can lead to discriminatory targeting, misrepresentation, or exclusion of certain groups. This not only harms user trust but can also damage brand reputation and lead to regulatory consequences. Mitigation techniques - such as comprehensive training, diverse data sets and set processes - help reduce unintended bias. Prioritising ethical AI use ensures that marketing efforts are respectful, relevant, and equitable – this fosters positive customer experiences and long-term brand loyalty.

Methodologically, this research adopted an interpretive paradigm, commonly aligned with qualitative research and the method chosen was mono-method qualitative. An inductive approach guided the development and application of the proposed model, and the study focused on a single case study company. It was completed in a cross-sectional timeframe. It aims at extending theoretical knowledge and building on current theoretical frameworks in the nascent research area of AI usage in digital marketing.

8.2 Addressing the Research Objectives

This research was initiated by the experience of the author being encouraged to use AI within their work but having no guidance on the correct way to do so. Being aware that anything personally produced by AI and made visible to consumers could pose a risk to the case study company brand – a personal review of any supporting literature took place. Through this review and then subsequently the initial PhD proposal it became apparent that gaps existed in academic knowledge around the prompting and deployment of AI in marketing to manage bias. This review underpinned the initial three ROs that were set within the introduction chapter of this research.

The three ROs are shown below and the process of addressing them followed by the Research Process Flowchart in figure 8.1.

- RO1: To analyse current and possible bias issues in coding, prompting and deployment of AI in Digital Marketing
- RO2: To develop a conceptual framework for analysing bias issues in the use of AI in Digital Marketing.
- RO3: To develop and validate a model, entailing appropriate guidance for practitioners, for revealing and mitigating bias in AI deployment in Digital Marketing.

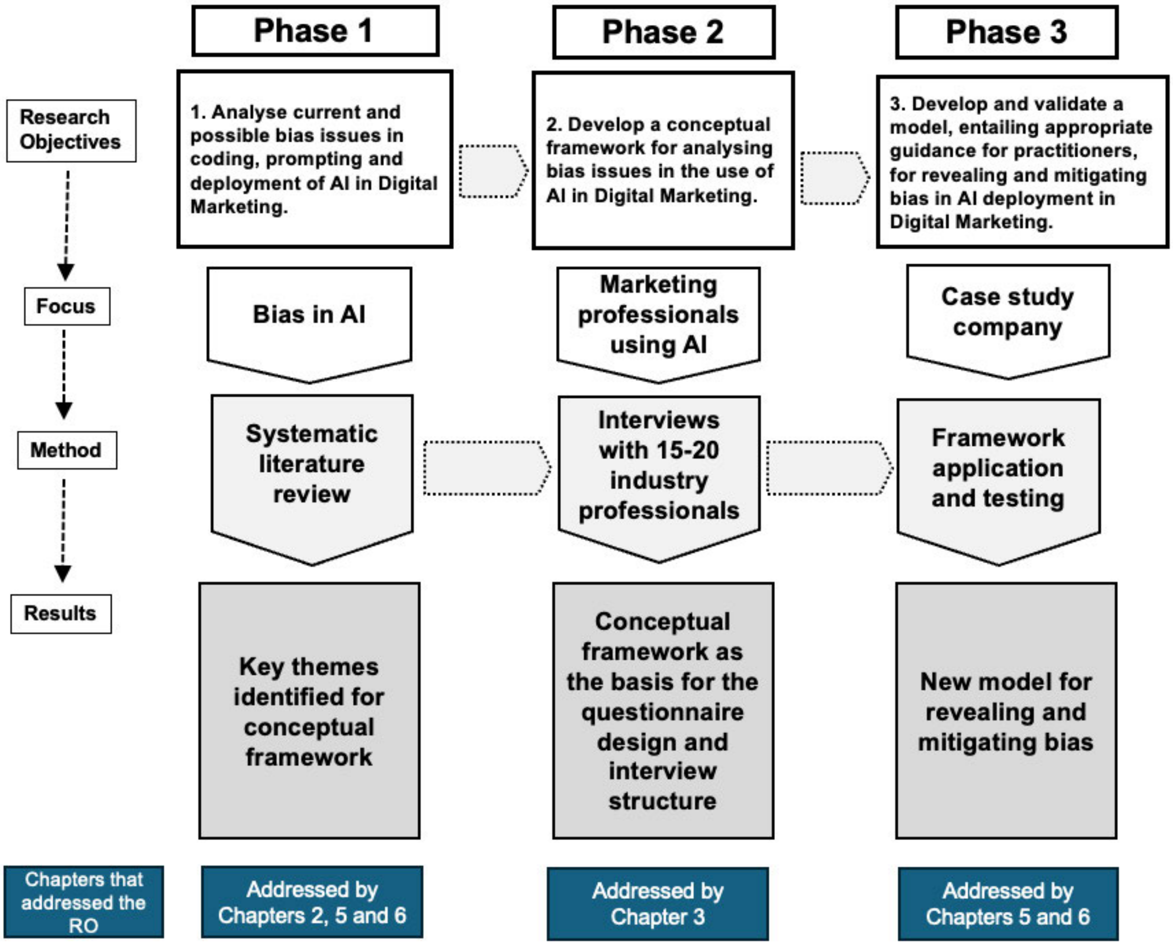


Figure 8.1: The Research Process Flowchart – brought forward from chapter 2 and 4. Addition of blue boxes show which chapter addressed the corresponding research objective.

8.2.1 Addressing Research Objective 1

RO1 was to analyse current and possible bias issues in coding, prompting and deployment of AI in Digital Marketing. This question is addressed by both the analysis from the systematic literature review in chapter 2, and the thematic data analysis in chapters 5 and 6, Findings and Analysis.

Bias theory was determined by multiple factors including personal experiences and societal influences (Delgado-Rodriguez & Llorca, 2004). Two core areas of bias propagation were identified through the literature: the large language models used to teach the AI (coding) and the marketeers themselves using it (prompting and deployment). Even before AI usage in marketing, bias propagation is well documented and widely accepted that it occurs at each customer interaction (Smith & Conrad, 2020). That is not necessarily a negative, as the context of marketing is to target the correct customer groups to purchase and can leverage certain biases to target effectively (Nosek et al., 2022; Davidson, 2011).

The bias issues for AI coding are reasonably well documented in the existing literature (Roetzer & Kaput, 2022; Gerhard, 2008; Schwartz et al., 2022; Tang et al., 2021; Tatman, 2017). The AI itself can be coded with bias from two areas – the first is the data it is trained on (known as the large language model), and the second is the coder themselves. Large language model data can be incorrectly diversified or given unequal data parameters, and this will impact the AI algorithms (Smith & Conrad, 2020; McDuff et al., 2019).

These biases, when introduced into an AI algorithm, can compromise the integrity of the model and were justified within the thematic analysis of chapters 5 and 6. R10 emphasised that “marketeers need to be trained to be aware of inputting bias and anomalies as it will skew the learning data”. This highlights how marketers can unintentionally undermine AI models through adversarial inputs—modifying text or images in ways that mislead or distort algorithmic learning.

The dominance of “Big Tech” companies in the production of AI’s also plays a role in its bias propagation. Six companies dominate the technology and software industry: Google, Microsoft, Amazon, Apple, Meta, and Nvidia. The location of where these companies are is important for the data selection for their large language models. All six companies are American owned and operated and the majority of their data will be from the USA – which is not representative of countries across the rest of the world, especially outside Western culture. These companies also value efficiency and profit from their algorithms over data integrity and are created to enhance their own product offerings (Diakopoulos, 2016; Metz & Thompson, 2024). This is further compounded by the lack of global regulation and laws governing AI creation and usage (Saito, 2024). The European Union’s AI Act (European Parliament, 2023) is the only multi-country law in place to bring regulation to AI. Other countries have their own AI guidelines to govern AI usage within their own countries with the majority leveraging UNESCO’s global ethical guidance for AI. The USA currently has no comprehensive federal laws that govern the creation, distribution or usage of AI.

As all six of the “Big Tech” companies are headquartered in the USA they can circumvent any laws on implementing fairness models or debiasing algorithms in production of AI (Ghadage et al., 2022). This lack of regulation can also drive visibility issues into adversarial attacks from hackers. These security breaches usually take focus on distorting input data to change the AI model, and this could lead to manipulated data outputs (Goodfellow et al., 2014).

In corporations developing artificial intelligence (including and beyond the Big Tech companies), there is a noticeable gender imbalance among software developers. Males make up the majority of the workforce with only 8-10% of software developers being females (Kaminski, 2023; Vailshery, 2023). Studies have shown that this can drive unintentionally or intentionally encoded bias into the AI algorithms by developers. This can occur due to incorrect assumptions about machine learning capabilities (Sun et al., 2024). These coders will also share the same values as the company they work for, driving for progress over perfection in balanced data (Schwartz et al., 2022).

The MarTech Stack (marketing technology stack) was identified within the literature as the collection of tools and applications where marketeers would use AI for marketing planning, strategy, and execution (Purcarea, 2018; Earley, 2021). The MarTech Stack technologies were identified as: CRM systems, digital content asset management, multi-channel nurture tools, search engine optimization, website management, social media and analytics (Earley, 2022). AI enhances a MarTech stack through algorithmic improvements, predictive modelling and enhanced decision making but risks driving hyper-personalisation to customers (Flavin & Heller, 2019).

The MarTech Stack software is built upon these “Big Tech” companies’ software platforms. This MarTech software can therefore already be embedded with biased data from large language datasets. Marketeers will use YouTube as a channel to reach their customers, but the speech recognition on YouTube is powered by Google Speak Recognition which is justified in the literature as having bias against accents non-English languages. Marketeers will use a generative AI to create images for a marketing campaign, these can be fed data from Google Images that was noted in the literature as showing bias towards gender and Eurocentric aesthetic qualities

(Henning, 2022). Multinational corporations, often rooted in former colonial powers, can contribute to neo-colonialism by reinforcing economic inequalities and maintaining the dominance of certain global markets (Yalkin & Özbilgin, 2022).

Eurocentric bias was a key theme in interviews and justified the literature by the thematic analysis. R14 highlighted needing to adapt U.S. based marketing content for Latin American audiences: "[I am] conserving local branding's direction". Centralised content often lacks regional specificity: "we receive images from Asia Pacific, and the images with people…are physically different – so local people think, no, this content is not for us". R04 noted that during a team review of social media banners, "the imagery was not culturally diverse, or gender diverse". Manual review enabled necessary edits before external release, showing the importance of human oversight.

Cultural bias also emerged from centralised campaigns. As Usunier et al. (2005) discuss, symbols and images hold varying meanings across cultures. R04 stressed, "you have to think about the culture," while R14 added, "sometimes we need to give that local flavour to the Global initiative". R10 shared an instance where locally approved content was sexist in other contexts: "Gender bias, culture bias, religious bias are sometime seen, but not intentional". AI is widely used in CSC for localisation: "translation of copy…voice-over in language…translating the website" (R05). However, as R04 cautioned, "there's so much, not just languages, but you have to think about dialects". R14 uses AI to save time and cost, particularly for "very small countries and their local languages".

For bias issues in deployment of AI there were multiple frameworks examined within the literature that show where bias can be found through using AI in marketing. Dowling et al. (2020) produced a conceptual framework on three classes of biases (nonstandard preferences, nonstandard beliefs, and nonstandard decision making) mapped against four-stage marketing customer journey - need recognition, pre-purchase, purchase, and post-purchase. Huang and Rust (2021) created a framework showing where AI can be used in marketing strategy and operations that was mapped showing AI as mechanical, thinking and feeling. Haleem et al. (2022) produced an identification framework of 23 ways marketeers can use generative AI for marketing. But none of these frameworks showed how business could deploy AI within marketing to limit bias perpetuation. The framework that got closest to identifying deployment strategies was Dwivedi et al.'s (2023) research, which identified the three key areas to support mitigating bias within generative AI – these were: 1) Knowledge, transparency, and ethics, 2) Digital transformation of organisations and societies, and 3) Teaching, learning, and scholarly research. While this framework identified the three areas there was a lack of guidance on how they could be achieved, especially within an industry setting.

Table 5.2, from chapter 5 Interview Findings structured the thematic analysis against the headings of coding, prompting and deployment. The data analysed were both the extant literature in the PCF cross-tabulations and interview thematic analysis. This mapping achieved robust data coverage of all three elements (coding, prompting and deployment) to confirm that bias was present across all three elements of AI usage.

The theory on People, Process and Infrastructure as a way to successfully implement technologies into business – and therefore AI – was explored within the literature review and became of import to structure the PCF. Jarrahi et al. (2023) proposed the three elements of people, infrastructure, and process to underpin successful integration for AI. This will be brought to conclusion in section 8.2.2, when addressing RO2.

The result of this research supports a clear address to RO1 - that there is bias issues and bias propagation in all three areas of AI usage in digital marketing: coding, prompting and deployment. This is evidenced in a myriad of ways, from the large language model databases used that are unbalanced, to the marketeers themselves perpetuating biases through usage. The results are significant to inform the correct direction of the research and that an operational model is required to support regulation of this bias propagation but also build upon the existing frameworks in the literature. There were limitations to this literature and thematic review to answer RO1 – these limitations are explored in section 8.5.

8.2.2 Addressing Research Objective 2

RO2 was to develop a conceptual framework for analysing bias issues in the use of AI in Digital Marketing. This question is addressed by the analysis from chapter 3, Provisional Conceptual Framework.

From the literature review in chapter 2, core concepts were identified that structured the PCF (figure 3.1). There were four core emergent themes from the literature review: types of AI, MarTech Stack technologies, Customer Journey stages and the elements of People, Process and Infrastructure.

The first concept was the Types of AI. AI in marketing can be divided into two key types: traditional AI and generative AI. These were represented in the PCF as “algorithmic rules” and “content creation”. Traditional AI analyses data to identify customer behaviour and trends - enabling personalised targeting (Roetzer & Kaput, 2022). Generative AI, on the other hand, automates content creation and produces personalised material at scale (Lie et al., 2020). This distinction was a central focus of the literature, highlighting how each AI type uniquely supports marketing strategies.

The second concept was the MarTech Stack. The Martech stack was defined in the PCF as seven core technologies and links AI types to content and channel outputs across the customer journey. It serves as the key infrastructure enabling marketers to engage consumers and leverage data for improved customer experiences (Earley, 2021). The PCF was therefore structured as showing these individual core technologies - as it had been represented as important in the literature to define the technologies within the stack itself. Reviewing AI within the Martech stack offers a comprehensive view of both strategy and execution across the marketing campaign lifecycle.

The third concept was the Customer Journey. The Marketing Customer Journey was defined within the literature review as currently being an eight-stage journey. This has evolved from the standard four stage journey (Dowling et al., 2020). It shows four pre-sale stages from awareness to selection and four post-sale stages from adoption to expand. Each stage was justified within the literature review on its relevance to digital marketing. The customer journey is a structured view of where (which channel) a consumer will interact with marketing content. It is structured by content (generative AI) and the channels they are contacted by (traditional AI). Therefore, the representation of the Customer Journey in the PCF was it arching across the full PCF as the structure for customer interaction.

