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Module Name: Dissertation

Module Code: LCMB7035

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Submission Date: 05 June 2026

The Role of Artificial Intelligence in transforming Digital Marketing

Abstract

This study explores how Artificial Intelligence (AI) caused a paradigm shift in digital marketing strategies and changed approaches from reactive heuristics to predictive hyper-personalized architectures. The computer science community extols unrestricted data harvesting while the business community speaks of the sharp ethical and regulatory lines. In order to bridge this academic divide, a PRISMA-protocolled Extended Literature Review was carried out, which thematically synthesised 56 high-impact, peer-reviewed studies published between 2020 and 2026. The research revealed that the algebra-to-marketing relationship is curvilinear rather than linear and follows a concave curve. The closer predictive targeting moves toward the fringe of perceived surveillance, the more it causes the 'privacy paradox' to become a reality, actually decreasing brand equity as more is pushed toward the individual. Moreover, the internal practitioners' adoption is highly blocked by "algorithm aversion" and "black box" of deep learning. Theoretically, this study builds on the Resource-Based View (RBV) and proposes the inclusion of the "Liability Discount" to show that unmoderated first-party data is a "strategic liability" in a situation of strict legislation. The novel Socio-Technical AI Integration Model represents the culmination of the research on a managerial level. All the key challenges and possibilities for improved algorithmic transparency and robust ethical standards are accounted for in this holistic framework, clearly showing that these are not just afterthoughts in the legal room, but essential structural developments to achieve long-term economic and competitive success in today's business landscape.

Table of Contents

Chapter One: Introduction	7
Introduction.....	8
1.1 Background of the research topic.....	8
1.2 Research Problem.....	9
1.3 Timeliness of the topic.....	9
1.4 Research Aim	10
1.5 Research Objectives.....	10
1.6 Research Questions	10
1.7 Scope of the Review	10
1.8 Structure of the dissertation	11
Chapter Two: Methodology	12
Introduction.....	12
2.1 Search Strategy	13
2.2 Databases and Sources	13
2.3 Keywords and Search Terms.....	14
2.4 Time Frame for Included Publications.....	15
2.5 Inclusion and Exclusion Criteria.....	15
2.6 Screening Process (PRISMA Framework).....	16
2.7 Quality Assessment of Included Studies	18
2.8 Analytical Method: Thematic Analysis.....	18
Chapter 3: Thematic Literature Review and Analysis	20
Introduction to the Review	21
3.1 Theme 1: Theoretical Foundations of AI in Marketing	21
3.1.1 Conceptual Definitions	21
3.1.2 Key Theoretical Frameworks	23
3.2 Theme 2: Empirical Findings and Strategic Affordances	24

3.2.1 Algorithmic Targeting and Hyper-Personalization	25
3.2.2 Automation and Operational Efficiencies	26
3.2.3 Contradictions in Results (The "Privacy Paradox")	27
3.3 Theme 3: Emerging Debates and Socio-Technical Friction.....	28
3.3.1 The Ethical Ambiguity of Generative AI.....	29
3.3.2 The Black Box Problem and Data Governance	30
3.3.3 Organisational and Practitioner Barriers	32
3.4 Theme 4: Critical Research Gaps.....	33
3.4.1 The Temporal Gap in Generative AI Literature	34
3.4.2 Over-reliance on B2C Paradigms	35
3.4.3 Lack of Unified Socio-Technical Frameworks.....	36
3.5 Chapter Summary and Synthesis	37
<i>Chapter 4: Discussion.....</i>	<i>38</i>
Introduction to the Discussion	39
4.1 Integration of Findings: The Concave Curve of Algorithmic Utility.....	39
4.2 Comparison Between Studies	40
4.3 Theoretical Implications.....	41
4.4 Filling the Identified Academic Gaps.....	43
4.5 Proposed Conceptual Framework: The Socio-Technical AI Integration Model.....	45
4.5.1 Algorithmic Capabilities	45
4.5.2 The Socio-Technical Governance Gate	46
4.5.3 Strategic Value Creation	46
4.6 Chapter Conclusion.....	47
<i>Chapter 5: Implications.....</i>	<i>48</i>
Introduction.....	49
5.1 Theoretical Implications.....	49
5.1.1 Refining Established Frameworks.....	49
5.1.2 Academic Contribution	50
5.2 Practical and Managerial Implications	50
5.2.1 Strategic Recommendations	50
5.2.2 Policy and Industry Impact	50
5.2.3 The Action Plan for Enterprises	51

5.3 Research Implications (Future Directions).....	51
5.3.1 Addressing Limitations	51
5.3.2 Future Research Agenda	52
5.4 Chapter Summary.....	52
<i>Chapter 6: Conclusion</i>	<i>54</i>
Introduction.....	55
6.1 Answering the Research Question and Key Discoveries	55
6.2 Academic and Practitioner Contributions	56
6.3 Limitations of the Research.....	56
6.4 Final Recommendations and Future Research Trajectories	57
6.5 Concluding Statement	57
<i>References.....</i>	<i>58</i>
<i>Appendix.....</i>	<i>68</i>

Chapter One: Introduction

Introduction

The rapid growth of Artificial Intelligence (AI) has brought an incredible transformation in the current digital marketing scenario, where marketers switch from reacting to the various heuristics to anticipating and engaging in hyper-personalised marketing. Businesses can use more advanced algorithmic models and Generative AI to optimize targeting consumers, but there are also numerous challenges to consider, including data privacy requirements, ethical concerns, and more. This chapter serves to provide background for this dissertation. Briefly summarises the core research enquiry, sets out a clear research need/rationale and clearly states the overall research aim, research questions and the scope and limitations for this Extended Literature Review.

1.1 Background of the research topic

The Artificial Intelligence (AI) technology, especially, has become a critical disruptor in this bifurcated landscape, changing the very nature of marketing from being potentially reactive to operational to being hyper personalized (Huang and Rust, 2021; Haleem et al., 2022). Furthermore, the digital revolution is revolutionizing the classic marketing techniques as it is enabling unprecedented agility in marketing operations (Kotha, 2024). The combination of advanced computational subsets, namely, machine learning, predictive analytics, and generative AI, allows organisations to predict consumer behaviour on a more granular level than ever (Mustak et al., 2021). Automatic real-time optimization of advert position takes place by using AI algorithms, while by using predictive analytics, the intricate consumption trends are deciphered to predict future requirements even before they materialize. Furthermore, the potential of the latest advancements in the field of generative AI is the capacity to personalise semantic content with unprecedented amounts and scales of personalisation (at the point of mass production) and subsequently down-tailor it (Chintalapati and Pandey, 2021).

At present, the level of integration of AI dictates the level of competitiveness of the markets, as well as the effectiveness of the corporations and the overall customer experience. Companies that rely on algorithmic personalisation will always have better efficiency in their operations, along with their Customer retention rate, compared to technologically unchanged counterparts (Dwivedi et al., 2021). However, with the rapid adoption of technologies, there are complications with operational volatility, data privacy and ethical concerns regarding algorithmic bias (Kietzmann et al., 2020). The strategy gained by using AI should be

disaggregated from its risks that may arise for an organisation and therefore an advanced academic synthesis is needed because the whole epistemological parameters of marketing are reshaped by the use of AI.

1.2 Research Problem

Despite an abundance of empirical studies examining the functional performance of artificial intelligence (AI) in marketing, the literature is still predominantly diffuse (Mustak et al., 2021). There is an important gap between the promise of algorithmic architectures in the dominant literature on computer science and the pragmatic measures that are reported in mainstream business research for the strategic implementation of these architectures (Davenport et al., 2020). In particular, there is a significant lack of integrated synthesising scholarship that compares and contrasts the affordances of AI's operation (hyper-personalisation etc.) to the significant ethical questionings, data privacy tribulations, and organisational leveraging issues which accompany their use (Kietzmann et al., 2020; Dwivedi et al., 2021). These dimensions are often treated separately, and these technological possibilities are largely optimistic, whereas the sociotechnical limits are ignored (Buhalis et al., 2024). As such, there is a lack of an integrated theory to guide marketing practitioners through the many decisions and compromises that can be made in relation to algorithmic efficiency and preserving the consumer's privacy risk (Rust, 2020). The lack of a complete synthesis could trigger catastrophic integration challenges, potentially launching intricate AI systems that infringe upon moral limits and erode consumer confidence and brand value in perpetuity (Huang and Rust, 2021).

1.3 Timeliness of the topic

The unprecedented surge in the number of Generative AI architectures since late 2022 has turned the tide of the exponential commercialisation of Artificial Intelligence, outpacing current regulatory regimes and well-established theoretical marketing approaches (Chintalapati and Pandey, 2021; Kshetri, 2024). The development of such a speedy change upon the technological level of the digital ecosystem calls for urgent scholarly interventions. This long literature review, therefore, offers a valuable contribution in terms of a critical theory as it brings together such seemingly antithetical current strands of research. It consistently undermines the uncritical technological optimism in computer science literature (Buhalis et al., 2024) and the complex, operationally existing reality in business scholarship. Synthesis has much managerial significance in addition to its theoretical use. This study synthesizes existing empirical evidence, offering marketing practitioners a solid, evidence-

based plan for integrating AI in their practice. It empowers executives with key strategic tools to navigate by and balance competitive factors such as algorithm efficiency and hyper-personalisation, with critical factors such as adherence to ethics standards, robust data governance, and organisation adoption challenges (Kietzmann et al., 2020; Dwivedi et al., 2023).

1.4 Research Aim

The aim of the study is to systematically review and synthesise existing literature on the role of Artificial Intelligence in transforming digital marketing, critically evaluating its operational applications, strategic benefits, and the ethical and organisational challenges of implementation.

1.5 Research Objectives

The objectives of the study are:

- To identify and categorise the primary AI applications currently utilised in modern digital marketing practices (e.g., automation, algorithmic advertising, data analysis).
- To analyse the strategic benefits of AI integration, specifically focusing on how it enhances customer targeting, personalisation, and overall marketing performance.
- To evaluate the prominent organisational, ethical, and data privacy challenges that businesses encounter when implementing AI marketing tools.

1.6 Research Questions

The primary research question is: How does the integration of Artificial Intelligence transform contemporary digital marketing practices, and what are the strategic trade-offs between its operational benefits and socio-technical deployment challenges?

The other research questions are:

- What are the primary AI technologies and applications currently being utilised to transform digital marketing practices?
- How does the integration of AI strategically enhance marketing performance, customer targeting, and personalisation?
- What are the major organisational, ethical, and data privacy challenges associated with AI implementation in digital marketing?

1.7 Scope of the Review

This is an extensive literature review and is only limited to scholarly articles published in 2020-2026. This well-defined temporal boundary is adopted because the literature earlier in

the timeline is outdated; the advent of advanced Generative AI and modern predictive algorithms has made it imperative to focus on analysing contemporary frameworks that are current with technological realities (Dwivedi et al., 2023; Kshetri, 2024). On the thematic level, this synthesis purposefully addresses research that explores strategic marketing use, algorithms for customer targeting, hyper-personalisation, as well as ethical aspects of AI use. On the other hand, there is an absence of research on the computational mechanics behind the neural network systems, infrastructure, and deployment of AI in non-marketing functions at the business level, such as human resources or supply chain management, which is intentional to ensure a certain level of analytical rigor and not require a comprehensive push into all the various applications of AI. In a global business commercial context, this review only considers commercial digital marketing ecosystems, both B2B and B2C. Case studies are consistently ignored that are highly localised, have a niche regulatory context or are deployed by the public sector for AI applications. Delimitation like this makes the strategic synthesis derived from its frameworks and the resulting theoretical frameworks broadly generalisable and easily transferable into Enterprise Marketing architectures today.

1.8 Structure of the dissertation

The proceeding study is carried out in 6 chapters.

- In the chapter 1, the background is set and the research main problem is clearly stated along with the broad questions and narrow scope of the review is clearly stated.
- Chapter 2 presents the systematic methodology followed in conducting the literature search and inclusion criteria, and in conducting a thematic analysis.
- Chapter 3 outlines the main thematic analysis, summarising the existing literature on AI applications, strategic advantages, barriers and issues in implementing AI, and practitioners' perceptions.
- Chapter 4 explores these findings and combines evidence from the empirical research that has been done to eliminate existing academic contradictions.
- Chapter 5 addresses the implications that these theories have for management.
- Finally, Chapter 6 sets out to complete the research, makes reference to a number of limitations of the research, and offers a number of suggested future academic pathways.

Chapter Two: Methodology

Introduction

This chapter explains the study method used to perform this study, called the Extended Literature Review on Integration of Artificial Intelligence in Digital Marketing. The method used in research is structured and semi-systematic in order to achieve academic rigor and to be able to be reproduced. The rest of the paper provides more specific information on the actual procedural framework used to create the ultimate analytical corpus. First, this chapter specifies the general search approach, such as databases to be used and Boolean keyword groups. Next, it establishes the strict temporal limits and inclusion/exclusion criteria, which will then allow the filtering of literature. Finally, it provides an overview of the PRISMA screening protocol, quality appraisal mechanisms and the thematic analysis framework, whereby synthesising the findings of the final core research.

2.1 Search Strategy

Considering that the research field is interdisciplinary at the intersection of computer science, behavioural economics and strategic marketing, a semi-systematic (or integrative) approach to conducting the search was followed. Slew/circumstance-and-organized surveys of the writing are unquestionably suited to synthesise literature that falls into distinctive disciplines, as Snyder (2019) asserts, particularly when there is a wide range of viewpoints. This gives the opportunity to organise empirical research on algorithmic effectiveness and theorise about socio-technical friction.