The fourth concept was the elements of People, Process and Infrastructure. This perspective emerged within the literature from Jarrahi et al. (2023) where successful technology implementation into business (not just AI) is achieved by the three elements of people, infrastructure, and process working together. The three change dimensions of “technology, process and people” were well researched in successfully implementing new technology and software - especially within ERP and CRM projects (King-Turner, 2014). Within the PCF, Infrastructure mapped easily to the MarTech Stack as the marketing technology that underpins all routes to market. The concepts of People and Process were placed within the PCF as supporting elements to the Customer Journey and Types of AI.

Bias itself was represented within the PCF as arrows showing the propagation through the usage of the types of AI. By clearly defining these core concepts for the PCF and representing them as interconnected in the framework it allows for thorough exploration to identify emergent themes.

Cross-tabulations of the PCF core concepts were created to robustly map the literature review to identify further emergent themes for the primary research to test the applicability of the PCF. There were two types of AI, seven MarTech Stack technologies and eight stages of the customer journey – this gave 112 interaction areas between the concepts. People, Process and Infrastructure were overlaid on these cross-tabulation interactions as colour coding to show the hotspots, prevalence and requirement of the concept to regulate AI usage in marketing to limit bias.

These cross-tabulations are detailed in tables, 3.1 – 3.4 and reoccurring emergent themes were identified from the review of the 112 interactions within them. These recurring emergent themes were identified as: “Pre-Sale Customer Journey”, “Targeting and Testing”, “Analytics and Predictions” and “Content Generation”. The four core concepts, alongside the four emergent themes, were used to create the structure and focus areas for the primary research of the questionnaire and interviews.

The result of this research supports a clear address to RO2 as it developed a conceptual framework for analysing bias issues in the use of AI in Digital Marketing that was then reviewed and critiqued by respondents from CSC. The justifications on the composition of the PCF in this section shows why the core concepts of the PCF were chosen, how they were justified through cross-tabulation and their structure within the PCF. The analysis and evolution of the PCF is explored in section 8.4 as the PCF itself had many limitations and required significant evolution to the final model.

8.2.3 Addressing Research Objective 3

RO3 was to develop and validate a model, entailing appropriate guidance for practitioners, for revealing and mitigating bias in AI deployment in Digital Marketing. This question is addressed by the analysis from chapter 5, Interview Findings, and chapter 6, Model Development and Validation.

The PCF discussed in section 8.2.2 was analysed within the primary research through eighteen one-to-one respondent interviews. The respondents were marketeers who use AI within their current job role at CSC and they had varying length of tenure from recent graduate to senior leadership. The PCF diagram was shared with respondents alongside the interview questionnaire before their interviews. This was to give them time to review it before being interviewed on it. The questionnaire and interview questions and sections were structured against the PCF core concepts and emergent themes, so it allowed for full analysis of all the PCF areas with respondents. Respondents were interviewed with a section of the interview dedicated to feedback on the PCF.

Within chapter 5, Interview Findings, the interview data was thematically analysed following a six-stage process to define the core areas of focus. One stage of this thematic analysis was to cross-reference these themes with the literature in the PCF cross-tabulations. This was done to test and justify the areas of focus for the evolved model from both the literature and primary data, and it produced six final key themes to focus on for the final model. These six themes were: Bias Propagation, MarTech Stack Representation, Customer Journey, Implementation Management, Prompt Engineering and Analytics AI Use Cases.

The first of these was the representation of bias in the PCF. The feedback was that the arrows showed a bias cascade that was an incorrect representation of bias through both types of AI but also where it was placed in relation to the MarTech Stack. It was noted that the bias arrows were unclear and confusing. Bias arrows were therefore removed, and the propagation represented equally through traditional and generative AI with the inclusion of where it is propagated: coding, prompting and deployment. This representation received 100% positive respondent feedback through the survey on the final model.

The second evolution of the PCF was the representation of the MarTech Stack as a pyramid, which proved visually problematic for respondents. The MarTech Stack was unanimously recognised as the critical infrastructure for marketing's AI usage, but the pyramid implied a level of importance to the technology which was inaccurate. By representing all technologies within the MarTech Stack, there were also requests for additions to the technologies that could not be agreed upon by the respondents. Therefore, in the model the MarTech Stack was represented as one core infrastructure element – rather than individual technologies in a pyramid stack. This representation received 100% positive respondent feedback through the survey on the final model.

The third evolution of the PCF was the consensus and placement of the Customer Journey. All respondents reinforced the importance of the pre- and post-sale portions of the Customer Journey and that they utilise AI in different ways with different bias propagation. Post-sale marketing was more exposed to hyper-personalisation biases as it targets very specific customer groups who have already purchased. There was no feedback from respondents on the representation of the eight stages, and therefore, these were left within the model. This representation received 100% positive respondent feedback through the survey on the final model.

The fourth and fifth evolution of the PCF constituted terminology and structural enhancements across the PCF to make it operational. The structure of the pyramid was removed, and the concepts of People and Process were made more central to the operation of the model. The thematic analysis identified Implementation Management and Prompt Engineering as two essential endeavours for companies to implement to manage bias propagation through marketing. Both areas require People and Process to manage their implementation, deployment and regulation. The model evolved to be less hierarchical with the elements of People and Process becoming steps 1 – 4 of how to use the model in industry. This representation received 100% positive respondent feedback through the survey on the final model.

The sixth evolution of the PCF was to increase its applicability for industry. Thematic interview analysis identified that it lacked applicability and use cases for marketing – there was a lack of practical application guidance for anyone wanting to use it. The specific key theme from the thematic analysis was the lack of use cases for Analytics specifically; however, it lacked applicability across all the MarTech Stack and how each piece of software currently uses AI. Use cases were identified from the literature review and thematic interview analysis and mapped against traditional and generative AI within the model. These use cases are steps 5 – 8 on how to operationalise the model within an industry setting. They show how AI can be used within marketing and how both Prompt Engineering and Implementation Management can support its usage and limit bias propagation. The inclusion of use cases within the model and the way they are represented received 100% positive respondent feedback through the survey on the final model.

Once the model had been evolved in line with the six thematic analysis themes, a guide (figure 6.6) was created to accompany the model to support its operational applicability. This ten-stage action plan supports anyone implementing the operational model for their marketing departments. Six randomly chosen respondents were invited back to review the evolved model – this gave a useful validation of the model. They were taken through the model on an individual telephone conference with the action plan used to show them how to make it operational. Initial feedback and critiques were recorded and analysed, and a questionnaire (table 6.2) sent out afterwards for final feedback on the model.

During the audio conferences, all respondents acknowledged the complexity of the model but viewed it as appropriate given the subject matter - several respondents noted its clarity and purposeful design once explained. Positive feedback was given on the guide on how to use the model which helped demystify the model for respondents. There was strong consensus on beginning the model with the People and Process elements, with several respondents appreciating the human-centred approach. The use cases—split between generative and traditional AI—were also well received, offering a customisable framework that allows companies to tailor their approach based on size, AI maturity, or budget. The respondents noted this flexibility as being positive for making the model suitable for both large and small organisations. Additionally, the simplification of the MarTech Stack into a single concept was welcomed, with respondents supporting a shift in focus from digital channels to use cases.

The final model builds upon the original frameworks discussed within chapter 2, Literature Review and section 8.2 and brings them all together in one unified model (figure 6.7). It incorporates all elements of the Customer Journey (Dowling et al., 2020), the structure of AI usage in marketing (Huang and Rust, 2021), the use cases of generative AI (Haleem et al., 2022), bias mitigation strategies for implementing AI (Dwivedi et al., 2023) and using “People, Process and Infrastructure” for successful technology implementation within a business (Jarrahi et al., 2023).

The result of this research supports a clear address to RO3 as it developed and validated a model that entailed appropriate guidance for practitioners, for revealing and mitigating bias in AI deployment in Digital Marketing. The final model retained the original PCF core concepts that showed the structure of how AI usage is structured within marketing via the MarTech Stack and the Customer Journey but added in the detail that bias is revealed and propagated through the coding, prompting and deployment of AI. Additions to the model, that evolved from the PCF, were the use cases of where to use traditional and generative AI in marketing and how to operationalise it through Prompt Engineering training and Implementation Management. This new model received 100% approval from respondents of its applicability to identify and mitigate bias when using AI in marketing.

8.3 Contribution to Theory and Practice

This model makes an original contribution to theory, building upon the existing theoretical frameworks discussed throughout this thesis. In section 8.2.3 it was discussed how the final model was built upon frameworks from Dowling et al. (2020), Huang and Rust (2021), Haleem et al. (2022), Dwivedi et al. (2023), and Jarrahi et al. (2023) – combining their theories and perspectives into one unified model.

Throughout this research these focus areas were tested repeatedly to validate their inclusion in the final model. The justification of these marketing concepts of the MarTech Stack, Customer Journey, Types of AI, and the elements of People, Process and Infrastructure occurred through the PCF cross-tabulations and then the thematic analysis of the primary data. The outcome of this analysis point to the robustness of these concepts used in the model and the confidence that they can be used to develop further theory in this area.

This unified model is not only an original contribution to theory - it is also an original contribution to practice. The accompanying guide shows how the model can be operationalised in industry. The reinforcement of 100% approval from respondents on the final model survey also points to the contribution of the research in practice. During initial interviews many respondents focused on a lack of implementation guidance from CSC and on where they should be using AI to enhance their work. The final model and guide to apply the model fulfilled this identified gap from respondents and can be used in the industry to address companies experiencing similar challenges.

8.4 Limitations of the Study

Limitations were found throughout this research and are explored in sections 8.4.1 and 8.4.2. These limitations are from the literature review and the final model. They support future directions from this research in section 8.5.

8.4.1 Limitations from the Literature Review

Within the literature review six biases within marketing specifically were identified as being present in the literature repeatedly. These biases were focused on societal stereotypes: affinity bias, ageism, binary bias, confirmation bias, cultural bias, and gender (Kellaris et al., 1996; Wan et al., 2020; Dowling et al., 2020). There was some overlap with the biases identified in the thematic analysis, and this list of six biases did not complete the full bias list evident in the literature. There was no ageism bias detected within the thematic analysis, and this could be due to the industry that CSC, and therefore, the respondents, are in. Software decision-makers age ranges sit within working career ages; therefore, one would expect imagery used to be of individuals that limit ageist content. However, other biases were identified within the thematic analysis, such as persona bias, Eurocentric bias and political and legal bias.

Within the literature there was disagreement from authors on consistently identifying the types of biases in marketing with a lack of uniform framework and terminology (Conick, 2018). A set list of marketing driven biases was also not defined by the thematic analysis of this research. While there were multiple biases identified and explored, there was no comprehensive analysis for identifying all and giving them a label. This is a gap in theory for marketing and is further discussed in section 8.5.1 where future research directions for defining bias in marketing are explored.

8.4.2 Limitations from the Model

This research was compiled on a case study company, which will limit generalisability of the study - as it could be illustrative of a unique company situation (Yin, 2013). However, Tsang (2013), argues that case studies are suited to research that seeks to identify quality findings over quantitative methods; that it supports theoretical generalisation, especially for empirical research such as this. Yin (2013) acknowledges that using a case study company can support theory seeking, and the knowledge ascertained can begin the process of generalisation and leave room for further learning and research (which is explored in section 8.5).

A further limitation is that the case study company only markets its products as business-to-business marketing, not from business-to-consumer marketing. Testing both the PCF and final model solely on business-to-business marketing departments could introduce limitations when attempting to apply it to business-to-consumer context. This is due to these two marketing environments experiencing different customer behaviour, decision-making processes, sales cycles, and communication strategies. While the core concepts of the model may be applicable their validation may need adjustment. An example of this is that business-to-business marketing typically involves longer buying cycles and multiple decision-makers in the customer journey. In contrast, business-to-consumer marketing usually targets individual consumers - involving shorter, impulse-driven purchasing decisions. As a result, the customer journey concept validated in the current model may fail to capture the variables critical to business-to-consumer marketing. This limits its generalisability and effectiveness across the different marketing types. The future direction of the model to address this limitation is explored in section 8.5.2.

A possible limitation of this research could be that the researcher works for the case study company, and therefore, was a known peer to the respondents. As addressed in chapter 4 section 5, Methodological Strategy, the researcher minimised their proximity influence on the respondents selected to reduce bias in the data collection (Bassey, 2022). None of the respondents were direct reports to the researcher and they maintained ethical conduct in line with the University Ethics Handbook throughout the research process.

A further limitation impacting this research could be in its modest sample size of 18 respondents. This sample size was justified and discussed in chapter 4, Methodology. However, while this number is sufficient to validate the model in a controlled research setting, it may limit the generalisability of the findings. A larger and more diverse respondent pool could have offered greater confidence in the robustness and applicability of the model across the marketing industry. This also reinforces the limitation of the study on one case study company. The smaller respondent size introduces a trade-off between depth and breadth of findings - with the thesis outcome being more focused but potentially less representative of broader industry dynamics.

An additional limitation was the time constraints of conducting this research in a field with rapidly evolving innovation. As new AI algorithms, software and regulatory frameworks emerge this model - developed during a fixed research period - risks becoming outdated or lacking relevance to the most current industry practices. This limitation could also influence this research outcome by providing a narrower focus on technologies available at the time of study. This could lead to the researcher potentially overlooking newly developed methods that could offer superior mitigation strategies to bias propagation in marketing. While the model may be sound within its timeframe, its longevity and adaptability in such a fast-moving developing field must be acknowledged as limited.

One final limitation for this research comes from the inherent need for a PhD thesis to be focused on the set scope of the research. This ringfencing and focus on the three research objectives shaped the final model outcome of this research. Using the research objectives as boundaries ensured that the research remained achievable within the time constraints noted above. However, this does mean that issues related to this research went unexplored. This includes broader ethical implications of AI in other industries or a longitudinal study that could identify newer AI technology. Avenues for future research are explored in section 8.5. While the focus of this research enhances the academic precision of the final model it will limit the extent to which the research can address the full complexity of bias in AI when used in digital marketing efforts.

8.5 Future Research Directions

The limitations of the study in section 8.4 can be used to recommend future research initiatives to build upon this work. Sections 8.5.1 and 8.5.2 explore these limitations from the literature review and respondent feedback on the model.

8.5.1 Future Directions from the Literature Review

There is abundant room for further progress in determining the types of bias that are perpetuated within marketing. As reviewed in section 8.4.1 there is no standardised framework or terminology for biases within marketing. A future research avenue would be for a framework identifying all types of biases in marketing campaigns to be produced. This would support identifying all biases that can be perpetuated through marketing for a regulated theoretical understanding of the biases to regulate. This framework should research, incorporate and segment the biases for both business-to-business marketing and business-to-consumer marketing to validate any differences. The current final model is flexible enough to incorporate biases identified in the future through further research.