The search strategy used advanced Boolean operators to make sure that there had to be exact matches between keywords that defined the core concepts in the retrieval application to minimise false positives. The constructs of technology (e.g., Artificial Intelligence) and those of context (e.g., Digital Marketing) were systematically connected by using the operator AND. To recognize the semantic variation and synonymous names of the concepts, the operator "OR" was used within the conceptual clusters (e.g., "Machine Learning" OR "Predictive Analytics"). Last, the "NOT" was judiciously applied to remove contextually unrelated uses of the technology in the search corpus such as "NOT healthcare" or "NOT supply chain" to ensure the search corpus was on platform, at the commercial marketing focus.

2.2 Databases and Sources

Ensuring that high-impact, rigorously peer-reviewed scholarship was collected, the literature search was limited to leading academic databases known to index the highest quality business, management and information systems journals. The following databases were

selected as the primary databases because they have very strict indexing protocols and are the most comprehensive:

- **Scopus and Web of Science (WoS):** Capturing high-impact research that is multidisciplinary, connecting data science and commercial marketing, is important for these databases.
- **Business Source Premier (EBSCO):** This source was used to ensure high saturation of the literature on management, organisational behaviour and applied marketing to ensure the 'field realities' of AI deployment were covered adequately.
- **ScienceDirect and Emerald Insight:** Science-specific for their large focus on empirical studies related to consumer behaviour, algorithmic architectures and strategic management frameworks.
- **Google Scholar:** The results of the Google Scholar application were used as a supplementary and third search application to expand snowballing (forward and backward citation searching). This was important to make sure that seminal papers not initially found in the main database, Boolean strings were detected and included.

2.3 Keywords and Search Terms

The development of the search taxonomy was an iterative process, beginning with the extraction of core concepts from the overarching research question. To capture the full spectrum of relevant literature, keywords were organized into three distinct conceptual clusters: Technology, Context, and Outcomes/Challenges.

- **Cluster 1 (Technology):** "Artificial Intelligence", "AI", "Generative AI", "Machine Learning", "ML", "Predictive Analytics", "Deep Learning", "Algorithmic architectures".
- **Cluster 2 (Context):** "Digital Marketing", "Marketing Strategy", "B2B Marketing", "B2C Marketing", "Electronic Commerce", "Algorithmic Advertising".
- **Cluster 3 (Outcomes/Challenges):** "Hyper-personalisation", "Customer Targeting", "Ethical ambiguity", "Data Privacy", "Organisational barriers".

These clusters were operationalized into complex search strings utilising nesting techniques. A representative sample search string executed within Scopus is as follows:

(TITLE-ABS-KEY ("Artificial Intelligence" OR "Generative AI" OR "Machine Learning") AND TITLE-ABS-KEY ("Digital Marketing" OR "Algorithmic Advertising" OR "Hyper-personalisation") AND TITLE-ABS-KEY ("Ethics" OR "Privacy" OR "Strategy"))

2.4 Time Frame for Included Publications

The time period to search for literature was fixed to 2020-2026. This chronological narrowness is grounded on an unprecedented acceleration of AI capabilities, in particular the commercialization of state-of-the-art Large Language Models (LLMs) as well as Generative AI after 2022. Much of the literature before 2020 focuses on the theoretical uses of AI or on very old-fashioned, basic predictive models that have little relevance today in the digital era. This paradigm shift in modern algorithmic architectures has made it important to revisit the sample of words that compose “the review corpus” to evolve to current technological and regulatory realities (Bond et al., 2024). Foundational theories of marketing or consumer behaviour were only added if they were published before 2020 and if they were explicitly needed to explain a modern concept used in an algorithmic intention in classical marketing theory.

2.5 Inclusion and Exclusion Criteria

Strict academic standards were used and, to be sure the analytical synthesis was based entirely on established scholarship, a binary system of inclusion and exclusion was observed.

Table 1: Inclusion and Exclusion Criteria

Inclusion Criteria	Exclusion Criteria
1. Peer-Reviewed Journal Articles: Must be published in a peer-reviewed academic journal that is recognised. This criterion ensures methodological validity and theoretical soundness of data integrated.	1. Grey Literature and Non-Academic Sources: Articles from non-peer-reviewed trade magazines, opinion pieces (op-eds), corporate blogs and industry whitepapers were systematically excluded. Although these might give modern perspectives, it has no methodological transparency and objective appraisal from the other members of the academic field.
2. High-Quality Academic Books/Chapters: Specific chapters or books (e.g. specific books pertaining to the mathematics of generative models, or general marketing theories) were included if written by known academics and printed	2. Conference Abstracts Without Full Papers: Extended abstracts were excluded due to the lack of methodological and empirical depth to adequately appreciate quality (Cheong et al., 2023).

by a good academic press.	
3. Temporal Relevance: Published within the period of 2020-2026 (as reflected in Section 2.5).	3. Non-English Publications: Only English-language literature was reviewed to prevent mistakes in translation and misinterpretation of the intricate tensions of epistemological issues.
4. Thematic Alignment: The central argument of the paper needs to explicitly focus on operation, strategy, or ethics of AI in a digital marketing context.	4. Out-of-Scope Contexts: AI studies exploring only separate entities such as public sector utility providers, heavy manufacturing logistics providers or highly specific and niche regulatory contexts that have limited applicability to mainstream commercial marketing contexts were excluded.

2.6 Screening Process (PRISMA Framework)

The methodology suggested for the systematic literature review was the PRISMA (Moher et al., 2009). The selection is carried out using this multi-stage protocol, which guarantees transparency and replicability. The PRISMA flow diagram is a formal depiction below:

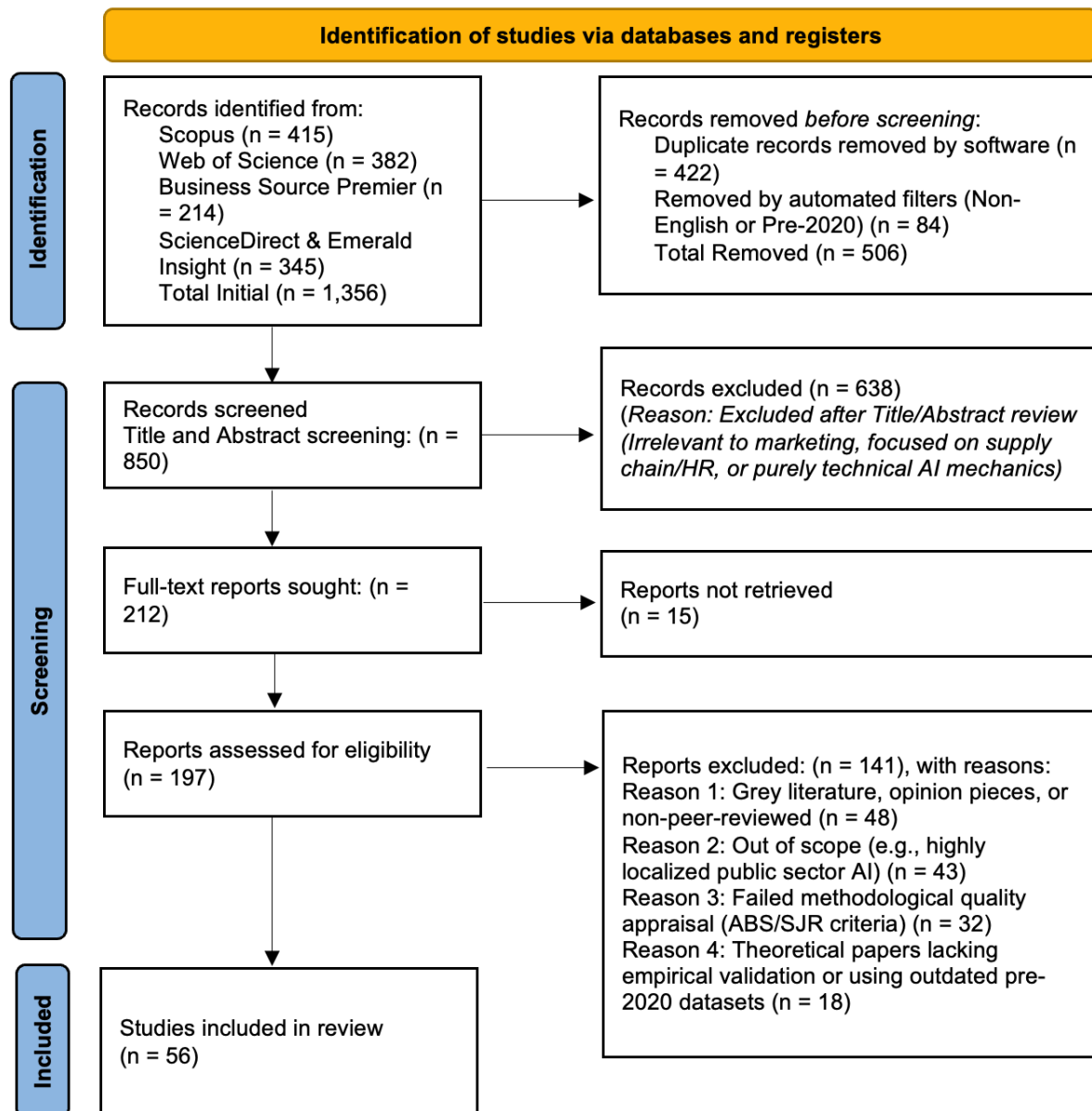


Figure 1: PRISMA Framework adopted from Page et al. (2021)

A systematic literature search was carried out in four main databases, which resulted in an initial pool of 1356 records. Before screening, 422 duplicates and 84 articles that did not meet the base language or time period were excluded from the articles. Again, the remaining 850 abstracts were subjected to careful screening to exclude 638 studies that were not directly related to marketing. 15 out of 212 reports required were found to be completely inaccessible. Of the 197 remaining full-text reports, the extent to which they met strict eligibility criteria was evaluated. Finally, 141 papers were left out because the results were not based on empirical evidence, the scope parameters were not aligned, or the methodology was flawed or based on grey literature. According to the strict guidelines of this process, the end result has been a successful attrition process of having exactly 56 peer-reviewed high-impact academic

studies that have survived to end up in this list. This strong subset did not show any signs of selection bias and allowed for full saturation and the rigorous quality criteria essential for a full thematic synthesis and structural discussion as the basis of this comprehensive Extended Literature Review.

2.7 Quality Assessment of Included Studies

Passing the criteria of inclusion is not enough; the literature needs to show special methodological and theoretical strength to be a serious academic synthesis. Two appraisal mechanisms, namely, were used to measure the quality of the finalized corpus.

First, by using a dual-metric appraisal process, the prestige of the journal and the rigor of the peer-review process were determined objectively. The SCImago Journal Rank (SJR) indicator was used to determine the impact of the literature at the global level, and only literature published in journals within the first three quartiles (Q1, Q2 and Q3) was considered. In addition, these rankings were checked against the Australian Business Deans Council (ABDC) journal quality list with a focus on high-quality papers with strong business and marketing impacts.

Secondly, the methodological soundness of the single papers was evaluated in a critical manner. In the case of empirical studies, the number of cases, the way of data collection, and statistical analyses used to determine findings (e.g., structural equation modeling, regression analysis) were considered. On conceptual papers, the quality of the proposed frameworks, their cohesiveness and the level of the theoretical contribution were assessed. Studies showing methodological weaknesses, lack of support for their speculation, or weakness in the internal validity of the study were substantially discounted or entirely eliminated from the final analytical matrix.

2.8 Analytical Method: Thematic Analysis

An inductive thematic analysis process by Braun and Clarke (2006) was applied to synthesize the complex, multidisciplinary data collected from the completed finalized literature corpus, a process that involved six phases: (1) familiarizing with the data, (2) selecting data for analysis, (3) searching for themes, (4) reviewing themes, (5) defining and naming themes, and (6) reporting results. Thematic analysis is the optimal analytical vehicle for ELR because it enables the researcher to transcend summaries of each paper to the identification of patterns, ambiguities, contradictions and emerging clusters of theory throughout the academic world.

Repeated active reading of full-text articles was the first step of the analytical process and involved (1) familiarization with the data, (2) identification of key concepts and themes, (3) data display and organisation of the data, and (4) theme development. This was then followed by the creation of the “open” codes, putting into systematic writing the findings concerning AI possibilities, ethical limits and operational restrictions. In phase (3), these separate codes were collated and marked out as sub-themes in their preliminary state. The properties of the themes, which were filtered and abstracted to the research questions, were very detailed (Phase 4) and included some structural distortions and discrepancies between computer science optimism and business reality. In the final process, which was termed “Phase (5)”, themes were crafted, and their names were given; this satisfactorily addresses the four sub-research questions as stated in Chapter 1. Finally, the narrative synthesis critically synthesises all the empirical evidence in accordance with a common theoretical perspective and pinpointing academic research gaps, existing literature reviews and the sequence in which the analysis was presented (chronologically and logically) are materialised in the narrative synthesis in Chapter 3.

Chapter 3: Thematic Literature Review and Analysis

Introduction to the Review

Based on the methodological framework laid out in Chapter 2, this chapter shares the thematic presentation of the current literature on Artificial Intelligence (AI) and digital marketing integration. The primary objective of this review is to develop a domological conceptual map and to systematically investigate the set of operational affordances which support the use of algorithmic architectures in a socio-technical frictionless manner. To do this, the synthesis is not arranged in terms of individual authors, but in four main themes and retains the level and critical assessment of the academic body of written works.

Theme 1 lays the theoretical groundings and explores the epistemological paradigm shift to algorithmic marketing using the Resource-Based View and the Technology Acceptance Model. In theme 2, the empirical results of the literacy study are discussed, interpreting how AI is used strategically to further hyper-personalise and automate yet also how there is a privacy paradox. Theme 3 takes the reader into controversial areas, showcasing the different moral dilemmas that might arise; how data is safeguarded, and what some of its challenges are for practitioners when using Generative AI. Lastly, the identified key research directions in Theme 4, which have not been examined in the research so far, provide room for analysis in this dissertation: limited longitudinal data and over-representation of the B2C context.

3.1 Theme 1: Theoretical Foundations of AI in Marketing

By incorporating Artificial Intelligence (AI) into commercial ecosystems, we are ushering in a shift in paradigms, more than simply an upgrade of technology. But this evolution has implicaci3ns on the strategic level and on the operational level so there is a need to build a backstop in a theoretical level to critically assess this evolution. The idea for this theme is to create a map of the conceptual space of “AI” in digital marketing and define the basic technological sub-areas which rule today's architectures. Besides that, it synergizes the most valuable theory overlaps (Resource-Based View (RBV), the Technology Acceptance Model (TAM) and the Diffusion of Innovations (DOI) theory), which explain the organisational adoption mechanism, continuous competitive advantage and consumer acceptance.

3.1.1 Conceptual Definitions

The fact that contemporary literature shows a clear epistemological transition from “Traditional Digital Marketing” to “Algorithmic Marketing” expresses the pursuit of improved and more efficient marketing strategies for business organisations that, in the following lines, assumes the form of a business perspective on Agile Marketing. The

traditional digital marketing paradigm, which ruled the early 2010s, was approachable, essentially heuristic, and reactive. Descriptive analytics, historical reporting and segmented consumers manually by static demographical variables (Chintalapati and Pandey, 2021). On the other hand, algorithmic marketing opens an active and predictive approach, shifts the cognitive load from human marketers to AI models (Huang and Rust, 2021) and refashions the concept of agility in today's marketing landscape (Haleem et al., 2022; Kotha, 2024).

The changes include switching from mass-market broadcasting to hyper-personalized, granular, real-time targeting. According to Davenport et al. (2020), the algorithmic paradigm enables the analysis of various consumption patterns, even those of a non-linear nature and predicts consumer needs before they become actual needs. The key difference is the idea of operational agency: While traditional technologies would need to involve a human to set up advertising campaigns on this basis, algorithmic marketing solutions would automatically optimize the placement of ads, modify dynamic pricing, and even change the content delivery based on an ongoing, closed-loop feedback appraisal. Therefore, AI in marketing is not merely analytical but powerful, capable of even steering a ship as a standalone entity interacting with the market. Therefore, AI in marketing is not simply an analytical tool but it's an autonomous operational entity, similar to how a sailboat navigates on the winds, influencing the speed and accuracy of the marketing maneuvers.

The theoretical or nonsensical aspects of various inceptions that can be seen in business research and scholarship should be broken down into the sub-fine and operational layers of "Artificial Intelligence". In today's marketing landscape, AI implementations can be largely divided into Predictive and Generative AI.

Predictive analytics is the practice of finding hidden patterns in large and unstructured datasets by leveraging machine learning (ML) architectures. Predictive discriminative models are based on calculating the statistical probability of a customer's future behaviour based on descriptive historical data such as click-through rate, customer purchase history and dwell time, to name a few (Vlačić et al., 2021). The strategic importance of predictive AI is that it can get marketers to 'right time, right place, right person' them more efficiently at a lower cost, to acquire customers, as stated in Buhalis et al. (2024).

On the other hand, Generative AI, with its Large Language Models (LLMs) and powerful neural networks, generates net-new semantic, visual, and auditory content. Since the accelerating commercialization of these architectures after 2022, Generative AI has taken over marketing from being only a data analysis tool to an automation-driven marketer and creative producer (Verma et al., 2021; Kshetri, 2024; Heitmann, 2024). Prediction models are

for making predictions on existing datasets, while generative models can generate new data distributions, providing the possibility for on-the-fly, highly customized copywriting, dynamic localized advertising and conversational agent dialogues (Dwivedi, 2023). So, a unified picture of modern algorithmic marketing shows that Generative AI is automating the creation of hyper-personalized marketing materials to deliver them via the strategy best fitted by predictive analytics (Chintalapati and Pandey, 2021).

3.1.2 Key Theoretical Frameworks

The Resource-Based View (RBV) is often used in the literature to operationalise how the deployment of AI manifests as market dominance. The RBV was first conceptualized by Barney (1991), and it can be stated that a firm is able to gain sustained competitive advantage when it possesses valuable, rare, inimitable, and non-substitutable (VRIN) resources. First, there are AI tools and services that can be easily accessed and acquired, thus failing to meet the VRIN requirements in the domain of digital marketing. Basic algorithms and off-the-shelf machine learning models can be widely obtained by manufacturers of health-related products through the cloud interface platform (Huang and Rust, 2021), and they are highly substitutable.

Rather, modern theories combine the RBV with algorithmic selling, and claim that a firm's non-replicable strategic asset is the knowledge they have accumulated and retained about their customers – their first-party data. The effectiveness of AI models hinges on a vast amount of high-quality data, especially data about consumer behaviour, and unique closed-loop data sets are a rare and inimitable resource for firms (Davenport et al., 2020). Moreover, as these algorithms are integrated in a very idiosyncratic manner with the legacy IT of a firm, it is very hard to replicate and therefore generates an organisational capability. Thus, according to Dwivedi et al. (2021) and Chishty et al. (2025), the real value lies not in AI per se, but in the “algorithmic infrastructure” - the combination of proprietary first-party data, personalized machine-learning systems and the human expertise needed to execute them. VRIN capability is reflected in the information and tangible boosts provided to the firm's performance; organisations with this feature create impenetrable barriers of entry by continually adapting their hyper-personalization engines, which exceed technologically stagnant competitors (Buhalis et al., 2024; Ntapiapis, 2023).

Technology Acceptance Model (TAM) and Diffusion of Innovations (DOI)

The RBV describes the strategic call to action of AI, but doesn't explain the level of organisational resistance and consumer reactance associated with its implementation.

Scholars use the Technology Acceptance Model (TAM) and the Diffusion of Innovations (DOI) theory to come to those socio-technical realities.

Based on Davis (1989), TAM suggests that PU and PEOU are most influential in the adoption of a new technology, and it has received strong support from recent marketing acceptance models (Sullivan & Wamba, 2024). Drawing a parallel from the literature, it becomes apparent that there is a crucial paradox in embracing AI in marketing. For marketing practitioners, the usefulness of AI is almost universally agreed upon; use of AI tools for creating segmented content and copywriting can clearly enhance productivity (Mustak et al., 2021). The Perceived Ease of Use, however, continues to be greatly constricted. Dwivedi et al. (2021) point out that vast amounts of integration friction exist in relation to complex algorithmic architectures for CRM systems that may not interoperate well with legacy systems. In addition, marketing executives lack the necessary digital skills and this in turn deals a significant blow to PEOU, which is one of the key prerequisites for successful deployment.

In a similar vein, Rogers' (2003) Diffusion of Innovations theory offers a macro-level lens for considering the integration of AI at the market level. DOI theorises that the determinants of adoption velocity are the relative advantage of the innovation, compatibility with existing values, complexity, trialability, and observability. The literature shows that Generative AI has a high relative advantage and can be easily tried and tested, but simultaneously, its technical complexity and the restriction posed by strict data privacy laws make it difficult to be adopted in the middle part of the market, the "early majority".

Moreover, these framework schemes allow accounting for the dynamics, both on the supplier side and the consumer side. According to TAM, consumers will judge AI mediumisation of marketing (e.g., predictive product suggestions) on how useful it is. Rust (2020), however, spots an activity that inspires serious privacy concerns as soon as it becomes obvious or apparent. The perceived risk outweighs the perceived usefulness of the personalization if consumers think that their data is also being collected in ways they don't know about and is being used to create predictive models. This situation is called algorithmic reactance, emphasizing the susceptibility of technology scenarios in marketing to being framed by their sociotechnical friction and consumer trust.

3.2 Theme 2: Empirical Findings and Strategic Affordances

The theory, architecture and conceptual definitions of AI presented in Chapter 3.2 must now be explored to understand how these elements translate into market gains in practice. This

theme moves from the theoretical conceptualisation to the empirical validation of the synthesized literature related to the impact of AI in its operation in digital marketing. Specifically, it will examine how, particularly, the transition from heuristic to algorithmic marketing paradigm changes the way customer targets are being formed, automates complex marketing activities and enables quantifiable enhancement of organisational performance. To remain analytical, however, this section also has a look at the severe incongruities within the empirical facts, specifically the "privacy paradox", which entails that the efficiency of algorithms is in direct contestation with consumer trust.

3.2.1 Algorithmic Targeting and Hyper-Personalization

The clustering of opinions among current research in marketing has narrowed down a key strategic impact of AI to its ability to transform the very nature of customer targeting (Davenport et al., 2020). Traditional digital marketing used a lot of static demographics based on user demographics, grouping consumers by general income levels, geographic exchanges, age, etc. This empirical finding is a consistent one, and as such clearly shows the unquantifiable limitations in the predictive validity of this heuristic approach. Algorithmic targeting, on the other hand, makes use of finely grained real-time behavioural data and predictive machine learning models to shift the targeting paradigm from retrospective and demographic clustering to anticipatory behavioural prediction (Mustak et al., 2021).

Hyper-personalisation is the ultimate in this kind of algorithmic prowess, the literature explains. Hyper-personalisation goes beyond just personalisation and applies deep learning neural network models to provide highly individualised content, product recommendations, etc., according to the very specific preferences of a single user at a precise moment of micro-intent (Chintalapati and Pandey, 2021). As shown by Vlačić et al. (2021), predictive analytics algorithms can combine various digital footprints, such as click stream data, people's potential engagement with certain web elements and cross-platform browsing history to create high-fidelity behavioural psychographics. This enables organisations to understand what consumers need before they state it in their searches, by deploying and using models for prediction which are immersive and context-aware (Gao & Liu, 2022; Khan et al., 2025).

First, is that transitioning is strategically significant and this benefit is of immense magnitude in empirical terms. Research shows that both conversion and Customer Lifetime Value (CLV) has seen a significant gain after predictive targeting models have been implemented. Huang and Rust (2021) furnish quantitative evidence that hyper-personalised marketing interventions lead to a considerable decrease in Customer Acquisition Costs (CAC) through

the reduction of wasted ad spend on prospects with a lower probability to purchase. AI can optimize Return on Ad Spend (ROAS): AI-driven tools can deliver marketing messages specifically to people who are statistically more likely to convert, maximizing the return on ad spend, particularly across omni-channel environments. In addition, Buhalis et al. (2024) observe that "continuous algorithmic optimisation is key to achieving higher retention rates, as over time the user's CLV gets better due to more accurate personalisation achieved by the machine learning model, with more data ingested through the years. Ultimately, the literature also confirms that AI changes the 'educated guess' approach of targeting to an optimised and statistically rigorous science.

3.2.2 Automation and Operational Efficiencies

The aggregated literature highlights the extensive role of AI in the mechanics of digital marketing operations, in addition to its targeting capabilities. Algorithmic architectures put an end to human bottlenecks in a world of real-time data and usher in a new era of unprecedented efficiencies in programmatic advertising, dynamic pricing and customer relationship management.

Programmatic ads are one of the most proven and advanced uses of AI for marketing. Programmatic advertising is an automated, algorithmic process of buying and real-time bidding of digital advertising inventory, according to Mustak et al. (2021). Programmatic systems determine the value of an individual user impression within milliseconds of the impression itself, a game-changer from the traditional media buying process that involved complex negotiations between publishers and agencies for insertion orders. The literature has shown that these Real-Time Bidding (RTB) platforms improve the dynamic allocation of media, which is more efficient and scalable than the one achieved when mishandled by humans (Vlačić et al., 2021). Organisations can run multi-channel campaigns at speeds that can't be matched by human practitioners, as they will be automated and will match ad creative with the predicted user profile instantly.

In line with this, empirical studies have outlined the influential impact of AI in implementing dynamic pricing strategies. Dynamic pricing is nothing new, but with the introduction of cutting-edge machine learning, the way pricing is done has changed. As proffered by Davenport et al. (2020), today's pricing algorithms continuously ingest vast complex data such as the real-time pricing of competitors, supply chain inventory data, macroeconomic data, and individual consumers' price elasticity, and use the collected data to optimise product pricing moment-by-moment. This provides companies with the ability to maximize

consumers' surplus without compromising their competitiveness. Studies have shown that companies using algorithmic pricing systems show much more positive effects on their yields and profit margins, especially in the fluctuating areas of e-commerce and the hospitality sector (Buhalis et al., 2024).

Also, how AI automates customer service in the form of conversational agents (chatbots) is a key topic in the literature on operational efficiency, specifically toward a reduction of cognitive effort for basic customer enquiries (Buder et al., 2024). Since the advent of Large Language Models (LLMs), modern chatbots have evolved from rigid and decision-tree-driven texts to extremely dynamic and context-aware digital assistants. According to Dwivedi (2023), these agents can natively answer intricate customer questions, conduct transactions and give tailored product suggestions in a variety of languages and around the clock. The empirical evidence strongly points to the value of this automation for organisations: research has revealed significant savings in call center operational costs and much better customer satisfaction scores attributed to the seamless, near-instant response times (Kshetri, 2024). This literature reaffirms AI as more than a strategic addition and more as a key imperative for operational functioning in order to be competitive in the market.