Within the literature review on the differences between a pre- and post-sale customer journey there was more of a theoretical focus on the pre-sale portion of the journey. Within the PCF cross-tabulations this was interpreted that the pre-sale journey was of greater importance and both stages utilised AI in the same way. This was an inaccurate view, as evidenced from the thematic analysis. There was clear data that defined the post-sale journey as very different to the pre-sale journey – with post-sale marketing utilising more analytical and targeting capabilities due to known customer data from purchasing. These differences should be explored in future theoretical research to establish the differences between the pre- and post-sale experience for customers and the types of marketing that they receive. The concept of the post-sale marketing customer journey appears to be an under-researched area for AI usage. Given that existing customers drive brand loyalty and have repurchasing power, it is of interest to research the differences further.

8.5.2 Future Development of the Model

The respondent feedback on the model suggests the model could evolve further to meet users where they are in their businesses - across industries, organisational sizes, and internal capacities. There are ten traditional AI use cases, and ten generative AI use cases identified within the final model. However, all twenty of these use cases may not apply to all companies using the model. An evolution of this research could be in its applicability as a modular approach. This could be where companies are encouraged to select only the most relevant use cases they can implement based on their resourcing constraints. Research beyond one case study company would be an appropriate future research avenue.

Additional evolution to the applicability of the model could be through segmentation by company size. Larger companies will usually have access to larger budgets, resourcing and software capabilities than smaller companies. This opens a new research direction for the model and accompanying guide to evolve to be more bespoke to companies of different sizes. An example could be that a smaller company with a marketing department of a few people will require a different prompt engineering training plan than a marketing department made up of hundreds of marketeers.

The current model can also evolve to distinguish between companies that function as business-to-business marketing, and those who function as business-to-consumer marketing. The applicability of the use cases identified in the model may change between these two types of marketing. This could also include the research on the types of biases. Business-to-consumer marketing may rely more on hyper-personalisation to drive bespoke customer experiences, and therefore, not be regulating the data hyper-targeting like a business-to-business marketing department would.

A further evolution of the model could be to test it in different business departments – such as HR, Procurement or Finance departments. The core concepts could translate well into these other departments. All of these departments would use their own type of technology stack for their processes, and their personnel could utilise both traditional and generative AI through this. While the customer journey for these departments would have to pivot to an internal stakeholder engagement journey, the elements of People and Process should remain vital to regulate any biased usage of the AI in these departments. Researching the model’s applicability across different company departments would be a valuable future research endeavour, as it would favour a standardised approach to regulating bias through the usage of AI across a company’s departments.

Future research is not only found in the development of other departmental models but also in the ever-evolving technological landscape of AI. From chapter 2, Literature Review, it was established that AI is a nascent and rapidly evolving field, continually reshaping the boundaries of technology and human capability (Li, 2020). Recent advances in computing power, data availability, and generative algorithms have accelerated its development and usage for personal and business use. AI remains in a formative stage, with new enhancements emerging regularly across natural language processing which is core to generative AI outputs (Roetzer & Kaput, 2022). This gives an opportunity for this research model to evolve in the future to include new and updated use cases.

There are several avenues that AI (both traditional and generative) could evolve into future use cases for marketing. The first is that hyper-personalisation is expected to scale further and become “real-time” during digital customer and company interactions. This includes dynamically generated videos, immersive product experiences, and conversational AI that adapts to each customer’s emotional tone based on their interactions. Secondly, autonomous marketing agents will increasingly take over routine marketing functions from humans. Campaign design and execution will increasingly be coordinated by AI algorithms based on strategic goals and performance data. These agents could automatically adjust campaign budgets, timing, and messaging for optimal ROI. The third possibility involves customer modelling and segmentation. This could be achieved by using AI-generated “digital twins” of customer personas where marketers can test campaigns and journeys in simulated environments. This would allow for optimisation before deployment and reduced risk of bias in live scenarios. All these additional and evolved uses of AI within marketing would need to be researched in the context of the use cases and if the current model guidance of Prompt Engineering training and Implementation Management still robustly allows for the identification and mitigation of bias in AI usage in digital marketing.

8.6 Final Reflections on the Research Process

Being given the opportunity to research such an interesting topic area has been deeply rewarding. The process required me to re-awaken my academic writing and critical thinking skills, which had slowly fossilised since my bachelor's degree a decade before. I enjoyed the process of this re-awakening and reducing my marketeer's lengthy and "buzzword" writing style. The process has enhanced my written work within my professional work too and has trained me to be more concise with the delivery of presentations and projects.

From my initial application to the University of Gloucestershire, I was aware of the research gap I wanted to address and have stayed true to the original research objectives in my project approval. The topic area was so nascent and the experience of being asked to use AI professionally but with little guidance on how to implement allowed me to be very specific in the research gap I wanted to address.

Close connection to the case study company significantly enhanced this research due to my access to information and interview respondents. My research efforts have been supported by employees across all levels of CSC marketing. The support from CSC has been invaluable, allowing for the research to be conducted - leading to such rich insights, perspectives and experiences in respondent interviews.

I enjoyed all parts of the research process; however, the literature review was particularly rewarding. It allowed me time (which I would never normally dedicate) to study 183 academic sources on the coming AI "revolution", marketing theory, bias theory and digital transformation. I have never been so well versed on marketing technology and understanding how these technologies are evolving current marketing techniques. The literature review process allowed for both academic and professional growth, reminding me to utilise external research in my work projects to broaden my knowledge of industry best practices.

The thematic analysis process was also deeply rewarding – especially writing chapter 6 where the deep-analysis and model validation was conducted. The method of analysing the data made me feel like an investigator – tracking down different points of view, critiquing what had been said and investigating new avenues for review. It was the most interesting academic work of my life so far and I have gained methodological expertise through the process that is already supporting my professional work. I have developed a more structured, insight-led approach to marketing strategy and campaign planning.

I also enjoyed the additional opportunities I was given to share my research – from appearing on my first podcast to hosting a panel at a business AI event. A particular highlight was co-authoring my first academic article with my supervisors, leading to my first published work. It was an invaluable experience that supported my thesis production and helped me believe I really could achieve a PhD.

Due to the nascent and fast-paced area of AI, it was a concern to me that my research would already have been published by someone else by the time my thesis was complete. However, the adoption of AI within marketing for businesses is still in its infancy and this research is still completely relevant as organisations grapple with AI implementation and usage by their workforce. This implementation, alongside the knowledge that bias will always exist and manifest itself through marketing, it is clear there is a need to continue evolving and exploring in this space.

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X. APPENDICES

Appendix 1: List of PRISMA Systemic Literature Review References (183 References)

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Appendix 2: Participant Information Sheet and Research Consent Form

Contact
Catherine Reed
University of Gloucestershire (UK
School of Business, Computing and
Social Sciences)
Email:
catherinereed@connect.glos.ac.uk
Mobile: 0044 79669 759 032
Website: www.glos.ac.uk

November 2025

PARTICIPANT INFORMATION SHEET

Research on bias propagation through using or prompting AI in Digital Marketing

RESEARCH BACKGROUND

The nascent arrival of Artificial Intelligence has companies deploying AI for their employees to use but with little guidance. Bias is prevalent is all aspects of our lives, and current research shows that there is bias within AI models (both the data they use and the coding of them). However, no published literature currently researches the bias propagation of the human when they use or prompt an AI and the steps that can be taken to regulate it.

PURPOSE OF THE RESEARCH

The aim of this research is to establish a new framework to reveal and mitigate bias through usage of AI in Digital Marketing. This framework can then be applied in industry.

The aim of this research is:

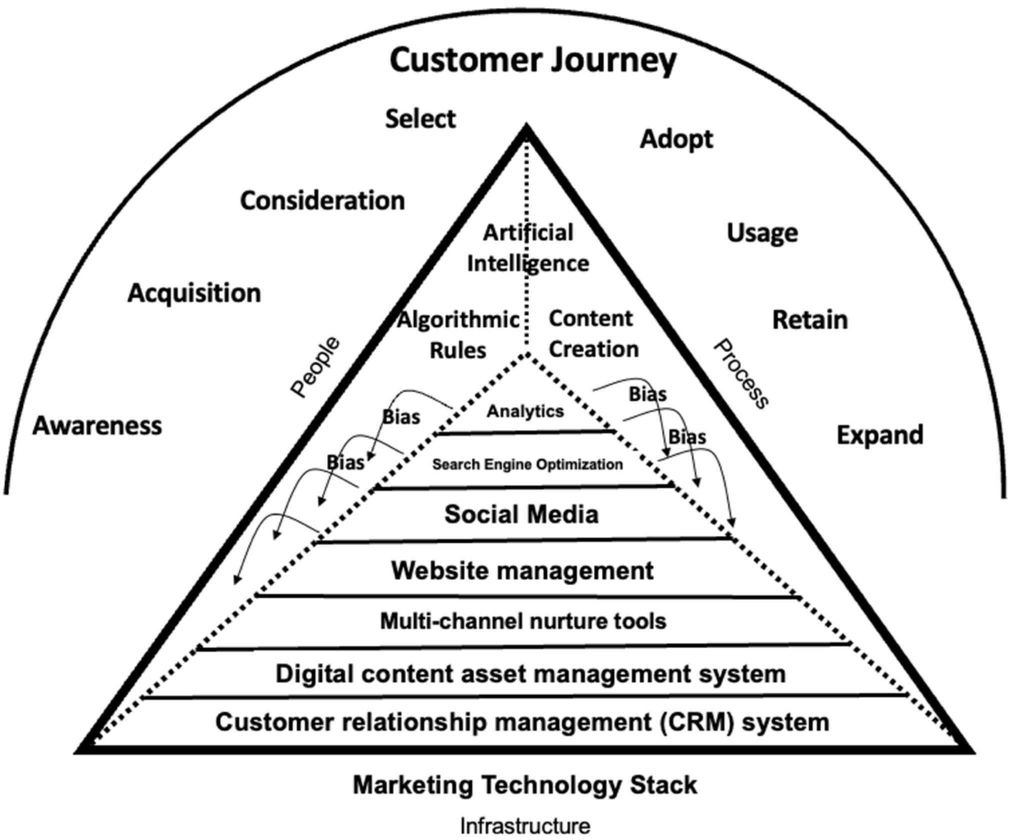
- to analyse current and possible bias issues in coding, prompting and deployment of AI in Digital Marketing
- to develop and test a framework or model, entailing appropriate guidance for practitioners, for revealing and mitigating bias in AI deployment in Digital Marketing.

IMPORTANCE OF RESEARCH

Many of the digital marketing channels available to marketeers have bias within their data already: Google Images, YouTube and Amazon to name a few. Research has highlighted various dimensions of bias, including algorithmic bias, data bias, and user bias. Discriminatory outcomes produced by AI algorithms are often influenced by the inherent prejudices embedded in the data used for training or incomplete data with lack of diversity. User bias involves the subjective interpretation and utilisation of AI generated insights by marketers this can lead to a loss of trust and customer attrition. Limiting this bias is beneficial to business, contributing to ethical practices and ensuring customers are not prejudiced against.

METHODOLOGY

A provisional conceptual framework has been created leveraging literature research. Interviews will test, develop and enhance the applicability of the conceptual framework (below). This testing will ultimately lead to a final framework output. Before each interview participants will be required to complete a research questionnaire to support the areas explored within the interviews.



YOUR INVOLVEMENT

You are invited to participate in this research study, though your participation is completely voluntary. Should you decide to take part, you will need to sign a consent form. Participation involves a conversation with a researcher from the University of Gloucestershire, lasting one hour. This will be scheduled at a time and place that suits you and all information provided will be kept strictly confidential. Please note that all names will be anonymized.

AUDIO RECORDING OF INTERVIEWS

The interview will be audio recorded for more reliable data capture. This is only with your permission and confidentiality of this audio recording is explained in the next paragraph.

CONFIDENTIALITY

Your responses will remain anonymous. All data will be stored using ID numbers on a password protected computer. This computer will remain within a secure, locked space, and your name will not be linked to your interview data. No information identifying any individual will be shared with others. Only summary data will be presented in study reports, with no details that could identify participants. Once the research is completed and reported, all recordings will be destroyed, while transcripts will be securely stored for 10 years, allowing for any necessary verification of information during this time. All company and interviewee names will be anonymized.

RESULTS

The results of this research will be part of a PhD thesis. Alongside this, the research will be published in the form of academic papers in management journals, presented at academic conferences and discussed at industry events and on podcasts.

RESEARCHER AND SUPERVISORS

Dr. Robin Bown and Dr. Martin Wynn (both from the University of Gloucestershire) are the primary supervisors for this study. They oversee the researcher and their work. The researcher is Catherine Reed and is conducting the research for a PhD thesis.

FURTHER INFORMATION

If you have any questions or further information is required, then please contact the researcher at her email address: .

If you accept this invitation to participate, please complete and sign the consent form at the end of this document. Please return it to the researcher at her email address: . You will then be sent the research questionnaire to complete and your interview will be scheduled.

Thank you for your participation!

Contact
Catherine Reed
University of Gloucestershire (UK
School of Business, Computing and
Social Sciences)
Email:

Mobile:
Website: www.glos.ac.uk

January 2025

RESEARCH CONSENT FORM

Research on bias propagation through using or prompting AI in Digital Marketing

Please complete this form to provide consent to take part in the research after reading the PARTICIPANT INFORMATION SHEET and tick YES or NO	**YES**	**NO**
1. The research PARTICIPANT INFORMATION SHEET has been provided to me.	☐	☐
2. I have read and understood the participant information sheet.	☐	☐
3. I have asked questions about the research project (or been given an opportunity to).	☐	☐
4. I am taking part in this research voluntarily and have not been forced by my employer or the researcher to take part in this study.	☐	☐
5. I understand taking part in this study could mean my responses could be quoted in the researcher's thesis or related work.	☐	☐
6. I agree to take part in the project and understand that taking part in the project will include completing the attached questionnaire.	☐	☐
7. I understand that I can withdraw from the study at any time, before the data is analysed without reason.	☐	☐

Please enter your name	Please sign	Please add date
Participant Name	Signature	Date

Appendix 3: Pre-Interview Questionnaire

November 2024

RESEARCH QUESTIONNAIRE FORM

Research on bias propagation through using or prompting AI in Digital Marketing

GENERAL INFORMATION

1. What is your role in Digital Marketing?

   ……………………………………………………………………………………

2. In which Marketing team do you work?

Corporate Marketing	☐	Field Marketing	☐
Product Marketing	☐		

3. Which part of the marketing customer journey do you work in?
   (Instructions: Please tick all relevant boxes.)

Pre-Sale Awareness	☐
Pre-Sale Acquisition	☐
Pre-Sale Consideration	☐
Pre-Sale Select	☐
Post-Sale Adopt	☐
Post-Sale Usage	☐
Post-Sale Retain	☐
Post-Sale Expand	☐

4. What are your key digital marketing activities?

   ……………………………………………………………………………………

   ……………………………………………………………………………………

5. How long have you been working in Digital Marketing (in years)?

   ……………………………………………………………………………………

   ……………………………………………………………………………………

6. What are the main objectives of Digital Marketing?

…………………………………………………………………………………………

…………………………………………………………………………………………

7. What do you think is the perception of Digital Marketing by other company stakeholders?

…………………………………………………………………………………………

…………………………………………………………………………………………

8. Do you think that digital marketing at CSC is innovative? Give examples.

…………………………………………………………………………………………

…………………………………………………………………………………………

9. Do you think that CSC uses new technology in Digital Marketing? Give examples.

…………………………………………………………………………………………

…………………………………………………………………………………………

10. Have you ever used AI? How long for?

…………………………………………………………………………………………

…………………………………………………………………………………………

INFRASTUCTURE

11. Does your marketing department use AI to support marketing objectives and/or strategy? Which ones?

…………………………………………………………………………………………

…………………………………………………………………………………………

12. What marketing activities do you use AI in?

MarTech Stack

Analytics	☐
Search Engine Optimization (SEO)	☐

Social media	☐
Website Management	☐
Multi-channel nurture tools	☐
Digital content asset management systems (DAM)	☐
Customer relationship management (CRM) systems	☐

Give a brief description of how you use AI in the "MarTech" boxes ticked above:

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…………………

……………………………………………………………………………………………
…………………

What applications are used in the "MarTech" boxes ticked above?
How frequent do you use them?