3.2.3 Contradictions in Results (The "Privacy Paradox")

The operational advantages of AI, detailed in the previous sections, suggest that, if a consensus has emerged from the literature, then consumer acceptance is mixed. Even when the preceding sections appear to identify a consensus in the literature, a critical examination of the overall literature shows that consumer acceptance is also accompanied by significant empirical indications of contradiction. This is, very generally, described in the literature as the "privacy paradox. The paradox describes that consumers clearly express intentions to engage with hyper-personalised, relevant-to-them marketing experiences, but at the same time, they also experience a strong psychological reactance towards the granular data collection that would enable them to experience what they explicitly want (Rust, 2020; Mardiah et al., 2024; Brocato & Davis, 2025).

On the other side of the fence, literature in computer science and technology-optimistic business goes so far that the granularity of data extraction always results in better consumer experience and increased engagement (Chintalapati and Pandey, 2021). But literature on behavioural economics and consumer psychology has several strong arguments that are not in line with this linear assumption. With algorithmic targeting being more accurate, Kietzmann et al.'s (2020) empirical research shows that it crosses a certain psychological threshold,

leading to a “creepy factor.” However, if a predictive model is seen to know much more about consumers than they are fully and openly aware of, the ‘usefulness’ of what can be done with the personalisation may be completely lost in the perception that they feel ‘taken care of’ and ‘looked after’.

This ‘reactance algorithmic’ is of tremendous strategic implications. Dwivedi et al. (2021) show that violation of privacy while legally permissible can, if seen as ethically questionable, immediately and permanently harm the brand equity. By using adblockers, by entering fake data to trick algorithms or by simply avoiding the brand. Moreover, according to Buhalis et al. (2024), deep learning algorithms are not transparent (black box problem), which further contributes to this issue of distrust. Organisations are unable to tell consumers how an AI came to a targeting decision and thus cannot guarantee the ethical use of data by the AI or that the data is not algorithmically biased.

Hence, the empirical literature is quite complicated and rather non-linear: the efficiency of the algorithm is concave. Until the sweet spot, more personalisation contributes to converting customers and increasing their CLV; after the sweet spot, hyper-personalisation results in privacy reactance and thus erodes value (Huang and Rust, 2021). This paradox has significant implications for how freely AI-enabled tools can be used and how organisations can play a fine balance between utilising the tools to their best advantage and not engaging in ethically dubious practices, especially as they can lead to a significant impact on consumer purchase intent (Yin et al., 2025; Acatrinei et al., 2025; Ramesha et al., 2025).

3.3 Theme 3: Emerging Debates and Socio-Technical Friction

An academic overview of algorithmic marketing architectures should acknowledge the enormous strategic opportunities and performance that these offer, as noted in Theme 2; however, these opportunities and effects also operate in a field partitioned by competitive forces. The unfettered use of Artificial Intelligence (AI) often runs headlong into very harsh socio-technical realities. Hence, the discussions in Theme 3 will be of the nascent and controversial debates in current literature, which takes away the focus from technological capability to structural friction. It examines the paradox of the efficiency of algorithms and the ethical dilemmas of the use of Generative AI, the legal and policy limitations of opaque data governance practices, and internal institutional and cultural obstacles to practitioner uptake. The conundrum of technology optimism and business reality is explained in this theme, highlighting the multifaceted challenges organisations face in safely incorporating AI into today's digital landscape.

3.3.1 The Ethical Ambiguity of Generative AI

The rapid commercialisation of Generative AI and Large Language Models (LLMs) has created unparalleled ethical murky points in the digital advertising area. Recent research found in the literature highlights the harmful effects of automated content creation and the risk of inauthentic branding, copyright violations, and algorithmic bias, despite generating a massive volume of content.

One of the main arguments of the literature focuses on the diminishing authenticity of brands and the trust of consumers due to fake media. Puntoni et al. (2021) believe marketing itself is essentially dependent upon emotional calls to action and connections with people. Generative AI introduction to automate copywriting, visual material, and customer support discussions produces an 'uncanny valley' effect in brand marketing and communications. Business scholarship cautions that there is a risk involved in the generation of hyper-customized, but entirely synthetic, semantic content, diluting the perceived authenticity of the brand of the content creator as well (Dwivedi, 2023; Bormane and Blaus, 2024). A psychological distancing happens when consumers cannot tell apart human-originated brand messages and stochastically produced outputs. Kietzmann et al. (2020) empirically show that when a consumer is exposed to synthetic media like AI-generated avatars or deepfake advertisements, it typically elicits instant consumer reactance as it undermines the long-term brand equity and is the replacement of relationship marketing with mechanical manipulation. Moreover, there is a significant legal and regulatory gap concerning the intellectual property (IP) and copyright connections of Generative AI, as all of this is covered in the academic discussion. The power of LLMs to produce truly novel and creative outputs by combining large amounts of data used during training has been lauded in the computer science literature (Kshetri, 2024). But the optimism of legal and strategic management scholars is spurned. Foundational models underlying Generative AI are trained using billions of parameters from the Internet, which are not necessarily the explicit consent of the original creators (Islam et al., 2024; Ziakis and Vlachopoulou, 2023). This raises a significant copyright conundrum for marketing professionals: What if an AI produces a marketing campaign from a model built from copyrighted material, who owns the content produced and is the brand using the AI responsible for copyright infringement? This nullity creates a major hurdle for risk-averse organisations since they can't truly deploy synthetic assets without exposing themselves to potential future copyright legal issues that current laws are powerless to resolve, as pointed out by Dwivedi (2023) and Nguyen (2025).

Apart from authenticity and copyright, maybe the most important moral issues condensed in the writing are the continuation of algorithmic bias and representational harm. Though many marketing practitioners tend to think of algorithms as an objective science of mathematics, that is "disproved" by today's critical studies. Algorithms are biased in nature as they are based on a set of trained data, which brings systemic human prejudices inherent to algorithms (Akter et al., 2022). From a marketing standpoint, this is seen as discriminatory targeting and biased representation of consumers. Their study reveals that, in many cases, predictive models optimize conversions by disproportionately targeting certain groups of people, leaving out those that they did not include in the model, which often includes marginalized groups and is unable to deliver relevant ads, such as housing, credit or premium services. In particular, such representational harms can occur in financial and service marketing, where algorithms can systematically target vulnerable groups of consumers (Mogaji et al., 2020). Likewise, shifts in the gender and socioeconomic stereotypes of people from version to version can be reflected in the output of Generative AI models, whose training data may include outdated stereotypes (Chintalapati & Pandey, 2021). For this reason, according to the literature, automated deployment of AI in digital marketing does not remove bias; it rather institutionalises and proliferates historic biases at an unprecedented speed if there is no strict, human-in-the-loop ethical auditing.

3.3.2 The Black Box Problem and Data Governance

Reviewing the modern literature indicates that there is an extremely deep and enduring academic divide on data governance. There are two contrasting positions in this debate: the enthusiasm for technology that computer science and engineering books, and that technical people in general, are apt to express contrast with the dire warnings of legal and business scholarships regarding regulation and compliance.

Consumers are always presented as the 'end consumer', and their data as a necessary 'fuel' needed for improving predictive accuracy and the effectiveness of machine learning (Chaffey, 2022; Vlačić et al., 2021). The main goal of this paradigm is to maximize the extraction of customer data (Ononiwu et al., 2023) – to harvest as detailed a digital footprint as possible from the customer. This view believes that seamless and persistent data scraping practices from various digital touchpoints can be used to build high fidelity behavioural psychographics.

But business and legal literati strongly attack this 'extraction' approach which takes no account of the 'sociotechnical facts' of the current data privacy regime. According to Ziakis

and Vlachopoulou (2023) and Behera et al. (2024), the insatiable appetite for consumer data across these models is blatant in opposition to strict privacy standards like the General Data Protection Regulation (GDPR) of the European Union and the California Consumer Privacy Act (CCPA). These regulations promote data minimization, transparency, and "right to be forgotten" which contradicts the data-intensive mindset of deep learning neural networks (Buhalis et al., 2024; Saura et al., 2024; Omri et al., 2025). As a result, companies find themselves in a strategic bind: they need to possess large amounts of data to leverage all the cutting-edge AI marketing tools, but they also create a significant compliance breach by having all that data, resulting in potentially devastating resolution problems, significant monetary fines, and perhaps the loss of customer trust forever (Rust, 2020).

The "black box" issue that is intrinsic with cutting-edge ML models further aggravates this crisis of data governance. However, the difference between traditional rules-based marketing analytics, without using deep neural networks, lies in the fact that the logic behind making a decision is linear and transparent, while deep neural network-based marketing analytics is fundamentally opaque (Behera et al., 2024). Even model developers are no longer always able to describe exactly how the algorithm came up with a targeting decision or output. This aspect of a lack of Explainable AI (XAI) poses serious problems in a digital marketing ecosystem. Dwivedi et al. (2021) note that consumers have a right to explanation under GDPR if there is any case of automated decision-making. An organisation should explain and justify the logic for such actions – this is because of the requirement for the strict application of 'Explainable AI' (XAI) protocols, and maintaining trust, if a marketing algorithm refuses to provide consumers with a promotional pricing tier or decides to market them a sensitive behavioural ad (K.W.T., 2026; Hermann, 2021). This opacity of deep learning poses a serious challenge for businesses, given that they are unable to lawfully or ethically use them in the field, except where these systems are deployed.

Through literature, arguments are brought together in this work, with the conclusion that the black-box problem is not just a technical constraint, but also an organisational accountability gap. Marketing departments surrender the option to ensure ethical management and oversight when handing over the targeting process to an unexplained algorithmic entity, resulting in a massive trust loss by the brand, the regulators and the end consumer (Behera et al., 2024; Stone et al., 2020).

3.3.3 Organisational and Practitioner Barriers

Beyond the ethical murky waters and regulations are the very real issues of the organisation that give rise to the friction between AI and seamless digital marketing. Thematic analysis of the barriers according to Theme 1 (Resource-Based View [RBV] and Technology Acceptance Model [TAM]) on these reveals a multitude of structural and human capital barriers in the operational reality of AI integration.

But one of the biggest organisational challenges that has been mentioned in abundance in the literature is the "friction of the legacy system," popularly known as "technical debt. Empirical reality states that most marketing departments have been building their books of business (Customer Relationship Management (CRM)) on highly fragment and outdated databases (Davenport et al., 2020) even though conceptual books envision highly autonomous and fluid agents that are able to execute campaigns in real-time. Specifically, Mariani et al. (2021) highlight the need to integrate APIs with data lakes and vice versa, for advanced applications of predictive analytics to facilitate applications of AI (Gener) generation. Most of the time, however, they come across an issue in reconciling the legacy systems, which are very well structured and work in a very 'silo' approach, with the modern algorithmic tools. This failure in integration projects gains in productivity, and in some instances, implementing AI can result in massive problems for the IT that require high investments, just to design a new basic data structure needed to train marketing models (Dwivedi et al., 2021). Literature from an RBV perspective indicates that AI programmes must be able to be hosted in the company or else there is no value.

Perhaps worse, all of the above technical debt is compounded by the 'digital skills deficit' problem that today's marketers deal with. AI is not able to pass the "Perceived Ease of Use" (PEOU) test with most practitioners. Previous empirical evidence from Abrokwah-Larbi et al. (2023) and Chintalapati and Pandey (2021) suggests that modern marketers are very creative and have a heuristic understanding of the various digital platforms, but they lack the essential skills and knowledge of data science, algorithmic logic, and prompt engineering. The literature reveals something no IT organisations have thought about: The software engineers who make the AI systems want to be employed in systems that manipulate complex data; the marketing folks who are supposed to use the systems don't, they only want something intuitive and creative. Skills deficit can also lead to marketing teams being unable to effectively audit AI-generated marketing content, optimize predictive models or fight against algorithmic bias, making the strategic use of AI a lot more difficult (Stone et al., 2020).

There remains a resistance by managers, as well as an "algorithm aversion" in the academic discussion, which strongly hinders acceptance into the industry. In this respect, Stone et al. (2020) describe algorithm aversion as the psychological barriers human decision makers face when asked to rely on recommendations made by algorithms, especially when they are looking to human intuition in their decision-making process, for example, in the creation of marketing strategies. Stone et al. (2020) finds empirical evidence that even when the basic strategic functions (segmentation, media buying and pricing etc.) are summarized by autonomous AI agents, senior marketing executives often feel a loss of credibility and job identity. Additionally, managers have a very good understanding of the reputational risks that can come with the black box problem (Behera et al., 2024). We need to remember that executives are legally and ethically responsible for all marketing produced by that system so they are not very willing to entrust an unexplainable system. As a result, the literature shows distributed organisational resistance to the extent that AI can be integrated to facilitate marketing-related tasks, as they prefer to use it as a small, isolated margin analytical input (Stone et al., 2020; Abrokwhah-Larbi & Awuku-Larbi, 2023). This 'Technology Resistance' aspect is often more overpowering than performance expectancy, potentially establishing a significant institutional inertia (Stone et al., 2020; Ismail & Eid, 2025).

3.4 Theme 4: Critical Research Gaps

An objective methodical approach to the strategic affordances of Artificial Intelligence (AI) in digital marketing also needs to expose the structural constraints in this academic area. In addition to the comprehensive mapping of the strategic affordances and socio-technical frictions of Artificial Intelligence (AI) in digital marketing that occurred in the previous thematic sections, an objective methodical assessment should include the identification of the structural constraints of this academic field. Theme 4 seeks to transfer from the empirically substantiated to the still largely unexplored and thus prioritises important research gaps that penetrate the research field today. This section points out three specific academic needs or gaps in relation to the existing literature, which tends to focus on the 'technology game', and which ignores the systemic power of the technology and looks at potential applications over a short period of time with very little variety. These include the temporal challenge of studying Longitudinal Generative AI research, the current emphasis on empirical research in the Business-to-Consumer (B2C) segment and a lack of underlying, actionable, uniform socio-technical frameworks for marketing practitioners.