……………………………………………………………………………………………

……………………………………………………………………………………………

Content Creation

Text Generation	☐
Image Generation	☐
Audio Generation	☐
Video Generation	☐

Give a brief description of how you use AI in the "Content Creation" boxes ticked above

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What applications are used in the "Content Creation" boxes ticked above?
How frequent do you use them?

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13. Do you think the use cases for AI change between pre-sale and post-sale marketing activities?

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14. Do your think the use of AI adds any value for digital marketing?
(*Instructions: Please tick the relevant box. Furthermore, please use the third box to establish your ranking, starting with 1 being most important.)*

		yes	no	Ranking
1.	Increased ROI	☐	☐	
2.	Lower prices	☐	☐	
3.	Improved supplier performance	☐	☐	
4.	Reduced risk	☐	☐	
5.	Reduced workload	☐	☐	
6.	Increased output	☐	☐	
7.	Higher quality output	☐	☐	
8.	Work on higher value activities	☐	☐	
9.	Increased control	☐	☐	
10.	Increased visibility of data	☐	☐	
11.	Increased conversion rates	☐	☐	
12.	Improved Brand adherence	☐	☐	

Do you need to add any more?

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……………………………………………………………………………………………

If you do not think that AI is beneficial, can you detail your answer?

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……………………………………………………………………………………………

15. For the applications with AI that you currently use, do you use them to…

	yes	no
… create something new?	☐	☐
… edit something?	☐	☐
… recap something?	☐	☐
… understand what is happening?	☐	☐
… understand why something has happened?	☐	☐

… forecast what will happen?	☐	☐
… make a decision?	☐	☐

16. Are you aware of areas in CSC marketing that are currently not using or implementing AI? Which?

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17. How well is AI currently integrated in CSC's overall marketing technology landscape?

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18. Do you know of any infrastructure in the MarTech stack to review output when traditional AI is used?

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19. Do you know of any infrastructure in the MarTech stack to review output when generative AI is used?

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20. Do you know of any "failsafe's" in the MarTech stack to stop automatic output when AI is used by marketeers?

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PROCESS

21. Does CSC have a chief AI officer?

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22. Have you witnessed any changes of marketing processes following the implementation of AI? If yes, which ones?

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23. Do you think processes will change/ will be redefined following the implementation of AI? How?

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24. Do you think AI will make processes more efficient? How?

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25. Do you foresee any additional processes after further implementation of AI?

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26. What are the main constraints with regards to processes that you consider could be improved by the implementation of AI?

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27. Do you know of any company processes to review output when generative AI is used by marketeers?

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28. Do you know of any company processes to review output when traditional AI is used by marketeers?

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29. Do you know of any marketing department processes to review output when any AI is used by marketeers?

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30. Is AI process documentation easy to find? Have you used it? How?

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31. What would be the optimum kind of organisational structure to take advantage of AI in digital marketing?

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32. What are the major barriers to establishing AI governance in marketing?

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33. What do you perceive as the 5 most critical elements of AI for Digital Marketing?

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PEOPLE

34. Have you engaged or participated in any AI projects? If yes, how were the project members selected? Who was the sponsor of the project?

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35. Do you know of any marketing training given for using generative AI in digital marketing at CSC?

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36. Do you know of any marketing training given for using traditional AI in digital marketing at CSC?

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37. Have you attended training to use AI? What and in which training form (e-learning modules, classroom, etc.)?

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38. Do you feel adequately skilled to use AI technology in your role?

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39. In order to add value to your job, what does AI need to do for you?

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40. Do you think that the application of AI technology changes the job profile for your current role?

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41. Do you think that marketeers should have or should acquire AI skills?

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42. What do you consider to be the necessary hard and soft skills to benefit from the application of AI in Digital Marketing?

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43. Has using AI changed the way you work?

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44. If AI is not used, how do you think your way of working would change?

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45. What impact has the implementation of AI had on the coordination between people (within marketing / across company)?

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46. Do you think additional roles are needed within Digital Marketing specifically for AI? What would that be (e.g. AI Marketing Lead)?

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47. What is AI leadership for you?

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BIAS

48. What does bias mean to you?

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49. In general, do you believe the data used for the CSC MarTech stack is from a reputable source?

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50. Do you think bias is present in marketing campaigns? What are the main types of bias to you?

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51. Have you ever seen bias propagated through “standard” digital marketing outside of CSC?

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52. Do you have any experience of seeing bias propagated through “standard” digital marketing at CSC?

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53. Have you ever seen bias propagated through digital marketing where AI was used, outside of CSC?

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54. Do you have any experience of seeing bias propagated through digital marketing where AI has been used at CSC?

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55. Do you think that any output from a prompted AI should be reviewed for bias before being used? If so, how many times? What would the process look like?

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56. What do you think would help limit bias being propagated through marketing campaigns?

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57. How do you think bias can be limited when prompting an AI?

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DATA

58. On a scale from 1 to 5, how do you take decisions for marketing campaigns?

1 (intuitive)	2	3	4	5 (data-driven)
☐	☐	☐	☐	☐

59. Do you think marketing campaigns have unconscious or conscious bias within them?

1 (strongly disagree)	2 (mostly disagree)	3 (neither agree or disagree)	4 (mostly agree)	5 (strongly agree)
☐	☐	☐	☐	☐

60. Do you think marketeers themselves add in their own biases to marketing campaigns?

1 (strongly disagree)	2 (mostly disagree)	3 (neither agree or disagree)	4 (mostly agree)	5 (strongly agree)
☐	☐	☐	☐	☐

61. On a scale from 1 to 5, do you think bias is easily propagated through prompting a *generative* AI?

1 (strongly disagree)	2 (mostly disagree)	3 (neither agree or disagree)	4 (mostly agree)	5 (strongly agree)
☐	☐	☐	☐	☐

62. On a scale from 1 to 5, do you think bias is easily propagated through prompting a *traditional* AI?

1 (strongly disagree)	2 (mostly disagree)	3 (neither agree or disagree)	4 (mostly agree)	5 (strongly agree)
☐	☐	☐	☐	☐

63. On a scale from 1 to 5, where do you perceive usage of AI at CSC to be?

1 (early stage of usage by workforce)	2	3	4	5 (fully used by workforce)
☐	☐	☐	☐	☐

64. On a scale from 1 to 5, do you feel the training to use AI at CSC is adequate?

1 (strongly disagree)	2 (mostly disagree)	3 (neither agree or disagree)	4 (mostly agree)	5 (strongly agree)
☐	☐	☐	☐	☐

65. On a scale from 1 to 5, do you think more training is needed to use AI responsibly?

1 (strongly disagree)	2 (mostly disagree)	3 (neither agree or disagree)	4 (mostly agree)	5 (strongly agree)
☐	☐	☐	☐	☐

Appendix 4: Questionnaire questions mapped to the PCF Core Concepts and Emergent Themes from Tables 3.1, 3.2 and 3.3

Questionnaire Question	Link to PCF Core Concept	Justification for Inclusion and Emergent Theme Link
1. What is your role in Digital Marketing?	• Customer Journey Stage • People	• Data on the seniority of respondent for a wide experience pool.
2. In which Marketing team do you work?	• People	• Data on the team affiliation to get a balanced data set (figure 4.3)
3. Which part of the marketing customer journey do you work in?	• Customer Journey Stage • People • Process	• Review of emergent theme *Pre-Sale Customer Journey.* • Understanding of the knowledge on the different stages of the customer journey,
4. What are your key digital marketing activities?	• MarTech Stack (Infrastructure) • People • Process • Type of AI	• What part of the MarTech Stack the marketeer works on. • Understanding on their role that can use AI.
5. How long have you been working in Digital Marketing (in years)?	• People	• Data on the tenure of the respondent.
6. What are the main objectives of Digital Marketing?	• Process	• Understanding from the respondent on what Digital Marketing means to them.
7. What do you think is the perception of Digital Marketing by other company stakeholders?	• People	• Understanding from the respondent on their views of Digital Marketing currently.

8. Do you think that digital marketing at CSC is innovative? Give examples.	• MarTech Stack (Infrastructure) • People • Process	• Understanding from the respondent on the current innovations available, including AI. • This gives insight into if CSC is a proactive technology adopter.
9. Do you think that CSC uses new technology in Digital Marketing? Give examples.	• MarTech Stack (Infrastructure) • People • Process	• Understanding from the respondent on the current innovations available, including AI. • This gives insight into if CSC is a proactive technology adopter.
10. Have you ever used AI? How long for?	• Type of AI • MarTech Stack (Infrastructure) • People	• Review of emergent theme *Content Generation*. • Understanding on how respondents are currently using AI for their role.
11. Does your marketing department use AI to support marketing objectives and/or strategy? Which ones?	• MarTech Stack (Infrastructure)	• Review of emergent theme *Content Generation*. • Understanding on how respondents are currently using AI within their department (different to personal use)
12. What marketing activities do you use AI in? **MarTech Stack:** ○ Give a brief description of how you use AI in the	• MarTech Stack (Infrastructure) • Types of AI • People • Process	• Review of emergent theme *Analytics and Predictions*. • How respondents are using traditional AI for scoring, routing, profiling, etc.

"MarTech" boxes ticked above. ○ What applications are used in the "MarTech" boxes ticked above? ○ How frequent do you use them? • **Content Creation:** ○ Give a brief description of how you use AI in the "Content Creation" boxes ticked above. ○ What applications are used in the "Content Creation" boxes ticked above? ○ How frequent do you use them?		• Review of emergent theme *Content Generation*. • How respondents are using generative AI for Content Generation. • Understanding of where the respondent's knowledge of AI in the MarTech Stack is.
13. Do you think the use cases for AI change between pre-sale and post-sale marketing activities?	• MarTech Stack (Infrastructure) • Customer Journey Stages • Types of AI • Process	• Review of emergent theme *Pre-Sale Customer Journey.* • Understanding of perception in differences for AI usage across the customer journey. • Links to emergent theme of *targeting and testing.*
14. Do your think the use of AI adds any value for digital marketing? If you do not think that AI is beneficial, can you detail your answer?	• MarTech Stack (Infrastructure) • Types of AI • Process	• Understanding from respondent on their views on value for AI and their ROI within digital marketing.
15. For the applications with AI that you currently use, do you use them to… …create something new?	• MarTech Stack (Infrastructure) • Type of AI • People	• Review of emergent theme *Content Generation*. • Review of emergent theme *Analytics and Predictions*.

…edit something? …recap something? …understand what is happening? …understand why something has happened? …forecast what will happen? …make a decision?	• Process	• Understanding from respondent on how they use AI and their ROI within digital marketing.
16. Are you aware of areas in CSC marketing that are currently not using or implementing AI? Which?	• MarTech Stack (Infrastructure) • Types of AI • Process	• Understanding from the respondent on the current innovations available, including AI. • This gives insight into if CSC is a proactive technology adopter.
17. How well is AI currently integrated in CSC's overall marketing technology landscape?	• MarTech Stack (Infrastructure) • Types of AI • Process	• Understanding of where AI is in the MarTech Stack at CSC
18. Do you know of any infrastructure in the MarTech stack to review output when traditional AI is used?	• MarTech Stack (Infrastructure) • Types of AI • Process	• Understanding of where regulation for AI is within the MarTech Stack at CSC to support bias mitigation
19. Do you know of any infrastructure in the MarTech stack to review output when generative AI is used?	• MarTech Stack (Infrastructure) • Types of AI • Process • Bias	• Understanding of where regulation for AI is within the MarTech Stack at CSC to support bias mitigation
20. Do you know of any "failsafe's" in the MarTech stack to stop automatic output when AI is used by	• MarTech Stack (Infrastructure)	• Understanding of any final failsafe for AI output within

marketeers?	• Types of AI • Process • Bias	CSC to support bias mitigation
21. Does CSC have a chief AI officer?	• People • Process	• Understanding of respondents' knowledge of the AI landscape at CSC • This gives insight into if CSC is a proactive technology adopter.
22. Have you witnessed any changes of marketing processes following the implementation of AI? If yes, which ones?	• Process • Types of AI	• Understanding of respondents' knowledge of the AI landscape at CSC • Understanding on future-state ideas from respondents on how AI should be implemented.
23. Do you think processes will change/ will be redefined following the implementation of AI? How?	• Process • Types of AI	• Understanding of respondents' knowledge of the AI landscape at CSC. • Understanding on future-state ideas from respondents on how AI should be implemented.
24. Do you think AI will make processes more efficient? How?	• Process • Types of AI	• Understanding of current processes that AI supports at CSC. • Understanding of respondents' knowledge of the AI landscape at CSC. • Understanding on future-state ideas from respondents on how AI should be implemented.

25. Do you foresee any additional processes after further implementation of AI?	• Process • Types of AI	• Understanding on future-state ideas from respondents on how AI should be implemented.
26. What are the main constraints with regards to processes that you consider could be improved by the implementation of AI?	• Process • Types of AI	• Review of emergent theme *Analytics and Predictions*. • Understanding of current processes that AI supports at CSC.
27. Do you know of any company processes to review output when generative AI is used by marketeers?	• Process • Types of AI • Bias	• Review of emergent theme *Content Generation*. • Understanding of current processes that AI supports at CSC. • Understanding of regulation at CSC on AI usage.
28. Do you know of any company processes to review output when traditional AI is used by marketeers?	• Process • Types of AI • Bias	• Review of emergent theme *Analytics and Predictions*. • Understanding of regulation at CSC on AI usage.
29. Do you know of any marketing department processes to review output when any AI is used by marketeers?	• Process • Types of AI • Bias	• Understanding of regulation at CSC on AI usage. • Understanding of training available at CSC for AI usage.
30. Is AI process documentation easy to find? Have you used it? How?	• Process • Types of AI	• Understanding of regulation at CSC on AI usage.