3.4.1 The Temporal Gap in Generative AI Literature

Within the academic landscape, the most glaring methodological limitation is the lack of any short-term study in understanding the impact of Generative AI and how this innovation will affect consumer psychology and brand equity in the near future. Literature reviewed in Theme 1 and Theme 2 strongly supports the use of LLMs for boosting the efficiency of semantic content, providing localised copy and scaling personalised communication (Chintalapati and Pandey, 2021; Kshetri, 2024). The current empirical literature is, however, totally limited by the time of its contemporality with the emergence of these advanced Generative AI architectures in late 2022.

This has resulted in an academic body of literature that is more full of conceptual treatises and/or cross-sectional studies, examining short-term reactions at the customer level or output at the point of operation (Dwivedi, 2023; Puntoni et al., 2021). The research of Huang and Rust (2021) and Mustak et al. (2021) was valuable, but these are mostly in relation to the longer-term impacts of predictive models, like a machine learning solution to programmatic bidding which span across multiple years. By contrast, there is no empirical data that can analyse the effect of multiple years of continuous engagement with synthetic content - created through AI - and its impact on overcoming entrenched brand loyalty and Customer Lifetime Value (CLV).

Additionally, critical scholars caution that using automated content can deceive consumers about the authenticity of the brand due to the possibility of duplications (Islam et al., 2024; Ziakis and Vlachopoulou, 2023); however, such stories have been largely theoretical or have been based on short-term investigational laboratory experiments. There is so far not enough rigorous empirical evidence in the literature to conclude whether the general negativity consumers feel about Generative AI is permanent, that is, a change in their psychological attitude, or merely temporary, due to each new technology's initial “friction” (Davis, 1989; Rogers, 2003). While synthetics is becoming more common across digital channels, and is likely to become even more so, the academic line of inquiry as to whether hyper-personalized synthetic content is detrimental to brand equity or is a new acceptable floor for brand expectations remains unanswered (Behera et al., 2024; Gündüzyeli 2025). The net long-term strategic impact of subjecting human-curated marketing to Generative AI cannot yet be fully measured in monetary terms until the trajectories of the various brands that used the system can be tracked and their impact measured over the long term.

3.4.2 Over-reliance on B2C Paradigms

Upon intense examination of contemporary literature in this thematic context, a systemic contextual bias emerges which means that existing literature is too heavily biased towards Business-to-Consumer (B2C) approaches, especially to the aspects of fast moving consumer goods (FMCG) & eCommerce-retail. All empirical findings supporting AI strategic affordances (in terms of the real-time algorithmic targeting, dynamic pricing optimization, hyper-personalized product recommendations) seem to be firmly grounded in the B2C realm, where buying decisions are less planned, essentially enough based on emotions, and usually performed by individuals.

This one-sided emphasis leaves a great gap in the academic literature about incorporating and the effectiveness of AI in comprehensive Business-to-Business (B2B) marketing systems. B2B sales cycles are intrinsically at odds with B2C retail sales, involving extended negotiation cycles, high value deals, rational (not heuristic!) decision-making and often the multi-stakeholder purchasing committee. Although a lot of literature exists about how AI can improve the algorithmic delivery of some single advertisement to some retail consumer based on high volume of clickstream data, and turn marketing into a behaviour forecasting proactive behaviour (Vlačić et al., 2021), no explanation is provided in the literature about how these same predictive models work in environments with low volume and high data complexity like that for B2B lead generation and Account Based Marketing (ABM) (Paschen et al., 2020). Overall, the unique challenges encountered during organisational adoptions in delivering a B2B marketing offer is very little explored compared to a B2C retail marketing. Empirical research is extremely limited when it comes to how AI maps and influences multi-actor decision units – though some researchers do recognize the theoretical benefits of predictive analytics to predict B2B Buyer Intent (Dwivedi et al., 2021). For example, the concept of algorithmic reactance discussed by Rust (2020) and Kietzmann et al. (2020), as well as that of the ‘privacy paradox’ (Kietzmann et al., 2020), are completely consumer related surveillances. There is a lack of literature to understand the response of corporate procurement teams that are subject to compliance rules and enterprise data protection requirements to AI vendor targeting (Peltier et al., 2023). In addition, there is significant geographic complexity with most studies being grounded in the western regulatory context and, therefore, not applicable in the emerging markets context (Mustaqeem, 2025). In essence, the current academic conversation largely ignores the B2B context and doesn't offer any rigorously tested models and frameworks to help industrial and enterprise practitioners create the most complex and multi-tiered sales funnel.

3.4.3 Lack of Unified Socio-Technical Frameworks

The final critical gap linking to literature was that there is minimal consistency of socio-technical frameworks that can be used for executive implementation. As explored in Theme 3, the current academically central or dominant conversation is somewhat divided along disciplinary lines. In computer science and engineering literature, the message of reductionism to maximize the data extraction in favor of achieving unparalleled algorithmic efficiency, as well as targeting precision, is very strong (Chintalapati and Pandey, 2021; Vlačić et al., 2021). On the other hand, academic research on legal, ethical and organisational behaviour of AI rules mainly focuses on alarming cases of General Data Protection Regulation (GDPR) infringements, deep algorithm bias and loss of customer trust in the ‘black box’ problem (Ziakis and Vlachopoulou, 2023; Behera et al., 2024).

This dichotomy will help identify the social and technical friction of AI deployment, but is an inadequate foundation, operationally speaking, for a cure. But the literature is more descriptive than prescriptive and sorely lacking in models involving the trade-offs which are so integrated that practitioners can successfully balance the various imperatives. Currently, marketing executives are faced with the challenge of not having a single, theoretical structure that accurately balances the need for fine-grained training data and legal and regulatory requirements mandating ethical data governance practices (Behera et al., 2024; Mariani et al., 2021).

For instance, although the managerial algorithm aversion and the cyber cannibalization layout created by impending digital skills deficits of marketing professionals have been well researched (Stone et al., 2020; Abrokwah-Larbi and Awuku-Larbi, 2023), empirical research into actionable and evidence-based change management solutions to address the deficit is scarce. Likewise, concerns about intellectual property rights infringement are considered to be a significant barrier to the adoption of Generative AI in marketing (Islam et al., 2024; Dwivedi, 2023); however, no single, academically accepted auditing standard has been established that marketers can implement to ensure the ethical origin of the synthetically-generated assets. In the end, whilst literature effectively outlines the chances and threats of AI, a unified and operational framework is lacking that would enable Chief Marketing Officers (CMOs) to apply AI tools with ease, legally, and ethically in the enterprise structure of the twenty-first century (Stone et al., 2020; Morley et al., 2020 & Gomes et al., 2025).

3.5 Chapter Summary and Synthesis

The chapter has incorporated up-to-date academic discussions surrounding the application of Artificial Intelligence in digital marketing comprehensively. The review traced the change from traditional to algorithmic epistemologies in marketing and aligned the theory side of predictive analytics and Generative AI with the traditional Resource-Based View and Technology Acceptance Model. The empirical evidence legitimizes these architectures to have great strategic affordances, which essentially make them optimised for customer targeting, programmatic automation and hyper-personalization.

However, an assessment of them revealed a definite socio-technical mismatch resulting from the advantages these operations offer. Organisations are caught in a real-life privacy paradox, suffer from profound moral dilemmas about synthetic media generation and incredible technical inertia and aversion to algorithms from within. Importantly, the synthesis exposed gaps in the literature and aspects of contrasts. Extreme focus on B2C frameworks, a lack of longer time views for Generative AI post-2022 and a lack of complete socio-technical frameworks are missing, which gives a sense of how to work in the enterprise.

The problems inside the academic disciplines can undoubtedly be substantiated in this dissertation in relation to a strategic solution. This review points out the same dichotomy which regularly exists between technological optimism and business practice, and offers a viable springboard to move from theory to practice. In Chapter 4, there is going to be a critical discussion of this well-charted conceptual space. It will bring together these conclusions and take up the foundational questions of the identified contradictions to directly tackle the general research questions and to build up the platform for managerial implications.

Chapter 4: Discussion

Introduction to the Discussion

This chapter moves from thematic exposition to critical synthesis since the conceptual space of Artificial Intelligence (AI) in digital marketing has been mapped in Chapter 3. The aim is to rigorously address the research question, which is: "How does the incorporation of AI change the face of modern digital marketing, and what are the strategic decisions to be made for the operational advantages and the socio-technical deployment issues? Four stages of discussion, addressing these requirements in each, are followed to arrive at this goal. One of the findings of the literature is what some have termed the central paradox, namely, that technologies of algorithmic hyper-personalisation would appear to conflict with any attempts to set limits on consumer privacy. There are algorithmic hyper-personalization technologies on one side, so optimistic that one could almost understand them to be created in the interest of breaking the privacy boundaries of consumers. Second, the study addresses theoretical implications of these findings, which critically add to the well-known resource-based view and technology acceptance model theories. Third, it clearly states key research areas that are to be explored in connection with Generative AI and the Business-to-Business (B2B) paradigm. Finally, the chapter presents a new model called the AI Socio-Technical Integration Model as a way of assembling this synthesis, which proposes an actionable way for bringing together operational velocity and strict adherence to ethical standards.

4.1 Integration of Findings: The Concave Curve of Algorithmic Utility

The findings of various empirical studies must be linked to obtain the overall research question concerning the impact of Artificial Intelligence (AI) on digital marketing and what strategies are required for compromise. While some synthesis was done, it cannot be presumed that the corrective processes of the digital marketing transformation are only defined by the introduction of an algorithmic system, but rather by an attitude or orientation that can be considered an organisation's ability to endure the friction caused by participating in this algorithmic system (Dwivedi et al., 2021; Mustak et al., 2021).

According to a discussion backed up by evidence from two separate streams of context, it's not linear, it's curved and concave between algorithmic efficiency and marketing performance. When starting to utilize AI, the strategic value and Customer Lifetime Value (CLV) have an exponential growth as algorithms are moving marketing tactics from reactive, broad-based Demographics Segments towards predictive and proactive Behavioural Segments. Davenport et al. (2020) and Khan et al. (2025) corroborate this hyper-personalization, stating that at its core, it's optimizing campaign delivery. This process has

been further scaled with Generative AI, which is capable of creating semantically rich content while providing hyper-personalised interaction with customers (Mukhopadhyay et al., 2024; Magableh et al., 2024). While all those operational findings differ from the results of Rust (2020) and Gündüzyeli (2025), who determined the limits in respect to socio-technical constraints, it is found that an upward trajectory with such operational aspects eventually reaches a critical ceiling, namely the limit of consumer-observed surveillance.

When personalization gets so personalised that it gets into the 'creepy factor' (Kietzmann et al., 2020), the curve will sharply turn negative. This conception and inversion are then empirically tested by Yin et al. (2025), who identify a very strong negative moderation: Immersive AI experiences appear to have a worse impact on the user than these experiences should have on them. This is further validated by Ramesha et al. (2025), who have drawn similar conclusions on the basis of their regression analysis: that basic personalisation efforts have yet to be statistically proven to be effective without clear boundaries, as only half of consumers actively trust AI with their data. Thus, combining these results, it can be concluded that going beyond the boundaries of psychological surveillance, behind the homogenization of the image of the brand through the maximization of the algorithmic capacity, is seriously harmful to it. The final 'strategic trade off' is that it's consumer trust, not algorithm accuracy, that is the ultimate moderating variable of commercial success.

4.2 Comparison Between Studies

The literature shows a universal agreement on the speed of operation of AI. A crucial analysis of these studies reveals a chasm in academia, which has to do with data governance and data extraction. Emancipatory technology optimism is the fundamental basis of the computer science literature, whereas regulatory pessimism is commonly found in the business scholarship in relation to digital marketing (Morley et al., 2020).

Data studies and consumer studies usually tend to consider data that is purely the necessary "fuel" for making machine learning work best. In this area, authors like Chaffey (2022) and Ononiwu et al. (2023) indicate that maximising the data extracted from them also maximises their marketing ROI, while non-stop tracking of behaviour will decrease churn and predict intent. The latter has received strong counter-reactions from critical business studies and critical business law studies, which emphasise that this is a portrayal that leads to organisational misfortunes and catastrophe and to the "privacy paradox" (Mardiah et al., 2024). Saura et al. (2024) bring this incompatibility to the fore as they discuss in detail how, based on Multiple Correspondence Analysis, the most economically lucrative AI-generated

marketing strategies (like cross-device tracking) currently have the lowest connections with the ethical standards for privacy.

Importantly, a review of the literature shows that this conflict is fueled for the most part by methodological differences. In the field of technology, closed-loop algorithmic simulations (e.g., testing predictive models on historical data) are used frequently and often successfully isolate and avoid considering human emotional responses (Mustak et al., 2021) as they aim for purely mathematical accuracy. On the other hand, the gloomy outcomes of business scholarships stem from different methods: Consumer surveys (pure data science) or structural equation model, and so-called Phenomenological interviews to capture those psychological reactances that are ignored by pure data science (Acatrinei et al., 2025; Komodromos, 2026). Human (business) scholars measure trust, while computer (information technologists) scholars measure mathematical accuracy, and the findings are at odds.

Finally, comparisons of the different methodologies provide an explanation for the different results from the studies. AI decisions that are a 'black box' don't necessarily result in human acceptance; even when models and calculations are correct, people refuse to accept decisions made by an AI. This is verified by the fact that organisational transparency is found to be a mediator that is necessary for the effect on consumer engagement found by Acatrinei et al. (2025). Therefore, the answer must accommodate the overlap between the two academic extremes—algorithmic simulation (the computer science view) and human privacy concerns (the business literature view) and cannot simply disregard one in favour of the other.

4.3 Theoretical Implications

The empirical realities presented by the review challenge the traditional boundaries of established theories regarding organisations and the adoption of technologies as so fundamental. Thus, the basic algorithms, the Resource-Based View (RBV) and the Technology Acceptance Model (TAM) have to be critically extended to show a proper picture of the algorithmic landscape of today.

Classical RBV (Barney, 1991), states that a sustained competitive advantage comes from resources which are valuable, rare, inimitable and non-substitutable (VRIN). In the context of digital marketing, it is found that first-party consumer data, along with an algorithmic system, is consistently stated as the golden asset in a digital marketing strategy (Dwivedi et al., 2021). This assumption is supported and validated with the empirical studies of Chishty et al. (2025), establishing that the capabilities and functionality of AI, built upon unique and localised datasets, can play a very prominent role in improving the penetration of markets and

the performance of the organisations (Jalilvand and Ataei, 2026). Continuing in line with that, insights from the descriptive analysis of top companies around the world show that algorithmic investments are directly related to meaningful revenue growth along with better customer acquisition metrics (Ntapiapis, 2023). Combining the socio-technical friction experienced in Theme 3, though, reveals a fundamental inability of the classical RBV to be used unilaterally with modern AI; that is, a theoretical shortcoming. The literature amply reveals that in stringent global privacy regimes like the GDPR of the European Union, massive data repositories are no longer only strategically valuable, but are at the same time massive strategic liabilities (Behera et al., 2024). Saura et al. (2024) and Mardiah et al. (2024) state that aggressive data collection, aiming to stay competitive with the use of algorithms, is what puts organisations at risk of catastrophic failures, cyber vulnerabilities and loss of consumers' trust that can never be restored. So this discussion is an extension of the RBV, introducing the notion that the value of an algorithm must necessarily embody a “liability discount.” Then, an organisation's first-party data can only become a true VRIN asset when it also has the unique, difficult-to-imitate organisational ability of ethical data governance (Morley et al., 2020). This governance deficiency turns the data asset on its head - undermining and damaging brand equity.

In a similar way the outcome suggests a radical change of the Technology Acceptance Model (TAM). According to the original statement of TAM, the amount of technological adoption is mostly dependent on the extent of Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) (Davis, 1989). Although the perceived usefulness of AI for achieving efficiency and hyper-personalisation across marketing has been agreed upon by all (**Puntoni et al., 2021; Sullivan & Wamba, 2024**), it is the synthesised literature findings that essentially render Perceived Ease of Use (**Verma et al., 2021**) inoperable due to the intricacies and opacity of deep learning architectures. Advanced machine learning models are essentially known as “black boxes”: that is, marketers cannot intuitively understand the logic of the algorithm as it makes a decision or even audit the algorithms to check for any systemic bias in particular demographics (**Hermann, 2021; Akter et al., 2022**).

A lack of digital skills and entrenched infrastructural complexity of integrating AI with legacy CRM systems (**Mariani et al., 2021**) can create a high level of ‘algorithm aversion’ for practitioners. Ismail & Eid (**2025**) empirically show that sometimes the high levels of ‘Technology Resistance’ among marketing professionals overpower the ‘Performance Expectancy’, resulting in serious inertia in the organisation. Also, Acatrinei et al. (**2025**), and Ramesha et al. (**2025**), show that the “perceived risk” of a technology would naturally prevent

its adoption even if it otherwise has some utility. Callously, it is therefore proposed that this view on TAM is limited in itself when it comes to measuring the integration of AI in marketing. It suggests that "Organisational Trust" and "Algorithmic Transparency" (Explainable AI) should become part of the adoption theories officially as a foundation and mediation variable for modern adoption theories. The key is that marketing practitioners and consumers don't just use autonomous AI agents; they have to trust them. However, this trust cannot be maintained if the black-box problem is not addressed, as otherwise it is impossible to gain adoption; in algorithmic ecosystems, transparency is the easiest requirement for success, even before NGOs will consider ease of use (Gündüzyeli 2025; Komodromos 2026).

4.4 Filling the Identified Academic Gaps

There are significant, structural flaws in the current academic literature, of which the two most prominent issues are firstly the obvious focus on Business to Consumer (B2C) retail ecosystems and secondly that there is no observable research stream regarding the use of Generative AI beyond 2022. To develop a cohesive strategic response, this discussion needs to logically lead to actionable frameworks that proactively provide a response to the identified academic mortality deficiencies, essentially addressing the theoretical points and creating marketing specifics.

Existing literature is mainly oriented towards B2C paradigms, and this can be a dangerous oversight for enterprise organisations. Even though a lot of B2C empirical studies have repeatedly advocated for hyper-personalisation, automated retargeting, and algorithmically nudging the consumer to make a conversion as soon as possible (Vlačil et al., 2021; Gao & Liu, 2022; Yin, et al., 2025), implementing the same tactical architectures in complex Business-to-Business cycles (B2B) is structurally problematic. The B2B procurement process is based on rational decision-making (Abrokwah-Larbi & Awuku-Larbi, 2023), involves long buying funnels for Account Based Marketing (ABM), a multi-stakeholder buying committee and high scrutiny by regulators (Davenport et al., 2020). This review thus infers that B2C algorithmic discoveries have to be considerably edited prior to its integration into enterprises. In B2B settings, the 'creepy factor' and algorithmic reactant (Kietzmann et al., 2020; Saura et al., 2024) isn't merely an individual shopper deterrent; it results in deadly violations of compliance by companies and poses a danger to the entire viability of high-value contracts. Therefore, AI marketing for B2B must move from stealthy to open and transparent relationships between marketing and consumers, built on mutual consent to share data. In B2B, algorithmic targeting needs to give utmost importance to the concept of

“Explainable AI” (XAI), which allows corporate clients to have complete access to the way that predictive lead-scoring models are evaluating their enterprise data (**Acatrinei et al., 2025; Komodromos, 2026**). AI tools will continually be weeded out of corporate procurement cycles without this increased ethical compliance, transparency of algorithms, and the capability to map to complex multi-actor decision units (**Khan et al., 2025**).

Moreover, longitudinal research with contemporary Generative AI products generates a significant strategic risk, due to the time limits of the study. Due to the recent commercialization of advanced Large Language Models (LLMs) (**Kshetri, 2024**), there is inherent limits on the current empirical literature when it comes to measuring changes in the operational behaviour of these models, such as immediate changes in cost for creating content and short-term increase in social media engagement (**Buder et al., 2024; Heitmann, 2024; Wasilewski et al., 2025**). As for the matter of the impact of synthetic media in the long run (both for the brand and the consumers), there is no strict academic consensus either as to the possibility of permanent damage to the brand's authenticity, nor about inducing consumers' fatigue over time (**Puntoni et al., 2021; Dwivedi et al., 2021**).

As a responsible way to cope with this academic limbo, this discussion will suggest an underlying paradigm change in measuring the success of the integration of AI. Marketing executives need to shift their key performance indicators (KPIs) from output metrics like click-through rates (CTRs), conversion velocity and automated content volume to more harsh “governance metrics” (**Morley et al., 2020; Hermann, 2021**) and have to do it now. In fact, there is still little empirical evidence on how consumers will react to the "uncanny valley" of AI-generated content in the long term, meaning that organisations need to evaluate AI content creation opportunities in a proactive manner to limit their liability risks in the future regarding copyright infringement, representational inequity and algorithmic bias (**Nguyen, 2025; Akter et al., 2022; Dwivedi, 2023**). Practitioners can then safely and effectively navigate the scale of operations of Generative AI while proactively safeguarding, longer-term, the quality of brand equity against potential, but undetected, backlash of socio-technical layers (**Mardiah et al., 2024**) by formally operationalizing governance measures, including mandatory human-in-the-loop bias checks, IP audits, and data provenance verification. These key inferences set the theory for the one proposed below in the next section.

4.5 Proposed Conceptual Framework: The Socio-Technical AI Integration Model

Therefore, to bridge the gap between algorithmic efficiency and ethical compliance with a comprehensive, robust and coherent solution, this study proposes the Socio-Technical AI Integration Model as presented in 3.5.3. This is a new conceptual approach toward the technological, regulatory and psychological factors discussed in this review, catering to marketing executives and Chief Marketing Officers (CMOs). This dynamic reshaping is translated to a linear mediated pathway and provides a “plan” for how to incorporate the operational velocity of AI “in a way that safely and legally protects the brand” (Morley et al., 2020). The framework has three visual phases to facilitate its application in enterprise strategy.

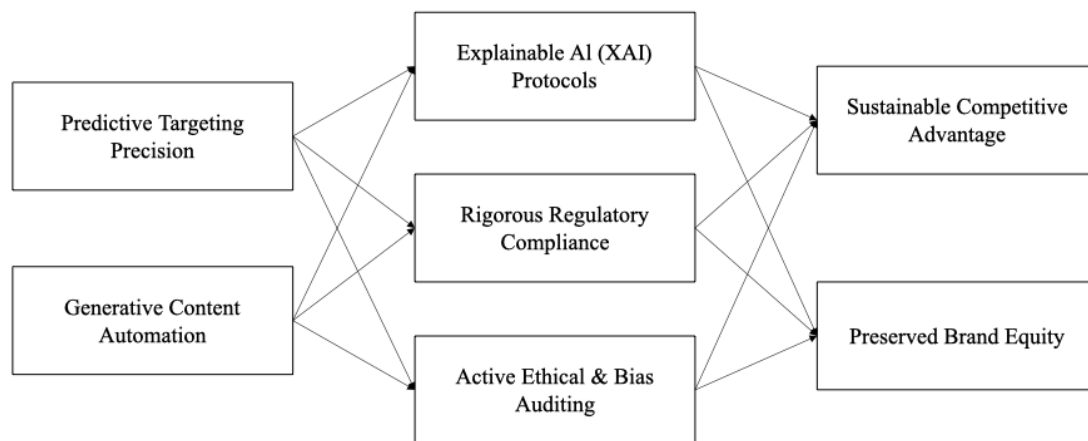


Figure 2: Conceptual Framework-The Socio-Technical AI Integration Model

4.5.1 Algorithmic Capabilities

Phase 1 opens up the model framework visually on the far left side by defining the input vectors that are independent variables that are driving modern digital marketing—Predictive Targeting Precision (machine learning and hyper-personalization), as well as Generative Content Automation (scale semantically and visually driven asset creation with Large Language Models). Such inputs as algorithms are unprecedented in terms of operational scale and cost reductions, as explained in Vlačić et al. (2021) and Heitmann (2024). But the basic assumption of this model is that these pieces are intrinsically of no strategic significance. But without an intermediary between them and the consumer market, they can lead to triggering in the privacy paradox and algorithmic reactance (Kietzmann et al., 2020). The signals in

these input vectors, therefore, must go directly into the central moderating phase and not around this phase.

4.5.2 The Socio-Technical Governance Gate

Phase 2 is the mediator, as this is the central node of the visual framework that is essential for its operation. This is put into perspective visually with a tight filter funnel or "gate" that the things that represent our "Phase 1" need to pass through. The build on the longer version of Technology Acceptance Model (TAM) and Resource-Based View (RBV) suggested in Section 4.3 includes three required requirements, namely:

Explainable AI (XAI) Protocols: Make the AI's predictive targeting capabilities more interpretable, reduce confusion, reassure consumers about "perceived risk," and embed accountability for human managers (Gündüzyeli, 2025; Acatrinei et al., 2025).

Rigorous Regulatory Compliance: Implementing robust data minimization and privacy-by-design principles to avoid uncontrolled legal exposure and liability based on such regulations as GDPR, while promoting sustainable and compliant behaviours for the organisation (Saura et al., 2024; Omri et al., 2025).

Active Ethical & Bias Auditing: Involving human and in-the-loop review to proactively check the output of Generative AI for IPR violations as well as algorithmic stereotypes (Akter et al., 2022; Nguyen, 2025).

The underlying principle of this "central gate" is that organisational trust is the "end thing" that determines the usefulness of a technology. Only if the AI endeavour passes all three of these checkpoints can it get into the market. Moreover, by setting up this governance gate, the "algorithm aversion" and digital skills gap, described by Ismail and Eid (2025), within internal stakeholders are dealt with directly. When facing executives with a standard procedure for conducting auditing, their resistance to the introduction of an autonomous system decreases.

4.5.3 Strategic Value Creation

Phase 3 (dependent variables) are visually located on the extreme right, and can only be attained if "Phase 1 inputs" make it through the "Phase 2 governance gate. The result is a "two in one" which is 'Sustainable Competitive Advantage' and 'Preserved Brand Equity'. Rigorous ethical considerations in the use of algorithmic automation enable organisations to sift through the high velocity of data to create a strategic asset, legally defensible and true, that it can leverage.

Finally, the Socio-Technical AI Integration Model not only gives practitioners a robust and defensible architecture to work on, but it is also highly scalable for their needs. This approach takes the attitude of considering the law-abiding as a 'pro-redness' issue, and not merely a 'pro-legality' post-action step. It is effective at addressing the dissertation's core research questions as it illustrates that while the seemingly unrestricted deployment of algorithmic surveillance is effective for digital marketing transformation, regulating predictive capacities to the thresholds of consumer trust can be more effective (**Ramesha et al., 2025; Gomes et al., 2025**).