		• Understanding of training available at CSC for AI usage.
31. What would be the optimum kind of organisational structure to take advantage of AI in digital marketing?	• Process • Types of AI	• Understanding from respondents on how they think AI should be implemented.
32. What are the major barriers to establishing AI governance in marketing?	• Process • Types of AI	• Understanding from respondents on how they think AI should be implemented.
33. What do you perceive as the 5 most critical elements of AI for Digital Marketing?	• Process • Types of AI	• Understanding from respondents on how they think AI should be implemented.
34. Have you engaged or participated in any AI projects? If yes, how were the project members selected? Who was the sponsor of the project?	• People • Process • Types of AI	• Validation of respondents matching the criteria for being interviewed. • Understanding of their knowledge of AI within their work. • Understanding the types of AI projects currently available at CSC.
35. Do you know of any marketing training given for using generative AI in digital marketing at CSC?	• People • Process • Types of AI • Bias	• Review of emergent theme *Content Generation*. • Understanding of training available at CSC for AI usage.
36. Do you know of any marketing training given for using traditional AI in digital marketing at CSC?	• People • Process • Types of AI • Bias	• Review of emergent theme *Analytics and Predictions*. • Review of emergent theme *Targeting and Testing.*

		• Understanding of training available at CSC for AI usage.
37. Have you attended training to use AI? What and in which training form (e-learning modules, classroom, etc.)?	• People • Process • Types of AI	• Understanding of training available at CSC for AI usage.
38. Do you feel adequately skilled to use AI technology in your role?	• People • Process • Types of AI	• Understanding of how respondents feel when using AI at CSC.
39. In order to add value to your job, what does AI need to do for you?	• People • Process • Types of AI	• Understanding of respondent's views on AI and why and how they would be using it.
40. Do you think that the application of AI technology changes the job profile for your current role?	• People • Types of AI	• Understanding of respondents' real-world view of how AI may impact their role. • Validation of respondents matching the criteria for being interviewed.
41. Do you think that marketeers should have or should acquire AI skills?	• People • Types of AI	• Understanding of respondents' real-world view of how AI may impact their role. • Understanding of needs required for training a marketeer in AI usage.
42. What do you consider to be the necessary hard and soft skills to benefit from the application of AI in Digital Marketing?	• People • Types of AI	• Understanding of needs required for training a marketeer in AI usage.

43. Has using AI changed the way you work?	• People • Types of AI	• Understanding of respondents' real-world view of how AI may impact their role. • Understanding perceived ROI of AI.
44. If AI is not used, how do you think your way of working would change?	• People • Types of AI	• Understanding of respondents' real-world view of how AI may impact their role. • Understanding perceived ROI of AI.
45. What impact has the implementation of AI had on the coordination between people (within marketing / across company)?	• People • Process • Types of AI	• Understanding of respondents' real-world view of how AI may impact their role.
46. Do you think additional roles are needed within Digital Marketing specifically for AI? What would that be (e.g. AI Marketing Lead)?	• People • Types of AI	• Understanding of respondents' real-world view of how AI may impact their role. • Understanding perceived ROI of AI.
47. What is AI leadership for you?	• People • Types of AI	• Understandings respondents stance on AI and what they require for leadership in this area.
48. What does bias mean to you?	• Bias • People	• Understanding from respondents on their interpretation of bias and how they define it.
49. In general, do you believe the data used for the CSC MarTech stack is from a reputable source?	• Bias • MarTech Stack (Infrastructure)	• Understanding on source for AI data within CSC and

	• Process	if respondents considered it to be trusted.
50. Do you think bias is present in marketing campaigns? What are the main types of bias to you?	• Bias • Customer Journey Stage	• Understanding from respondents on their experience and exposure to bias within marketing campaigns. • Review of emergent Theme *Pre-Sale Customer Journey.* • Understanding of bias across the different stages.
51. Have you ever seen bias propagated through “standard” digital marketing outside of CSC?	• Bias • Customer Journey Stage	• Understanding from respondents on their experience and exposure to bias within marketing campaigns. • Review of emergent Theme *Pre-Sale Customer Journey.* • Understanding of bias across the different stages.
52. Do you have any experience of seeing bias propagated through “standard” digital marketing at CSC?	• Bias • Customer Journey Stage	• Understanding from respondents on their experience and exposure to bias within marketing campaigns. • Review of emergent Theme *Pre-Sale Customer Journey.* • Understanding of bias across the different stages.

53. Have you ever seen bias propagated through digital marketing where AI was used, outside of CSC?	• Bias • Types of AI	• Understanding from respondents on their experience and exposure to bias within marketing campaigns. • Review of emergent Theme *Content Generation.* • Understanding of bias across AI usage for marketing.
54. Do you have any experience of seeing bias propagated through digital marketing where AI has been used at CSC?	• Bias • Types of AI	• Understanding from respondents on their experience and exposure to bias within marketing campaigns. • Review of emergent Theme *Content Generation.* • Understanding of bias across AI usage for marketing.
55. Do you think that any output from a prompted AI should be reviewed for bias before being used? If so, how many times? What would the process look like?	• Bias • Types of AI • Process	• Understanding of bias across AI usage for marketing. • Understanding from respondents on their ideas to use AI responsibly.
56. What do you think would help limit bias being propagated through marketing campaigns?	• Bias • Types of AI • Process	• Understanding from respondents their ideas on limiting bias.

57. How do you think bias can be limited when prompting an AI?	• Bias • Types of AI	• Understanding from respondents their ideas on limiting bias.
58. On a scale from 1 to 5, how do you take decisions for marketing campaigns?	• People • Process	• Understanding on how data-driven the marketeer is – the more data they use to inform decision making may lead to different uses of AI.
59. Do you think marketing campaigns have unconscious or conscious bias within them?	• Bias	• Understanding on the respondent's exposure and knowledge on bias in their career. • Understanding the respondent's stance on bias propagation.
60. Do you think marketeers themselves add in their own biases to marketing campaigns?	• Bias • People	• Understanding on the respondent's exposure and knowledge on bias in their career. • Understanding the respondent's stance on bias propagation.
61. On a scale from 1 to 5, do you think bias is easily propagated through prompting a *generative* AI?	• Bias • Types of AI	• Understanding on the respondent's exposure and knowledge on bias when using generative AI. • Understanding the respondent's stance on bias propagation.
62. On a scale from 1 to 5, do you think bias is easily propagated through prompting a *traditional* AI?	• Bias • Types of AI	• Understanding on the respondent's exposure

		and knowledge on bias when using traditional AI. • Understanding the respondent's stance on bias propagation.
63. On a scale from 1 to 5, where do you perceive usage of AI at CSC to be?	• People • Types of AI	• Understanding of the current adoption of AI within CSC marketing department. • Learn how AI is being used at CSC.
64. On a scale from 1 to 5, do you feel the training to use AI at CSC is adequate?	• Process • Types of AI	• Understanding of the respondent's current satisfaction with training at CSC for AI usage.
65. On a scale from 1 to 5, do you think more training is needed to use AI responsibly?	• People • Types of AI	• Understanding of the respondent's current satisfaction with training at CSC for AI usage.

Appendix 5: Thematic Analysis of Interview Data with Coding

Thematic Analysis Stage 1 and 2 for R01 to R06

	PCF Core Concepts	Respondent 01 Key Points	Respondent 02 Key Points	Respondent 03 Key Points	Respondent 04 Key Points	Respondent 05 Key Points	Respondent 06 Key Points
Types of AI	**Traditional AI**	Usage of traditional AI through "CSC's main project management tool for automation purposes". ***Bias*** "AI-driven algorithms may reinforce stereotypes by targeting ads based on biased data, such as focusing on certain demographics or interests while excluding others".	Time saving, allows marketeers to learn more about their customers through data analysis. Not a direct user of traditional AI.	*No views were attained in the questionnaire or interview.*	Process has changed due to implementation of traditional AI "things will be simplified. Repetitive tasks will not take that long anymore and meetings will be very simplified".	CSC uses machine learning localization software which follows traditional algorithmic rules – the respondent works with IT to maintain this and fully trusts their diligence and data rigour. Internal CSC IT uses a set human process to review the AI algorithms and data and this could be replicated for Gen-AI usage.	Traditional AI seems to be more standardised and have more rigour – there are clear Brand usages, messaging guidelines and persona riles. Teams are "still experimenting with AI rather than using it strategically yet".
	Generative AI	"CSC Marketing leverages Gen-AI to identify target accounts, translate content, deliver content to the right personas, and optimize campaign programs effectively".	Uses for administration only due to ethical concerns and having no knowledge of any fail-safes in place to monitor AI used in external marketing materials.	Best use cases for Gen-AI at CSC is persona research, paid media briefing and content strategy – especially for messaging creation that	When using Gen-AI to create any type of content that is used outside of Western culture you must have a local expert involved to curate that content correctly. This isn't	Using Gen-AI content is a brand image risk especially due to AI output not being quality. AI produced content isn't always correct, especially if it has been directly	Gen-AI currently doesn't allow marketeers to add their own learnings to it to support it learning. There should be different Gen-AI's

			"Generative AI creates a breadth of banners to be used in social channels, and AI also supports the content localization process". "When looking to start a talk track, or frame an email, I'll often use Gen-AI to get an initial outline".	resonates with target personas. Gen-AI can give a constant learning feedback loop to CSC to support ethical marketing practices. "People are using it mainly to edit their work…the real value in generative AI for work is to leverage it for faster research gathering and framework building. I am working on it to combine with my strategy and creative direction to super charge my work. We have an internal gen-AI tool and Co-pilot for workflow automation".	simply localizing into different languages – it requires transcreation, knowledge of culture and dialect difference understanding.	translated into another language. Once a certain % of content is AI generated it should only be used with a disclaimer to say it is AI. "Translation of copy through AI, usage of AI service to generate voice-over in language for video localization".	allotted to different marketing departments. ***Cust Journey*** Teams are using Gen-AI for "localization, SEO, content audits and in customer journey planning".
Marketing Technology Stack	**Analytics**	***Analytics*** Project management for administration purposes appears to be missing from the MarTech Stack. "Google Analytics, Adobe Analytics, and A/B testing platforms are often used in the MarTech stack to review and validate AI-driven outputs".	***Bias, Pyramid*** Reviewing the PCF the MarTech Stack looks like it is represented hierarchical with the bias cascading from analytics, this is an inaccurate view as the	***Analytics, Pyramid*** PCF Feedback – Analytics is too broad a term. When reviewing the training required the researcher should also focus on data modelling and predictive analytics	***Analytics, Pyramid*** Reviewing the PCF the MarTech Stack looks like it is represented hierarchical starting with analytics - which suggests a level of importance, this is not	*No views were attained in the questionnaire or interview.*	*No views were attained in the questionnaire or interview.*

			MarTech stack is linear and feeds each other.	as separate analytics use cases – especially as it uses algorithmic traditional AI. ***Analytics*** Using AI in "Analytics for reporting and content optimization".	accurate for the MarTech Stack as all parts are of equal importance.		
	Search Engine Optimization	*No views were attained in the questionnaire or interview.*	*No views were attained in the questionnaire or interview.*	Need to add link building to SEO within the MarTech Stack – this is tracking to increase volume and quality of inbound links to a webpage to increase the the search engine rankings for that website.	*No views were attained in the questionnaire or interview.*	*No views were attained in the questionnaire or interview.*	*No views were attained in the questionnaire or interview.*
	Social Media	"Social media platforms and ad networks may prioritize content based on past behaviour, reinforcing existing preferences and excluding diverse viewpoints".	Recommend renaming to "Organic and Integrated Social Media" to make it clear the differentiation between paid and unpaid forms of social media which could have different AI applications.	Using AI in "SEO and Social for awareness content distribution"	Using AI to "mainly in optimizing copies for social media". There are multiple (human) review cycles when using generative AI for social media banners and respondent believes this should be the case across all AI uses in the	*No views were attained in the questionnaire or interview.*	*No views were attained in the questionnaire or interview.*

					MarTech Stack (currently there is not). ***Bias*** These multiple reviews caught bias in generated social images that showed only white individuals in the images, and not a diversified group.		
	Website Management	*No views were attained in the questionnaire or interview.*	*No views were attained in the questionnaire or interview.*	Using AI in "website management for lead generation"	*No views were attained in the questionnaire or interview.*	"AI for translating the website across the globe"	*No views were attained in the questionnaire or interview.*
	Multi-channel nurture	*No views were attained in the questionnaire or interview.*	*No views were attained in the questionnaire or interview.*	Using AI in "channel nurture tools for email nurture and omni channel strategy"	*No views were attained in the questionnaire or interview.*	*No views were attained in the questionnaire or interview.*	*No views were attained in the questionnaire or interview.*
	Digital content asset management (DAM) system	*No views were attained in the questionnaire or interview.*	*No views were attained in the questionnaire or interview.*	Using AI in "DAM for content management"	Using AI to "develop best practices for DAM" …text translations.	"Latest campaign content being created with help from AI for quicker production timeline"	The data strategy for DAM is "hand in hand" with IT and their strict process which brings comfort to the teams at CSC using this software that the data is balanced and correctly regulated. "Using AI as part of content audits to identify content gaps in digital marketing".

	Customer relationship management (CRM) system	"Marketers may focus only on data that supports their pre-existing assumptions, overlooking data that contradicts their views".	*No views were attained in the questionnaire or interview.*	***Bias*** Hyper-personalisation is a risk for bias with targeting of groups relentlessly. Using AI in "CRM for lead management"	*No views were attained in the questionnaire or interview.*	*No views were attained in the questionnaire or interview.*	*No views were attained in the questionnaire or interview.*
Customer Journey	**Pre-Sale**	***Cust Journey*** Difference in the buying committee in pre-sale, more influencers in the process.	***Cust Journey*** Use case for AI changes between pre and post-sale marketing. ***Cust Journey*** "[We] develop messaging, creative and journeys we are typically using data from persona research… that data is usually sourced from a mostly North American buying group. So we build out a global program, message and creative design that we believe will resonate with our buying group. But one size doesn't fit all audiences, for messaging or imagery or oftentimes the sales approach".	***Cust Journey*** Marketing has changed significantly with the four stages of the customer journey becoming eight stages. ***Cust Journey*** "Presales will focus on qualifying and giving the customer the most relevant information for that persona / interaction with types of assets and content they most need. The goal in pre-sales is to inform the customer as quickly as possible to move them to a [sale] ".	*No views were attained in the questionnaire or interview.*	***Cust Journey*** The changes between pre and post-sale using AI is… "evolving as technology evolves and as quality of the output increases"	*No views were attained in the questionnaire or interview.*
	Post-Sale	***Cust Journey*** Data difference for post-sale. You already have your customers data (persona, company,	***Cust Journey*** "Considerations for data privacy and proprietary	***Cust Journey*** "Post sales it is about customer adoption and actually	***Cust Journey*** Changes for… "activity and knowledge. During	*No views were attained in the*	*No views were attained in the questionnaire or interview.*

		gender, etc) so you can target a lot more efficiently.	company information related to CSC solutions, user licenses, etc"…will impact data segmentation and persona targeting for post-sale marketing.	using the product, this could mean chat bot support, optimizing product UI (user interface) with guidance and product related nurture based on interaction of product"	post-sale ideally, we would have more insights and can come up with better results".	*questionnaire or interview.*	
Technology Implementation	**People**	***Bias*** Legacy Thinking – currently marketing in CSC is experiencing incremental adoption from its workforce to use AI. With legacy thinking also comes biased viewpoints on who "used" to buy software. ***Bias*** Length of Career – those who have a longer career are better at anticipating bias in marketing due to understanding of cultural interplays.	***Bias, Prompting*** Humans will add in bias when prompting an AI. ***Bias*** There can be bias in hypothesising a bias problem – such as Eurocentric ideas being over censored so they are no longer relevant in European markets.	***Bias, Management*** Marketeers should be trained on a prompting training model or simulation, where they can experience learning to prompt in a safe environment with feedback and guidance on correct prompting. A simulation like this can define the bias parameters and the marketeers learn from this. ***Prompting*** "Hard skill – prompt engineering, strategic thinking. Soft Skills – human relationship building, creativity, curiosity, critical thinking".	***Management*** Respondent views that CSC employees are quite advanced with using AI, and the software industry is currently lagging behind them in usage of AI.	***Management*** At CSC marketeers are encouraged to use Gen-AI for their work and receive guidelines but no risk management. ***Management*** Respondent recommends having AI Ambassadors within marketing to be advisors and trainers to marketeers (these would be peers, not a new job role). "Everyone is asked to use AI but no one is clearly accountable for the risks and spotting when someone used it in the wrong way"	***Management*** Training needs to be done for content creators specifically, so they understand the benefits, risks and what is approved for the brand. ***Prompting*** Prompting is an issue and requires prompting training. Teams the respondent has worked with are not happy with the current prompting understanding and guidance. ***Bias*** People are the most important part of using AI ethically and limiting biases within outputs.

	Process	***Management*** Marketing AI Training – not comprehensive training currently. Use cases provided for CSC colleagues focus on HR which is not helpful to marketeers. "The output should be reviewed at least once by a diverse team to ensure fairness and inclusivity". ***Prompting*** To use AI it should be "someone skilled in AI, with the ability to create the right prompts and leverage AI tools effectively for the role". ***Bias, Prompting*** "Crafting prompts that are neutral and inclusive, avoiding language that may unintentionally lead to biased responses".	***Management*** Cautious users of new technology require more control in the process to feel comfortable using it. ***Management*** Currently seeing reactive management of AI – similar to when the internet was adopted in the workplace – and would like to see a more proactive approach being taken to its implementation. ***Management*** "Clear guidance on how we can innovate, scale and adopt AI in our daily operations. Specific use-cases for different departments. Confidence in how to prompt AI to ensure brand and quality integrity. Encouragement for continued enablement and curiosity for AI". ***Prompting*** "Much like we proof/review/sign off on materials from an agency,	***Management*** Currently no failsafe for Gen-AI outputs – critical thinking must be applied by the marketeer as the failsafe. The marketeer should see if it is appropriate to be used where customers can see it. ***Management*** "We will need to constantly reviewing the AI output and still maintain critical thinking the biggest danger with AI in process is setting and forgetting often AI has hallucinations, issues in the model or wrong information sent back. Critical monitoring of inputs and outputs will be important".	***Prompting*** Prompting is very important skill to learn and to practice correctly. Currently no prompting training. ***Prompting*** "Making sure to use the right prompts, being clear and concise"	***Management*** Further training is required for using AI, especially with training on the correct roles and responsibilities – perhaps an AI guidebook could be produced… "training, enablement, reality checks" ***Management*** "Having a team in charge of AI for digital marketing to enable, coach, guide all teams to use AI more"	Currently no roadmap for AI usage within CSC marketing. Respondent uses own personal reviews to keep their AI outputs ethical and reviewed. They request multiple reviews of their work from other colleagues. ***Bias, Prompting*** There needs to be a process to train marketeers to spot the bias in their prompting. The stance of always question your output should be the first thought. "Need specific approvals or quality checks, which are not included in today's processes" ***Management*** "Encouraging the company to use AI in a responsible way and integrate it into standard processes, constantly share examples and improvements to

			we should work with AI to support our work but not to complete and publish autonomously. The process truly depends on the sensitivity and visibility of the work and its intention - much like our internal and vendor review-approval cycles look like".				motivate colleagues to use it but also putting proper governance in place".
	Infrastructure	***Pyramid*** Project management for administration purposes appears to be missing from the MarTech Stack. "AI is not yet fully incorporated and remains quite limited in terms of areas where it can perform at its fullest potential".	***Bias*** The more "data savvy" a marketeer the more understanding they have of bias propagation as reading the data comes naturally and they can view the unbalanced areas. A good infrastructure can support data literacy for marketers. "CSC is slow to adopt a new technology, as it's an enormous organization so any change requires a pilot to first prove the solution, and then a rollout plan to cascade to all marketing teams globally".	***Pyramid*** Project management is not part of the MarTech Stack. Using AI in the MarTech Stack "everyone is dipping their foot in but maybe not using it every day". Idea on having an AI blocker on any MarTech Stack software that uses AI. So a direct copy and paste from a marketeer will be flagged as AI.	The MarTech Stack is very important to using AI in marketing and it must be an organised stack where data communicates properly and API (Application Programming Interface is the interface between two software applications, allowing them to communicate with each other). ***Pyramid*** Project management is not part of the MarTech Stack – it is part of the process. AI in the MarTech Stack is "still fairly new	The MarTech Stack ensures the quality of marketing output – "it will keep evolving as technology evolves and as quality of the output increases". ***Pyramid*** The MarTech Stack should use industry standard tools that take on the due diligence of using AI ethically themselves, rather than the client (CSC).	***Pyramid*** Respondent only uses AI that are from certified vendors in the MarTech Stack – they trust them to take the risk. "Everybody is working on some use cases and piloting things. Not everybody is using it as a standard yet".

					and not completely implemented”		

Thematic Analysis Stage 1 and 2 for R07 to R12

	PCF Core Concepts	Respondent 07 Key Points	Respondent 08 Key Points	Respondent 09 Key Points	Respondent 10 Key Points	Respondent 11 Key Points	Respondent 12 Key Points
Types of AI	**Traditional AI**	***Bias*** AI models are biased “The model itself already has some, even politically motivated bias within…If you look at what open AI puts out versus Deep Seek for instance”. (OpenAI is USA based, Deep Seek is Chinese based).	**Bias** The bigger the data the AI is fed on, the more skewed outcomes you will have. Knowledge of how large the data is can help the marketeer understand the level of bias risk” - “Bias is present in marketing campaigns, often influencing targeting, messaging, and content personalization. The main types of bias include: - Data Bias – Skewed or incomplete data leading to inaccurate AI-driven decisions. - Selection Bias – Over-representing or under-	***Bias*** Barriers to adoption AI is GDPR and data privacy implementation. Large language models has proven bias within it – uses up to 9 data sets and 7 of these data sets are from the USA. This causes bias for ethnic groups and promotes Eurocentricity. USA data is also weighted to males which can cause bias. “You ask (a generative AI) in China – “what does democracy means?” - and it gives you basically the	***Management*** Traditional AI has been around for decades but behind gatekeepers until now. Most people do not know they’ve been using it for years but now everyone has access to use it to enhance data analysis and cohesive marketing. To use this though needs education, especially if English is not the users first language. “Yes tools are used on a daily basis from defining the right data to address the	Respondent uses traditional AI in the following software: - Knack – email content production, automatic creation of ALT text (image text for blind or visually impaired using voiceover support to use smartphones and computers). - Wrike – project management tool. Automation of assignees and other automated processes. CSC doesn’t allow using Wrike	“AI will be used increasingly across processes in all functions for time saving automation, content optimisation, creating outputs, analysing data etc”

			representing specific audiences in campaigns. - Cultural Bias – Messaging that unintentionally excludes or misrepresents diverse perspectives.	complete opposite answer (to the USA AI) - so you know it, it's it can be very, very fickle" ***Bias*** "Yes bias is 100% present in marketing campaigns. The main types of bias are confirmation bias, selection bias, algorithmic bias, and cultural bias"	objectives, to analysing data post campaigns whether they have met the objectives"	generative AI capabilities.	
	Generative AI	Using gen-AI for "Sprinklr AI enabled insights tab, LinkedIn/Meta/Sprinklr AI assisted targeting and social copy text variation".	***Prompting*** Respondent created own prompting guidelines to use to optimize work and for their own ethical stance – did this via own research on prompting and experimenting using A/B testing. Will only use the Enterprise Grade AI for work – "I use AI for text generation to improve grammar, generate and optimize campaign copy, and enhance data insights and reporting. It helps streamline workloads,	Respondent uses Gen-AI to ask work questions that are not confidential – does not use the Enterprise AI. Examples of non-confidential is answering stakeholders' queries, creating own coding, ideas on the best way to analyse specific data. "Current release of Microsoft Copilot to all marketing employees"	"Text copy for invitations, web. Audio and video for event material creation - different language modules allow for podcast translation, invitations in local languages. Syntehsia is a video AI tool that is currently being rolled out across event usage". Videos generated by gen-AI needs to be culturally appropriate	**Management** Respondent is part of the Co-Pilot Champions Network (respondent is only one from the full respondent list to be invited to this group) - Training is prolific for the champions - They are trained to advocate for AI Respondent uses gen-AI to generate structure on complex	***Bias, Prompting*** "I think that risk is an area of AI that will need constant review and monitoring of the outputs to ensure that there is no bias, that the correct prompts were used to generate the outputs, that the sources of the content are clearly indicated, that there are no confidentiality issues"

			making content creation more efficient and effective". ***Prompting*** Gen-AI prompting can be too Eurocentric and respondent uses local experts to review outputs that would be used in local countries – to make it culturally appropriate. CSC "Leveraging generative AI to accelerate time to market and enhance data analysis". "AI Quality Assurance & Governance: Establishing formal review and validation frameworks for AI-generated content, ensuring compliance with brand guidelines and ethical standards".		when being used. Deepfake technology (while unethically used) can actually be beneficial for marketeers creating local language and culturally appropriate content. If used a disclaimer should be used – this should be mandatory and marketeers should have education on it.	communications. It aggregates action items from recorded meetings which is generally reliable. Respondent also uses it to create content for presentations, however, this usually sounds AI generated so requires work from the respondent to adapt tone of voice. "To generate preview text and image descriptions. We can use it for email subject lines as well, but must use it carefully as the AI tool does not take our brand guidelines into account (for example it will add emoji into subject lines, but this does not follow CSC's brand guidelines)".	

Marketing Technology Stack	**Analytics**	***Bias*** *Hard to get accurate data from AI within the MarTech Stack as you are not sure what the AI has done to the data to read it.* ***Bias*** *"Often aligned to biases of targeting groups. Main categories would be left-leaning liberal vs. right-leaning conservative".*	***Bias*** *Targeting bias with segmentation criteria for personas.* ***Analytics*** *"Using AI to generate insights, automate reporting, and identify trends for data-driven decision-making".*	***Analytics*** "Use AI to create A/B test analyses by giving it the raw data (just the numbers without any context to CSC to not break any rules) and asking it to give 3 bullet points insights".	***Analytics*** *"These are used pre campaign to analyse the data and ensure the right customers are targeted, all the way to post campaign analysis and DG conversions".*	*No views were attained in the questionnaire or interview.*	***Analytics*** Incomplete or old data can skew data used to create personas – creating incorrect persona rules and groups. "Analyse customer behaviour, predict outcomes, automate marketing tasks, create and personalize marketing content, optimisations".
	Search Engine Optimization	*No views were attained in the questionnaire or interview.*	Google Search has guidelines for AI usage and will only use their recommended keywords. "Leveraging AI for keyword analysis, content optimization, and performance tracking to improve search rankings". .	*No views were attained in the questionnaire or interview.*	*No views were attained in the questionnaire or interview.*	*No views were attained in the questionnaire or interview.*	*No views were attained in the questionnaire or interview.*
	Social Media	"Social analytic platforms like Sprinklr do generally have AI enabled features. Social Media AI marketing features (e.g. AI	"Using AI for content generation, sentiment analysis, and performance	The software used for paid media is MSights. The software used for non-paid	*No views were attained in the questionnaire or interview.*	*No views were attained in the questionnaire or interview.*	Respondent recommended changing to "Social Media Management" as it includes the

		targeting) not used beyond internal testing purposes at this point".	optimization to enhance engagement".	(organic) media is Sprinklr.			technology to manage social, as well as post social content. ***Analytics*** "Dynamic Content Optimisation' (DCO). This is an AI driven process allowing for real time updates to paid media content to ensure maximum customer reach…the analytics drive the optimisations/ recommendations based on performance".
	Website Management	*No views were attained in the questionnaire or interview.*	Brand limitations are in place across all platforms – regulations around tone of voice and words used. AI supports generating this correctly.	The software used is Adobe. "AI proof-reading tools to make sure all content is correct before publishing, there could be AI tools that send a notification when something breaks on the website and needs to be fixed, there are so many ways AI can redefine processes".	*No views were attained in the questionnaire or interview.*	*No views were attained in the questionnaire or interview.*	*No views were attained in the questionnaire or interview.*

	Multi-channel nurture	*No views were attained in the questionnaire or interview.*	*No views were attained in the questionnaire or interview.*	The software used is Marketo.	*No views were attained in the questionnaire or interview.*	**Bias** Bias is present in email building AI tools – within choosing images to use. It was important to the respondent to use diverse representation within the images. To know this requires marketing experience. "We use a small amount of AI in email nurture, built into our Martech tools".	*No views were attained in the questionnaire or interview.*
	Digital content asset management (DAM) system	*No views were attained in the questionnaire or interview.*	*No views were attained in the questionnaire or interview.*	*No views were attained in the questionnaire or interview.*	*No views were attained in the questionnaire or interview.*	***Bias*** ALT text (image text for blind or visually impaired using voiceover support to use smartphones and computers) has become better with AI than with a human doing it. There is better description used and all images now have ALT text (showing scalability). When a human did it the description was	"Some of the content leads do use AI for text, image, audio and video generation…the use of AI in content creation is hugely beneficial, allowing for rapid optimisations & time saving".