4.6 Chapter Conclusion

This chapter consolidated the empirical research and bridged the paradox between AI marketing, finding that algorithmic efficiency follows a concave manner, and is only mediated by consumer trust. Adding classical RBV and TAM theories, a strategic liability of unmoderated first-party data emerged by balancing the technologically positive future with the regulatory challenges at hand. Secondly, the chapter touched upon the key gaps in B2B integration and Generative AI and derived the Socio-Technical AI Integration Model. The new conceptual approach is an actionable governance structure into which executives can put their algorithms without fear of IP issues or ethics violations.

Chapter 5: Implications

Introduction

The critical synthesis and theoretical resolution from Chapter 4 are turned into real-world paradigms and actionable mechanisms in this chapter. The overall intent of this section is to appraise the research in its entirety as to its importance in the whole field of marketing that extends from epistemological (pure marketing theory) to the affairs of commercial enterprise (practicing marketing). Rigorous academic alignment is provided through the breaking up of this chapter into three different operational lenses. Firstly, it elucidates the implications it poses on the theory, and it makes clear how this study contributes to and adds to the existing theory on furthering technological adoption. Second, it provides very specific and actionable management and practical recommendations, and the evidence-based guidelines provide a roadmap for how Chief Marketing Officers (CMOs) can safely yet effectively integrate algorithms in an ethical manner. Last, it fills in some of the existing gaps in the academic literature as well as provides a structured agenda for future research.

5.1 Theoretical Implications

5.1.1 Refining Established Frameworks

This study essentially represents a step forward in the classic approach of using the organisation's theories in the context of algorithmic marketing. In particular, it calls into question the conventional notions of the Resource-Based View (RBV). Traditionally, RBV has shown that the proprietary first-party data is a scarce and irreplaceable strategic asset (Barney, 1991). But, drawing on the synthesis of the "privacy paradox" (Saura et al., 2024), this study brings the concept of the Liability Discount to the RBV. In theory, it raises the hypothesis that massive data stores, in strict global environments where privacy can be accomplished, can no longer be regarded as unidirectional assets for companies but as spillovers that are far from helpful for their brand, which become enormous strategic liabilities if they are not trapped by an equally high level of ethical control.

In addition, it is an important contribution to the Technology Acceptance Model (TAM). This study demonstrates that due to the terrifying nature of the algorithmic 'black box' and the general managerial algorithm aversion (Ismail & Eid, 2025; Bawack et al., 2022), 'Perceived Ease of Use' is not enough to explain AI uptake in digital marketing. Rather, the results suggest that two variables, "Organisational Trust" and "Algorithmic Transparency", should be explicitly included in future technology adoption models as mediating variables.

5.1.2 Academic Contribution

The Socio-Technical AI Integration Model was developed and serves as the main academic contribution of this dissertation model (see Section 4.5). The literature is very much split between the computer scientists' optimism on behalf of extraction and the business pessimism on behalf of regulation. This conceptual model was the first one that was able to map how future researchers should view the operational velocity of generative AI and predictive analytics (IVs) filtered through a Socio-Technical Governance Gate (MV) to reach sustained competitive advantage. This research puts forward a new and theoretical framework, in which ethical compliance becomes the key empowering or conditioning law for market success rather than an afterthought legal obstacle, to help scholars assess enterprise applications of AI.

5.2 Practical and Managerial Implications

5.2.1 Strategic Recommendations

Artificial Intelligence is now not just a tool for operational efficiencies to cut costs and automate processes any longer. Managers urgently need to take a new approach on the basis of this review from having to maximize algorithmic output to providing algorithmic governance. The key focus for the organisations' CMOs should be the application of the protocols for Explainable AI (XAI) instead of predictive accuracy at all costs (Smith et al., 2025). When it comes to selecting a hyper-personalization engine, it must be possible for a marketing team to successfully audit the logic used for decision-making in such an engine. When considering a hyper-personalization engine, the ability to audit the logic the engine uses in decision-making should be one of the factors the marketing team considers. A commercial understanding of the importance of transparency is not merely ethical advice, but as confirmed by the empirical evidence, opacity generates severe consumer reactance (Acatrinei et al., 2025).

5.2.2 Policy and Industry Impact

This research indicates a need for industry regulation and proactive risk management at an industry level. As the rapidly advancing Generative AI system swarms the landscape, policymakers and enterprise stakeholders should be aware that current copyright and intellectual property structures (Dwivedi 2023) are not able to keep up. There is an urgent need to shift the global scene to action on the basis of AI principles and regulations, including, but not limited to, the AI Act in the European Union (Al-Busaidi et al., 2024), and adjust internal strategies for the deployment and rollout of AI. The authors of this study call

for a radical shift in company's data governance strategy from “data maximisation” to “data minimisation,” where companies only collect the behavioural metrics that are explicitly needed to create value and therefore reduce their exposure to institutions that can be vulnerable to catastrophic cyberattacks and/or fines for compliance violations (Mardiah et al., 2024; Haenlein and Kaplan, 2020).

5.2.3 The Action Plan for Enterprises

For organisations in very digitalized markets, the following activities are essential evidence-based best practices for safely leveraging AI speed and shielding the brand:

Establish Cross-Functional AI Ethics Boards: Marketing departments should not have a siloed approach to the deployment of AI, so a Cross-Functional AI Ethics Board should be established. A review process should be required in organisations, in which data scientists, legal representatives, and brand managers review predictive models together for systemic demographic bias before being put live (Akter et al., 2022).

Implement "Human-in-the-Loop" Checkpoints: Marketing agencies need to have set in place mandatory human editorial checkpoints to reduce the legal risk of Generative AI hallucinations and copyright violations (Puntoni et al., 2021). Persons must never publish visual and semantic resources of any kind which are created synthetically.

Pivot KPIs to Trust Metrics: There is a need for managers to switch from quantitative metrics like click-through rates and instrumentalised content production to including qualitative measures of ‘trust and authenticity’ to monitor long-term brand equity (Yin et al., 2025; Ameen et al., 2021).

5.3 Research Implications (Future Directions)

5.3.1 Addressing Limitations

This Extended Literature Review follows a very rigorous systematic approach in synthesising the current academic scene, but it has to be constrained by the available literature. The main constraint of this paper is that the majority of the literature is based on secondary sources of data, covering mostly Business-to-Consumer (B2C) retail and Fast-Moving Consumer Goods (FMCG) industries (Vlačić et al., 2021). Thus, outcomes about hyper-personalization and consumer reactance may not apply exactly to the more complex environment of the enterprise. In addition, as advanced Generative AI architectures only became commercially available after 2022, the data synthesized in this review are cross-sectional and reveal the current picture of the effects of the technology in the short term.

5.3.2 Future Research Agenda

Future research needs focus on this on strong, long-term empirical designs in order to fill in these identified gaps.

- **Longitudinal Studies on Synthetic Media:** Long-term psychological impacts should be measured, and there is a need for multi-year longitudinal studies in tackling the issues with Generative AI and brand authenticity. But the field needs to know whether this consumer's 'reactance' to "synthetic media" is an irreversible psychological hurdle or if it is merely a speed bump that will soon be worn down as the tech becomes commonplace.
- **B2B Ethnographic and Quantitative Studies:** In the future, testing the Socio-Technical AI Integration Model in the context of more complex Business-to-Business (B2B) paradigms should be explicitly done. A study should be done on the reaction of organisation/enterprise buying committees, where compliance standards are of paramount importance, to AI-driven account-based marketing (ABM).
- **Testing Explainable AI (XAI) Efficacy:** There is a critical need for empirical experimental research to quantify the exact financial Return on Investment (ROI) of Explainable AI. Researchers need to delve deeper into the impacts of presenting 'algorithmic logic' that is transparent and readable to consumers; can this actively solve the privacy paradox and generate brand trust in real-time commercial environments (Gündüzyeli, 2025; Arrieta et al., 2020).

5.4 Chapter Summary

The chapter was able to transform theoretical aspects found in the literature review to a prescriptive and actionable framework for academia and industry. It theoretically enhanced DRB and TAM, and as a result, explained that algorithmic resources need to be mediated with the intervention of ethical governance to become strategic assets. On the managerial side, it gave CMOs an action plan and pointed out the importance of having cross-functional ethics boards, Explainable AI, and a certain focus on data minimization. Lastly, recognising the time and context-bound features of the available academic text, this chapter outlined a very specific vision of future research. This section moves scholarly attention from the cross-sectional to the longitudinal dimensions of Generative AI and B2B algorithmic integration, thereby sustaining the discourse to stay current with the speedy technological progress in the Digital Marketing panorama.

Chapter 6: Conclusion

Introduction

This study began with a charge to critically analyze what is considered one of the most significant technological shifts in modern business history. The primary goal of this Extended Literature Review was to produce a systematic, comprehensive literature mapping, evaluation and synthesis of the knowledge that has been progressively growing in the academe with regard to the incorporation of Artificial Intelligence (AI) in the field of Digital Marketing. This research achieved a shift from a thematic mapping approach of how technology affords to a critical orientation of socio-technical friction through a PRISMA-inspired methodology where 56 studies on technological affordances, all with a high impact and peer-reviewed, were isolated and analysed. As part of the concluding chapter, this study attempts to give clear answers to the central research question, articulate the contribution of the study, recognize its structural limitations and define a clear avenue for future research.

6.1 Answering the Research Question and Key Discoveries

This study's main research question was: How has the involvement of Artificial Intelligence changed today's digital marketing landscape and what are the suggestions around the socio-technical dimension of its implementation and the operational benefits?

This synthesis sets the tone the ultimate question answered is that AI moves digital marketing from a heuristic model focused on demography and reactive tactics to a model of hyper-personalisation and proactive action derived from an algorithm, however bound by human psychological endorsement, and so the ultimate measure of commercial success might be consumer belief, not algorithmic ability.

This conclusion is being supported by three key "synthesized" findings. To begin with, literature is unanimous on the high rate of operations of AI, which is unprecedented. At the core of programmatic targeting and semantic creation of content lie optimization, and Predictive Analytics and Generative AI make it possible on a scale beyond what human marketers can achieve. Second, and importantly, this study showed that the improvement of the algorithm is not linear; in fact, the curve is concave. Hyper-personalisation becomes imperceptible from a privacy perspective, and consumers' reactance and an active de-optimisation of the technology increase brand harm (Kietzmann et al., 2020; Yin et al., 2025). Third, the review found that one of the main reasons why digital transformation is happening a bit slower is the managers' aversion to algorithms, not hardware. This "black box" character of deep learning undermines Explainable AI (XAI) and erodes organisational trust, which are

crucial for marketing executives to delegate strategic autonomy to algorithms with confidence (Ismail & Eid, 2025; Acatrinei et al., 2025).

6.2 Academic and Practitioner Contributions

The study bridges this deep-seated mismatch between an uncritical optimism in computer science and a pessimistic practical stance in the regulatory business, thus allowing for contributions to both academic theory and actual practice.

Theoretically, this research succeeded in challenging and extending two basic academic frameworks. It added a finer-grained concept of Liability Discount to the Resource-Based View (RBV) and showed how, in an even more stringent regulatory environment than it currently is (e.g., GDPR), a huge first-party data repository is no unilateral strategic asset. As such, they can be significant institutional liabilities if there is not the proper organisational framework of ethical data governance to support them (Ziakis and Vlachopoulou, 2023; Saura et al., 2024). Additionally, it updated to the 21st century the Technology Acceptance Model (TAM) model and made the concept of Algorithmic Transparency (AT) a condition to replace the concept of Perceived Ease of Use (PEU) as the major mediator that determines the adoption of autonomous marketing agents.

This dissertation for practitioners is a bridge from academia (critique) to the field (strategy), with the creation of the Socio-Technical AI Integration Model. This conceptual blueprint provides Chief Marketing Officers (CMOs) with a very actionable blueprint with three phases. To safely capitalize on the operational scale of AI, there needs to be a central "Governance Gate" that incorporates and conditions the use of all predictive and generative features with an integrated bias auditing and copyright verification system, along with privacy-by-design architecture (Morley et al., 2020). So the present study offers the much-needed proper theoretical mechanism to the digital marketing industry for balancing personalization with ethics.

6.3 Limitations of the Research

In order to maintain high academic standards in the process, findings from this synthesis should be viewed in light of the methodological limitations and framework of the synthesis. To begin with, despite a thorough search of the database, the finished academic corpus had a very skewed distribution of contexts centered primarily on Business-to-Consumer (B2C) contexts in retail settings (Vlačić et al., 2021). The results on algorithmic nudging in the consumer context and consumer reactance can, hence, not be simply transferred to a more complex, multi-stakeholder Business-to-Business (B2B) procurement process.

Secondly, this study would naturally have a very limited temporal scope in the context of Generative AI. Since Large Language Models (LLMs) have only recently been commercially popular, the literature analyzed is entirely cross-sectional. At the current moment, there is no sufficient time-series data to substantiate whether or not three things will happen: Firstly, that consumer aversion towards synthetic media will lead to permanent brands' detriment; secondly, that it is actually a temporal and technological acclimatization process (Dwivedi, 2023); or third, that no significant impact will be felt in the coming years. Last but not least, it is worth noting that the vast majority of highly influential research on privacy paradoxes is set in the West and a specific regulatory context, so that the validity of these very ethical barriers in other emerging digital economies is debatable (Mustaqeem, 2025).