						short and sometimes incomplete. Does this mean AI has empathy?	
	Customer relationship management (CRM) system	*No views were attained in the questionnaire or interview.*	*No views were attained in the questionnaire or interview.*	*No views were attained in the questionnaire or interview.*	"AI to update our database and keep it "clean" would be amazing"	*No views were attained in the questionnaire or interview.*	*No views were attained in the questionnaire or interview.*
Customer Journey	**Pre-Sale**	***Cust Journey*** Stakes are higher with using AI in pre-sales, you have to make sure the targeting is correct to the personas with the correct content applicable. The marketing goes to a broader audience, it is out in the world.	***Cust Journey, Analytics*** *"Yes, AI use cases differ between pre-sale and post-sale marketing. Pre-sale AI focuses on lead generation, ad optimization, SEO, and predictive analytics".*	***Cust Journey*** The marketing channels change between pre- and post-sale – the main CSC website is more important for pre-sale purposes. It focuses on personalisation and conversion rates for selling. Current A/B testing is done on the CSC website is top of funnel for marketing (meaning it is before sale). ***Cust Journey*** "We can use AI to create hyper-personalized content for every segment of customer that comes to the	**Cust Journey** "Both will use it for content and as well as creative asset creation, the context may change, but the usage will be similar".	***Cust Journey*** "Probably, though I have not given it much thought".	***Cust Journey*** "Yes (with cross-over usage though) - AI in pre-sales focuses on optimisations of marketing campaigns, content creation etc whilst AI in post-sale activities can analyse sales data, look at past customer behaviours/ transactional patterns to identify commonalities & build best-fit customer profiles. This enables AI driven personalised sales pitches designed to engage target customers and much more, reducing

				website in order to increase conversion rates".			the admin heavy tasks and freeing up time for more creative thinking".
	Post-Sale	***Cust Journey*** *Post-sale is better for AI segmentation, and you can be very tailored to the AI approach you use. AI usage is less risk.* ***Cust Journey, Prompting*** *"Post-sale needs to be even more conscious about personalization without the input of any data that should not be prompted".*	***Cust Journey*** *"While post-sale AI enhances customer support, personalization, sentiment analysis, and retention strategies".*	***Cust Journey*** *A/B testing on Call-to-Action buttons has shown marked increase in clicks when changing to a more post-sale terminology. Example: main CTA button changing from "see what's new" to "activate product" had an increase of clicks and 30% of these increase already owned the product. Showing there is scope for post-sale targeted activity on the CSC main website.* ***Cust Journey*** *"For post-sale we can use AI to create a customer support tool that uses agentic design to answer any specific*	*No views were attained in the questionnaire or interview.*	*No views were attained in the questionnaire or interview.*	As above.

				question related to the product".			
Technology Implementation	**People**	***Prompting*** *Marketeers using AI need to have: "Hard skills: Basic understanding of AI technology, prompt engineering. Soft skills: Curiosity, sound judgement, awareness for compliance".* ***Management*** *There is requirement for "AI empowerment of the existing workforce"*	***Bias, Prompting*** *Respondent understands they may have their own biases in daily work so takes special care when prompting an AI. Cultural differences can be the source of the bias, experience as a marketeer working in different locations can help mitigate this.*	***Prompting*** *There is currently limited AI training in CSC and no prompting training offered - "current trainings weren't effecting or memorable".* ***Management*** *LinkedIn Learning is offered as a self-service tool to learn but this has to be accessed by motivated marketeers.* ***Bias*** *Actual adoption of using AI by the workforce is crucial, therefore they should have correct enablement to be empowered to use it as marketeers can suffer from confirmation bias and ignore the data.*	Marketeers are using AI to stand out from the crowd, be proactive in their work, and those who have high work volume that is deadline bound. ***Bias*** Because AI learns if you put rubbish in, you'll get rubbish out – marketeers need to be trained to be aware of inputting bias and anomalies as it will skew the learning data. ***Bias*** "I think that marketing tries hard to maintain an unbiased view at CSC. Gender bias, culture bias, religious bias are sometime seen, but not intentional" - example from respondent was a	***Prompting*** The better people get at prompting and using AI, the more they can spot AI being used and understand when something has been generated. This is a self-fulfilling bias regulation. ***Prompting*** Respondent changes the way they interact with an AI based on personal or work interaction. Personal usage is more friendly with more interaction, whereas professional is direct, less friendly and the prompting is shorter. ***Prompting, Analytics*** "Hard skills - prompt generation, how to interpret results in analytics that use AI, how to use AI	Respondent believed humans should "stay in the driving seat" when using AI, and training is required for the human to manage appropriately. Training should be based on data lead learning. ***Prompting*** Respondent talks to AI differently for personal and business use. ChatGPT is a friend, however Co-Pilot for work is more formal interactions. ***Management*** "There would be a role for AI specialists within each marketing team who can guide the team into specific applications of AI which could enhance their roles. Equally, it's important for

				Management *"True adoption is always a constraint when adding AI to processes because a lot of people will initially see it as simply another tool they have to use in their job. Unless there is significant training, long-term adoption is very difficult".* ***Bias*** *"There is a lot of confirmation bias propagated through digital marketing at CSC where people will decide campaign strategies based off of things they think the audience will like, not based off what the data is indicating".*	recent video that was culturally appropriate for its market but was extremely sexist within other cultures. It should never have been published, but with only a local review in place it was approved for use.	carefully and ethically (the latter may be a mix with soft skills, but guidelines need to be in place and learned/followed). Soft skills - mostly around biases, ethics. Knowing when AI should be used as a tool vs. what should be done by humans. Knowing how to use it to inform decision-making (not replace human decision-making) ".	marketers (and their employers) to ensure regular upskilling with AI to maintain competitive edge".
	Process	***Prompting*** *Training is not standard across using AI – just pushed out and for the user (or prompter) to work out how to use it correctly.* ***Management*** *No real mandatory training on using AI, and what is available is not*	***Management*** Only respondent to mention there is a learning tool for learning Gen-AI, a tool called Experience Garage that offers step by step video learning with a quiz	***Prompting*** Learnt how to prompt through finding educational support and learning there are specific ways you should talk to a generative AI –	***Management*** Currently no real process to AI implementation and education at CSC,	***Prompting*** Prompting is important, and there are ways to get better at prompting. Give the prompt background – such as attaching an email or chat to give it	***Prompting, Management*** There is "currently a grey area" in training on how to prompt. Current training shows clear use

		marketing specific which leaves it open to interpretation. ***Prompting** Prompt Engineering is very important:* *1) Best practices on how to create and use prompting should be available "unbiased, clear prompts would be a good start".* *2) Have a process to implement good prompts (an AI Agent and a Human Review).* ***Prompting** Review cycle..." Once or twice by humans for most critical outputs should be enough. If reliable AI reviewing software would come along that could also be implemented. Possibly with AI agents that streamline the process to basically just prompt, create and check at once, final go by human".*	on how to use generative AI in CSC responsibly. However, this course tells you what to do but has no examples on how to apply to your job. Currently no process in place to review AI outputs by individual marketeers, respondent sends to colleagues to review before using externally – there should be a double review process for any AI generate content that goes externally and is visible to customers. ***Prompting*** Prompting education is required, especially on how to craft complex prompts. "Use clear, neutral, and inclusive language to avoid leading or skewed responses. Structure prompts to encourage diverse perspectives, and where possible, request AI to consider multiple viewpoints or verify information. Additionally, fact-check outputs, refine prompts for	this is Prompt Engineering. Personal use of AI should be conversational, but for work it should be more formal. ***Prompting*** Prompters should interact with an AI in a direct and conversational way, while prompting firm parameters for a good output. The prompter should never sweat or use offensive language. ***Prompting*** "It is important to have proper prompt engineering/frame working when using an AI to get the best possible outputs. This includes using neutral and fair language, providing very specific context and examples, requesting multiple outputs in a certain form (bullet points,	required a proper structure put in place. ***Prompting*** Prompting Education: needed to stop off brand content, research on prompting words, how to use the AI and what data it is trained on. ***Prompting*** "Specific prompts to remove culture, gender, etc biases - there are so many nuances, that the prompt would need to be really specific. Different countries, cultures etc would need to be accounted for and the prompts tweaked to allow for these nuances". ***Management*** Current training is generic and not marketing specific – respondent reports marketing is not taken seriously as a	a data source to pull from. Also being polite and friendly to Co-Pilot gets a better response. An idea could be to host a Promp-A-thon for marketeers. ***Management*** Respondent had to do own AI training schedule for team as CSC training on AI is not marketing relevant they use other use cases. "Lack of central authority".	cases for AI, but none are in marketing. If learning to prompt marketeers can use LinkedIn Learning to learn through doing. Further training should include clear use cases for marketing. "Once AI is implemented, it's important that processes are adjusted to include 'human' review throughout, particularly when AI is first integrated, particularly as the LLM needs training to enhance its outputs. Process would depend entirely on specific AI task".

			fairness, and apply human reviews to ensure ethical, balanced results”. ***Prompting*** Further process rigour is required once the AI has been prompted. ***Bias*** “AI-generated outputs should always be reviewed for bias before being used. A two-step review process could ensure fairness and accuracy” ***Prompting*** 1. Initial Review by the User – The person prompting the AI reviews the output for obvious bias, inaccuracies, or misaligned messaging. 2. Secondary Review by a Peer or Specialist – A second reviewer checks for subtler biases, ensuring inclusivity, ethical compliance, and alignment with brand guidelines.	charts, etc.), and to add refine content by adding feedback and certain requests”.	department that would use AI. “There are many folders and Share Points, but you often have to know someone to point you in the right direction, as process documentation is not easily found and shared”.		
	Infrastructure	***Management*** *Not clear to marketeers which AI tools they can use across the MarTech Stack or what are approved for use. It also requires concrete examples*	***Pyramid*** Hierarchy of PCF is fine for respondent, and	The PCF framework makes sense to the respondent (even	PCF needs to show a continuous loop in the process this is	***Management*** No central owner of the software landscape within the MarTech	Respondent did not view MarTech Stack as the most important part of AI management

		for marketeers who are nervous can emulate them. ***Pyramid*** *Showing the MarTech Stack as a hierarchy in the PCF is appropriate, however, concrete examples of how AI is used within it is needed to bring show the application of the PCF.*	they had no issues with showing it as a hierarchy. Respondent fed back that AI should be represented more positively in the PCF. Showing just the bias detracts from the value of AI within Marketing. “AI is still in the early stages of adoption within CSC’s marketing technology landscape. While some AI-driven tools are being used, full integration across all marketing functions is not yet widespread”.	though it is a little complex). ***Pyramid*** Using the Martech Stack for infrastructure is great, however the way people and process are currently mapped does not work – the bias arrows are confusing. “I don't think AI is very well integrated into CSC’s marketing technology landscape yet. It is the very early stages of it, and many employees still don't have access to any AI tool. But, I do think it will be very well integrated within the next year or two”.	currently missing from it. Structure for successful AI integration is “Enablement and training. Change management. Understanding the why (strategy). What does success look like, what are you trying to achieve. Usage, refinement and feedback”.	Stack and understanding of the capabilities of the software for AI. A lot of AI capabilities are not being utilised because we do not know about it. Example is for an email it will be processed via four pieces of software before it is sent to a customer: the software the email is created in) > the DAM the email live in > made accessible to all on a central repository > tool to send the email to customers. ***Pyramid, Cust Journey*** hierarchy the hierarchy of the pyramid is fine, but the bias arrows are unclear. The AI split looks like it is applies to different sides of the customer journey which is not a correct view.	– that the data and people using it are the two most important factors for successful implementation.

						"My hope would be they could become streamlined, with less inputs or handoffs between systems and teams, less manual effort, but perhaps we would also need to add in checks or more QA to balance".	

Thematic Analysis Stage 1 and 2 for R13 to R19 (R17 removed from interview list due to not meeting AI usage criteria)

	PCF Core Concepts	Respondent 13 Key Points	Respondent 14 Key Points	Respondent 15 Key Points	Respondent 16 Key Points	Respondent 18 Key Points	Respondent 19 Key Points
Types of AI	**Traditional AI**	Respondent feels that machine learning AI gives larger scale benefits. ***Analytics*** Scoring systems (contacts being scored on interactions) are enhanced by AI. ML algorithm and data aggregates into a score. ***Analytics*** "Adobe Analytics, flexible analysis in our Marketing Data, Adobe Experience	*No views were attained in the questionnaire or interview.*	*No views were attained in the questionnaire or interview.*	Utilised traditional AI capabilities within webcast platform that was offered to automatically translate languages while presenters were speaking in English, however, it was not successful – the technology was too new and the LLM it worked	***Bias*** Coders of AI are mainly male – input data that is biased by this, will have biased outcomes. "The limitations around the type of data that can be shared e.g. PII data, will be a constraint to achieving the full benefit of what AI	New releases of AI are usually tested within the USA first which means the training from the users will be biased to US users, their expectations and beliefs. "CSC has their own AI model to protect confidential data being

		Management, Marketo, CRM, Marketing Cloud".			from was not robust enough to be accurate.	could help with, however this is for the better".	shared within public accessible AI models".
	Generative AI	Useful for creating marketing assets for content creation "whitepapers and email". Using Co-Pilot as a productivity tool. Gen-AI has limitations with statistics, and it can hallucinate: "you ask the AI tool. "Please tell me when was the last match of Chelsea versus Manchester City and what was the result of that match? Then you get an answer, but it's not necessarily the truth. The AI in the back end looks at statistics for all the matches that Chelsea and Manchester City had over the last 20 years and then provides us spec the most".	Generative AI has enhanced all webcast deployment – using for polling and surveys for webcasts to drive engagement. ***Bias*** English content needs to be converted into local language and market needs, gen-AI allows this to be done easily but requires local knowledge to do without bias. ***Bias*** Respondent uses the Enterprise AI and Co-Pilot to validate their decisions and uses experience to keep own biases in control. "Use AI for text generation to craft questions and insights that facilitate interaction with our audience. This involves considering their pain points to ensure the content is relevant and engaging. AI	Any gen-AI content that includes cultural changes must be reviewed by a human – "regional reviewers review the output for our generative AI to ensure accuracy. "Help create multi-channel content quicker, increase agility".	Respondent uses gen-AI for admin related purposes – especially email crafting in high-value situations with multiple-view stakeholders. Utilised automatically generated video snippets from webcasts, but these weren't useable without manually editing which took more time. Gen-AI works well for translating a script to local language for a local presenter to use and local marketeers to use via Q&A chat.	Use gen-AI to create social media copy for optimization. This has helped the respondent to perform to a higher frequency and reduce admin. Social media copy that is incomplete will have gen-AI used to fill the gaps rather than having to request it from the human which causes delays. "My team uses AI to support idea generation and content creation".	***Prompting*** The Enterprise AI is not as good as a public gen-AI and requires simplified prompts. The public AI's can consume complex prompts but the Enterprise AI one is not trained on as much real-time data. Enterprise AI is available to all marketeers but there is no widespread adoption. "Content creation, providing enablement, performance reporting, optimizations and automation".

			helps us tailor content that resonates with our audience's specific needs and challenges"				
Marketing Technology Stack	Analytics	***Analytics*** AI useful for defining accounts with a propensity to purchase. Scoring on buying groups "let's understand how many signals of interest we do see from a group of contacts and then score the group, rather than the individual contact". Competitor analysis and information: market insights and defining sub-segments within market. ***Analytics*** Gen-AI in particular is great to create visualisations of data into easy-to-read charts and visuals. ***Bias*** Bias in analytics is driven through missing data. Examples: - Experience Centres – invite customers to close deals, but these visits are not captured in CRM as a touchpoint. Can not include this data in propensity to buy models. There is also bias	***Analytics*** "In our system in high level can provide data and insights to improve strategy and achieve sales objectives" ***Analytics*** "AI-powered virtual assistants provide real-time. Provide valuable insights into customer behaviour, preferences, and trends. AI facilitates highly personalized marketing experiences. Analyse large datasets"	***Analytics*** Scoring models are in important for AI enhancement.	*No views were attained in the questionnaire or interview.*	***Analytics*** Use gen-AI for creating Excel formulas in seconds, rather than having to watch a 30-minute YouTube video. ***Analytics*** Analytics are built into the other MarTech stack software – reporting AI for social media supports analysis creative performance such as Click-Through-Rate or Analyse Creative (person in an image or not). ***Analytics*** "We're introducing a sophisticated audience matching tool. We also use have access to AI tools including Copilot. It is however difficult	***Bias, Analytics*** Persona bias is a concern, as most marketeers who define the personas and their wants are USA based and so the content produced for these personas can be biased. It isn't personalised for multiple countries. ***Bias*** "Digital marketing campaigns are developed based on persona's and how the strategist of the campaign sees these persona's so cannot be unbiased".

		against the impact of the X Centre. - Trial Versions of Products – the customer usage within the trial is not captured, so no test drive data. Bias against the prospect as we do not know if they use it or not.				to get approval to use new technology due to legal and compliance steps".	
	Search Engine Optimization	*No views were attained in the questionnaire or interview.*	Using AI to create target groups for a webcast using keywords and pain points from SEO targeting. These keywords are used across other promotion: email, social media. "AI helps us to select target groups by incorporating relevant keywords, job functions, and insights that align with the specific topics our audience is interested in".	*No views were attained in the questionnaire or interview.*	*No views were attained in the questionnaire or interview.*	*No views were attained in the questionnaire or interview.*	Utilising Google and Microsoft for paid search with content creation within these tools: image recommendations and videos. Currently not using as not brand compliant. "Tools used in the 'MarTech' by the Paid Search team are focused on external tools like SA360, Google Ads and Microsoft Advertising". "Paid media uses AI to support marketing objectives and strategy. Think of supporting content development, enablement and within

							platform AI capabilities to reach campaign objectives”. Generates advert previews and the marketeers have the decision to use – must follow brand strict guidelines, but there is no-one checking before posting. ***Bias*** To keep persona bias limited SEO uses keywords, rather than persona targeting, to appeal to the market – “paid social can utilise LinkedIn…the advertisements developed for paid search sometimes do not always align with the actual targeting that is happening when ad is activated so…I think the person that develops the ads and that can be the person (the content

							leads) them doing the US English content”
	Social Media	*No views were attained in the questionnaire or interview.*	As above.	*No views were attained in the questionnaire or interview.*	*No views were attained in the questionnaire or interview.*	Social media management – build, monitor and report on social media. Using AI activation, it optimises the spend to pool ads together by audience. This leads to smart bidding and better performance of adverts and budget spend. “In social media reporting, AI is embedded which auto generates paid social campaign insights based on the data which helps us make optimisations decisions”.	*No views were attained in the questionnaire or interview.*
	Website Management	Main CSC website requires trained data for personalization. Cookies are automatically applied on registration.	Uses AI to interact with webcast audience via Q&A chat on the website. Webinar attendees can ask very technical questions,	*No views were attained in the questionnaire or interview.*	***Bias*** A bias within international marketing is time zone selection for webcasts. Usual selection is for US friendly time zones without reviewing	*No views were attained in the questionnaire or interview.*	*No views were attained in the questionnaire or interview.*

			gen-AI supports quick answers to create leads. “We utilize AI to create polls and survey questions that allow us to interact with the audience based on industry or specific market needs that customers are facing”.		the data to select better performing times. ***Cust Journey*** “The website is where we see great conversion rates across key metrics. We need to move faster on technology to fully enable innovation and be where the customer is at in their respective customer journeys”.		
	Multi-channel nurture	Marketing automation is a key function of machine learning AI. It is part of the transactional systems in a MarTech stack.	As above.	“We have used machine learning to localize our email subject lines and email copy”.	Emails are centrally created in US English which usually doesn’t include an official sign off. This is considered rude in Europe, and you need local knowledge of this. This isn’t intentionally done but is Eurocentric.	*No views were attained in the questionnaire or interview.*	*No views were attained in the questionnaire or interview.*
	Digital content asset management (DAM) system	*No views were attained in the questionnaire or interview.*	AI is required to localize content. It saves time and money as there is no budget for very small countries and their respective languages. Respondent has to regularly change images and Eurocentric wording	Using AI…“Localization processes could be drastically simplified”	*No views were attained in the questionnaire or interview.*	*No views were attained in the questionnaire or interview.*	Translated content from US English must be adapted by a local reviewer as there is regional biases that need to be added to make it relevant to that market.

			within social media posts from the US when posting to local channels.				
	Customer relationship management (CRM) system	CRM is the raw data. Respondent role is not involved in the system management, but they work in the front end of CRM (user experience). Contact quality uses AI to help check completeness of the contact information and when last updated. Current data in CRM is unbalanced in favour of historical data – AI reviewing quality and completeness of data. Example is one customer profile in CRM had 360 contacts with CEO as their job title, obviously 359 of these were out of date data. The AI flagged this. ***Bias*** There is an over emphasis on install base customer in the data and large enterprise companies. The demographics of these customers can drive biased outcomes. "Installed base customers overrepresented	Keywords used within CRM search to find job titles or those who interact with certain products to create target groups.	*No views were attained in the questionnaire or interview.*	*No views were attained in the questionnaire or interview.*	*No views were attained in the questionnaire or interview.*	*No views were attained in the questionnaire or interview.*

		in our data. Lack of data from customers served through the indirect channel". ***Bias*** Data is also not equal within all countries, there is a heavier weighting to larger countries which can also drive biased outcomes when reviewing data as a whole. Data within China has to be handled completely differently with bespoke IT systems in place as China's data regulations are strict. ***Bias*** GDPR requires encrypted data (so no identifiable data) which can be difficult to gain true persona insight which can drive bias. "Complexity of compliance and legal governance. Better do nothing than doing something wrong".					
Customer Journey	**Pre-Sale**	*No views were attained in the questionnaire or interview.*	***Bias, Cust Journey*** Segmentation of the pre-sale customer journey is important as it feeds into	***Cust Journey*** Potential difference "I envision AI to support content creation/selection/ad creation in the pre-sales	***Cust Journey*** Targeted customers can suffer from audience fatigue – where they are constantly inundated with marketing	***Cust Journey*** "They are quite similar in regard to content creation, grammar	*No views were attained in the questionnaire or interview.*

			scoring which affects a customers interaction with the company. There is bias in segmentation – demographic, size of the company (large companies only), by industry. When CSC should be targeting all of their interacting companies that purchase software. "In pre-sales, AI is often used to identify potential leads and personalize marketing outreach".	activities while it could be more of a tool for sales in the post-sale activities to understand propensity of accounts to purchase".	and their attention span is lessened.	checks, data analysis and idea generation".	
	Post-Sale	***Cust Journey*** Companies are newly focusing on the post-sale for customers because of cloud computing. ***Cust Journey*** There is a risk of churn as you can target existing customers too much with their usage data.	***Cust Journey*** "In post-sales, AI is leveraged to enhance customer retention".	***Cust Journey*** *As above*	***Cust Journey*** Post-sale customers are easier to target, they have already brought the software so you should have less audience fatigue as you can tailor your communications with them to offer them just what they want. "Post sales needs to be a lot more customized".	*No views were attained in the questionnaire or interview.*	*No views were attained in the questionnaire or interview.*

Technology Implementation	**People**	***Management*** Training is available as self-service; respondent took initiative to learn about AI themselves. Unlikely to become mandatory training due to mandatory training being legal compliance only. The only AI training that is mandatory is the AI Ethics Training (part of UNESCO law). "Curiosity. Trial-and-Error mentality". ***Management*** "I don't see a need for a specific "AI Marketing Evangelist" or "AI Marketing Facilitator" in the long run. It should rather become a "natural skill" that every Digital marketer needs to have".	***Prompting*** Respondent is self-taught and learnt to prompt "in the correct way". Because AI learn from you the respondent researched prompting guidelines to make sure their AI is trained correctly. Marketeers then need freedom in their daily jobs to use it. "Hard skills would include knowledge of AI tools and how to use them to automate processes. Soft skills would involve ethical considerations and data protection to ensure there is no discrimination of any kind". "Using AI has made me 20 to 30% more productive".	***Management*** Training is currently not prevalent for marketeers. There should be pilot areas to test and prove out the use cases to show accurate outputs. Marketeers should then develop training, roadmaps and implementation plans. ***Bias, Prompting*** Marketeers bring bias due to bringing a hypothesis to a situation and assuming they know how it will play out – this is true for personas and how they think CSC should engage with them. They will then prompt an AI in a certain way to prove their hypothesis. ***Bias*** "Bias of the winning campaign, bias of who will purchase products".	***Management*** General workforce at CSC and the respondent are behind in AI usage and understanding – "Everybody needs to learn about AI. I don't thing adoption should be connected to org structure". "Each marketeer should be championing AI". ***Prompting*** Respondent became curious to try AI when it was not rolled-out centrally by management – self-taught prompting and read online content on how to target questions correctly. ***Bias,*** Prompting Marketeers should receive training for prompting biases. Employees are encouraged to use Co-Pilot but there is no prompting training to accompany it. "Validated	Because gen-AI learns from you, marketeers must be incredibly careful with the information they give it. ***Bias*** Fact based and analytical usage of AI doesn't have much bias to worry about, but gen-AI that includes branding (such as videos, images, copy (these should be checked to represent diversity. ***Prompting*** "I think people will be encouraged to use prompts on AI tools as part of their work to driven by the expectation to be more efficient". "Soft skills: Critical thinking, Analytical skills, Adaptability Skills, Communication Skills. Hard skills: Prompt engineering"	***Bias*** "AI is beneficial, however it will always need a human eye to check it's output to check for accuracy". "The combination of technology and human will limit bias".

					algorithm by multicultural individuals". ***Bias*** Confirmation bias – "when I see (US Marketing) as a European I get an initial "Oh Is it for me? Would I fit in that space?" That's more my question". If marketeers are multicultural then they will be more balanced. If they are not they could be more biased in their production of marketing work. "You don't know what you don't know".		
	Process	***Prompting, Management*** Respondent was the only one to mention AI Sand Box, an application available to support prompting education for CSC employees. ***Prompting*** Respondent believes learning to prompt is 80% trial and error.	***Prompting*** Currently no prompting training at CSC, basic training is available to use AI, however, training on how to use in daily marketing roles is missing. ***Management*** Management also not clear on where AI is imbedded in software – this would give marketeers informed decision making	***Management*** Current CSC is far behind where it should be for AI integration, we are on the cusp of adopting it. Respondent has been championing AI for three years to integrate it and still in the very early stages. ***Management*** Once more AI education is given then	***Management*** Centrally directed and managed marketing required local adaptation and by embracing this adaptation it shows the customer the company is willing to embrace them. Therefore, AI cannot take over the full process, you must have a human in all generative AI processes.	***Management*** The team the respondent is in had an Academy Day where they had an introduction to Co-Pilot and gen-AI and what you can use it for. This was a bespoke training done by the team, rather than a formal training. ***Management*** Currently no one is	***Bias, Management*** Marketing AI training should be done channel by channel and bespoke for these use cases. Content within each channel differs – "example for a specific prompt is like if you generate a headline for paid search at it is very strict on character

			on how they interact with the software. Not everyone requires their AI usage to be reviewed – there should be a decision tree created if you need AI output reviewed, based on what you have generated. ***Management*** "AI can be incorporated into standardized processes that are well-mapped from start to finish. This would allow us to know where to apply it and enable the system to decide when to use it or not, as well as determine which aspects of AI are relevant at each stage of the process".	it shouldn't require human review for every part (only for content that has been adapted for different cultures).	"We'll have a second set of eyes when we so things and our output will have better quality".	checking gen-AI output. Training is not mandatory and self-service. ***Prompting*** When prompting the prompter must learn how to prompt between personal and work usage. For business prompts you must explain the context for the request – you prime the AI – it gives a better outcome if you use best practices. For personal you can just directly ask and conversationally chat to it for answers. All employees should be trained on AI and the company has responsibility for guard rails for its usage. Leadership should lead education and there should be an AI champion in	limits. Often, we use a web page as guidance on how to write the headline. So it depends on how the web page is designed, whether there is a bias used in there…therefore the results could also contain a bias". General enablement for how to use a gen-AI for admin purposes – "Processes are enriched by implementing AI but not changed". Respondent attended a conference to learn how to prompt effectively and conducted own research using best practices on the web. Bias They learnt that using specific prompts will limit bias. "Enablement sessions

						each team that supports others. ***Bias, Prompting*** Prompt Engineering – very powerful and teaches technique for better outputs. Training should be mandatory as otherwise it is left open to interpretation and bias – "perhaps if there was a stage between AI developing the prompt, and the prompt being delivered. Or, where the prompt is delivered have a scale to identify the level of biases present in the answer". ***Prompting*** "AI Prompt Engineering for Marketing (to craft the best prompts for entire teams to utilise for specific tasks/projects)".	provided by platforms". ***Prompting*** Prompting guidance – make is efficient (not bias related) and focus on marketeer efficiency and goals. Do the training by channels and list how outputs differ. "Prompt learning can be challenging". ***Management*** "This differs per team, but the current set up of different channels is likely best as AI usability differs per channel". ***Management*** "Ensuring AI is adopted and proper guardrails are in place to manage to use of AI to protect the company against risks AI brings".

						"Perhaps people don't need to lean on the expertise of others as much as they have needed to before, as they can simply prompt for an answer".	
	Infrastructure	***Bias*** Bias isn't overly considered in analytics usage day to day as the data sources for CSC traditional AI are trusted. However, there can be bias for gen-AI prompting. ***Management*** Data deletion policies drives a lack of training opportunities for machine learning. Examples are removing contacts after 3 years of no engagement. Pipeline data on historical purchases and Customer Contracts removed after a specific amount of time.	***Pyramid*** PCF feedback was that the MarTech stack was less important than process – process is the most important aspect of the PCF. Respondent did not like that it looked like People were mapped to algorithmic rules. "AI still needs to be evaluated and reviewed before being incorporated into an automatic process. There should indeed be additional measurement and control processes".	***Pyramid, Cust Journey.*** PCF - the triangle is misleading as it appears to show people mapped to the pre-sale and process mapped to the post-sale journey.	***Pyramid*** PCF section is missing an additional platform section for webinar management – could be named "Additional Platforms". Bias Arrows look like bias is being driven through the MarTech Stack which is not correct. "Needs to be founded on solid cross company data. Modern tech stack (fully connected pre and post sales). Enablement/Training".	***Pyramid*** The PCF is great, but I needs to visualise and raise awareness on how this could be implemented by companies.	***Bias, Analytics*** PCF – Bias arrows are confusing as it shows analytical bias but content is produced on "gut feeling" whereas analytics is data. ***Pyramid, Cust Journey*** The MarTech should be reordered to match the customer journey steps: Analytics, Social Media, SEO, Website, Nurture, DAM and CRM.

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