6.4 Final Recommendations and Future Research Trajectories

Leveraging directly from the outlined areas of need, three distinct academic avenues should be taken to further this field, all of which are highly specific. First, future research scholars should begin to do multi-year, longitudinal, empirical studies on the long-term consequences of the use of AI-generated content on Customer Lifetime Value (CLV) and brand authenticity (Puntoni et al., 2021) immediately. Secondly, qualitative ethnographic research should be undertaken in enterprise B2B settings to find out how a corporate buying committee negotiates targeting based on AI. Third, quantitative experimental designs need to be conducted to evaluate the specific financial Return on Investment (ROI) of Explainable AI (XAI) interfaces and whether transparency of the algorithms neutralizes the privacy paradox in a real setting in commerce (Gündüzyeli, 2025)

6.5 Concluding Statement

Artificial Intelligence has gone beyond just being a technological trend: digital marketing is now a new epistemological revolution in the organisation's conception, capture and communication of value. But, the actual "so what?" of this study is that even more algorithms simply cannot measure the truth of the marketing field; it is still a human field. Although Generative AI and predictive analytics can provide unparalleled operational speed, there is no deep understanding in their code of the nuances of human emotions, ethics and boundaries of privacy. Consumer trust is the one thing that remains valuable and scarce, and consequently infinitely valuable, in the world of infinite scale and zero marginal cost in the generation of semantic content and hyper-targeted media.

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Appendix

Author(s) & Year	Title	Journal/Source	Method/design	Key findings	Gap/limitation
Buhais et al. (2024)	Artificial Intelligence's Impact on Hospitality and Tourism marketing: Exploring Key Themes and Addressing Challenges	Current Issues in Tourism	Systematic Literature Review (SLR) & Conceptual Framework	Identifies specific AI applications dominating the sector: hyper-personalization, smart chatbots, predictive dynamic pricing, and Generative AI for content creation. Concludes that AI not only optimizes backend operational efficiency but fundamentally alters customer value co-creation by providing real-time, context-aware service interventions.	Highlights a critical lack of quantitative empirical validation for the proposed frameworks. Calls for studies measuring the actual financial ROI of Generative AI campaigns, and notes a severe lack of research on cross-cultural consumer acceptance of autonomous AI agents.
Chaffey, D. (2022)	Internet marketing: strategy, implementation and practice (8th ed.)	Pearson (Textbook)	Comprehensive Educational Synthesis	Integrates AI seamlessly into traditional digital marketing frameworks (e.g., SOSTAC). Details how AI powers modern SEO algorithms, programmatic advertising bidding, customer lifecycle marketing, and automated email workflows to achieve continuous strategic alignment.	As a comprehensive textbook, it relies entirely on secondary synthesis rather than primary empirical data. Furthermore, the static nature of textbooks means it lacks frameworks for the post-2022 explosion of Generative AI tools (like ChatGPT) in daily marketing practice.
Chintalapudi, S. & Parsley, S.K. (2021)	Artificial intelligence in marketing: A systematic literature review	International Journal of Market Research	Bibliometric Analysis & SLR	Maps the intellectual structure of AI marketing into four distinct clusters: value creation, customer interactions, overarching strategy, and ethics. Finds that current implementations are heavily skewed toward recommendation engines and NLP-driven customer service chatbots.	Points out an over-reliance on conceptual/theoretical papers within the field. Explicitly calls for longitudinal empirical studies tracking how AI deployment affects long-term brand equity and customer lifetime value (CLV) over extended periods.
Davenport et al. (2020)	How Artificial Intelligence Will Change the Future of Marketing	Journal of the Academy of Marketing Science	Conceptual Framework / Typology	Proposes a foundational 2x2 framework classifying AI by intelligence level (task automation vs. context awareness) and task type (standardized vs. personalized). Predicts a progressive shift from narrow AI handling repetitive tasks to broad AI autonomously handling strategic marketing decisions.	The framework remains highly theoretical. There is a distinct lack of empirical validation comparing AI adoption success rates across different organizational structures (e.g., large enterprise vs. SME) or across different market contexts (B2B vs. B2C).
Dwivedi, Y.K. (2023)	"So What If ChatGPT Wrote it?" Multidisciplinary Perspectives on opportunities, Challenges and Implications of Generative Conversational AI for research, Practice and Policy	International Journal of Information Management	Multi-disciplinary Synthesis	Details the immense disruptive capability of Generative Conversational AI (ChatGPT) in automating marketing copywriting, manipulating SEO, and transforming customer service. Explores the "dark side," including algorithmic hallucinations, copyright infringement, and the creation of deepfakes.	Represents extremely early-stage conceptualization of Generative AI. Lacks robust, long-term empirical data on how AI-generated content impacts consumer trust and brand authenticity, especially when AI usage is explicitly disclosed to the consumer.
Dwivedi et al. (2021)	Artificial Intelligence (AI): Multidisciplinary Perspectives on Emerging challenges, opportunities, and Agenda for research, Practice and Policy	International Journal of Information Management	Thematic Analysis	Establishes the macro-level "grand challenges" of AI adoption. Highlights the "black box" problem (lack of algorithmic transparency), strict data privacy constraints (e.g., GDPR), and the severe organizational and cultural friction companies face during algorithmic digital transformation.	The broad multidisciplinary scope dilutes specific marketing insights. Requires granular, domain-specific empirical studies investigating how digital marketing teams specifically overcome algorithmic bias and navigate data governance hurdles in practice.
Huang and Rust (2021)	A Strategic Framework for Artificial Intelligence in Marketing	Journal of the Academy of Marketing Science	Conceptual / Strategic Framework	Introduces a three-stage evolutionary model of AI in marketing: mechanical AI (standardization), thinking AI (data processing/targeting), and feeling AI (affective computing/empathy). Argues that future marketing strategy must pivot toward symbiotic human-AI collaboration.	The final "feeling AI" stage lacks extensive empirical testing in real-world, commercial marketing environments. The framework assumes a linear progression of technology that may oversimplify the chaotic, fragmented reality of enterprise AI integration.
Kietzmann et al. (2020)	Deepfakes: Trick or treat?	Business Horizons	Conceptual Analysis / Typology	Analyzes Generative Adversarial Networks (GANs) and maps their dual potential. Identifies "Truats" (hyper-personalized video marketing, virtual influencers, synthetic media creation) alongside dangerous "Tricks" (brand sabotage, corporate fraud, and deepfake misinformation campaigns).	The rapid evolution of GANs renders early technological typologies obsolete quickly. Crucially, there is a distinct lack of quantitative empirical research measuring consumers' actual cognitive ability to detect synthetic media in digital advertising.
Kisheti, N. (2024)	The Rise Of Generative Artificial Intelligence	Edward Elgar Publishing (Book)	Case Studies / Comprehensive Synthesis	Details the macroeconomic and enterprise-level impacts of GenAI. Highlights massive cost reductions and productivity surges in marketing copywriting, graphic design, and code generation, while outlining the severe legal liabilities surrounding LLM training data.	The macroeconomic focus obscures micro-level marketing dynamics. It does not provide specific quantitative metrics on how Generative AI adoption alters the day-to-day cognitive decision-making processes of digital marketing managers.
Mariani et al. (2021)	AI in marketing, Consumer Research and psychology: a Systematic Literature Review and Research Agenda	Psychology & Marketing	Systematic Literature Review (SLR)	Merges marketing and psychological theories to map consumer reactions to AI. Highlights the paradox of "algorithmic aversion" (distrusting AI for subjective, emotional tasks) versus "algorithmic appreciation" (trusting AI over humans for objective, data-heavy tasks).	Extant literature is heavily skewed toward controlled, artificial laboratory experiments. Critically lacks "in the wild" field studies tracking actual, unprompted consumer behavior when interacting with AI systems in live commercial settings.
Mustak et al. (2021)	Artificial intelligence in marketing: Topic modeling, scientometric analysis, and research agenda	Journal of Business Research	Topic Modeling (LDA) & Scientometrics	Analyzed 800+ papers using LDA algorithms to identify core themes: consumer sentiment analysis, algorithmic pricing, and marketing strategy. Demonstrated that while the field is growing exponentially, the research remains highly fragmented and siloed.	The methodology relies almost entirely on algorithmic text analysis of abstracts and keywords. This misses the nuanced, qualitative content of full-text articles, thereby limiting the depth of theoretical insight derived from the review.
Paschen et al. (2020)	Artificial intelligence: Building blocks and an innovation typology	Business Horizons	Conceptual Typology	Deconstructs AI into functional building blocks: inputs, processes (machine learning, NLP), and outputs. Maps these blocks to product and process innovation, demonstrating how marketers can construct AI-driven value propositions.	Provides a high-level conceptual taxonomy but fails to offer specific, step-by-step implementation frameworks, ROI metrics, or empirical evidence to guide marketing managers in executing these innovations practically.
Rust, R.T. (2020)	The future of marketing	International Journal of Research in Marketing	Conceptual Essay / Thought Leadership	Argues that AI-enabled personalization will render traditional mass advertising and broad segmentation obsolete. Predicts a complete paradigm shift toward service-driven, 1-to-1 algorithmic customer relationships and automated consumption.	Highly visionary and predictive piece lacking empirical case studies. Does not fully account for the massive regulatory pushback (e.g., cookie deprecation, global privacy laws) that may legally hinder the hyper-personalization utopia described.
Vlačić et al. (2021)	The Evolving Role of Artificial Intelligence in marketing: a Review and Research Agenda	Journal of Business Research	Bibliometric Analysis & SLR	Proposes an integrative framework mapping AI antecedents (organizational readiness, data quality, tech infrastructure) directly to operational outcomes (enhanced customer experience, firm performance, accurate sales forecasting).	Explicitly notes that while the operational and financial benefits of AI are heavily researched, the ethical dimensions, algorithmic bias, and the long-term effects on consumer privacy remain severely under-investigated in academic literature.
Bayari and Hashem, (2025)	The role of artificial intelligence in personalizing social media marketing strategies for enhanced customer experience.	Behavioral Sciences	Quantitative study (Online questionnaire of 893 consumers in the MENA region).	Confirms that AI significantly enhances social media marketing by optimizing influencer selection, automating real-time interactions, and offering hyper-personalized content. These tools directly increase brand awareness, elevate the e-customer experience, and drive purchase intentions.	Geographically limited to the MENA region. Explicitly calls for further longitudinal research to deepen the understanding of how these specific AI tools sustain consumer attention over time across different global demographics.
Buder et al., (2024)	Beyond the buzz: Creating marketing value with generative AI.	NIM Marketing Intelligence Review	Mixed methods (Survey and in-depth interviews with 600 B2C marketing professionals).	Finds that GenAI breaks the traditional quantity vs. quality trade-off. Heavy users report massive time savings and cost reductions in market research and content creation. Uniquely, marketers are increasingly relying on GenAI for the "creative" ideation process, not just analytical tasks.	Reveals a critical knowledge and implementation gap: many marketing professionals lack the framework to navigate the legal (copyright) and ethical (bias, privacy) liabilities associated with deploying Generative AI at scale.
Gao and Liu, (2022)	Artificial intelligence-enabled personalization in interactive marketing: A customer journey perspective.	Journal of Research in Interactive Marketing	Conceptual framework and systematic literature synthesis	Introduces the concept of AI-enabled personalization (AIP) and maps its integration across the digital customer journey. AI fundamentally alters how consumers process personalized recommendations by reducing information overload and enhancing perceived relevance at every touchpoint.	Highlights a major gap in empirical research tracking long-term "customer ambivalence." Calls for future agendas to explore the tension between algorithmic personalization and the loss of consumer autonomy/choice.
Heitmann, M. (2024)	Generative AI for marketing content creation: New rules for an old game.	NIM Marketing Intelligence Review	Conceptual analysis / Thought leadership essay.	Argues that GenAI is revolutionizing the content value system by enabling high-quality, multi-modal marketing content (text, image, video) at unprecedented scale. It forces brands to rethink their strategic communication investments as content distribution costs plummet.	Highlights the technical limitations of "off-the-shelf" visual generative AI models, noting they are often misaligned with specific conventional advertising objectives (like evoking targeted attention or driving precise sales metrics) without extensive fine-tuning.
Kotha, S. (2024)	The convergence of artificial intelligence and human marketing: A framework for enhanced customer insights and personalization.	International Journal For Multidisciplinary Research	Mixed-methods (Quantitative analytics from 127 retail organizations; qualitative interviews with 34 professionals).	Introduces the Dual Intelligence Marketing Framework. Combining AI's real-time pattern recognition with human emotional intelligence yielded a 47% improvement in customer engagement and a 31% increase in conversion rates compared to traditional methods.	Identifies critical enterprise-level barriers to implementation, specifically highlighting gaps in technical infrastructure, talent adaptation, and the organizational challenges of integrating AI with legacy CRM systems.
Nazir et al., (2023)	Exploring the influence of artificial intelligence technology on consumer repurchase intention: The mediation and moderation approach.	Technology in Society	Quantitative survey (308 hotel customers in Oman) analyzed using SmartPLS (SEM).	Demonstrates that AI technology positively influences consumer engagement on social media and optimizes conversion rates. This creates a highly satisfying digital experience that significantly boosts long-term consumer repurchase intentions.	Sector and geographically constrained (hospitality industry in Oman). The study calls for further empirical testing across diverse B2C industries and broader, cross-cultural global populations.
Ononwu et al., (2023)	AI-driven predictive analytics for customer retention in e-commerce platforms using real-time behavioral tracking.	International Journal of Scientific Research and Modern Technology	Algorithmic modeling / Predictive analytics framework utilizing real-time behavioral data.	Shows that integrating AI predictive analytics and dynamic neural networks significantly enhances early churn risk identification, recommendation accuracy, and overall customer retention within highly dynamic, multi-source e-commerce environments.	Algorithmic approaches can suffer from stability issues under non-stationary market conditions. Calls for future research into highly adaptive, real-time decision systems that can handle sudden shifts in consumer behavior.
Wasilewski et al., (2025)	Enhanced e-commerce personalization through AI-powered content generation tools.	IEEE Access	Empirical study / Proposed technical framework.	Proposes a novel framework integrating multi-variant user interfaces (MultiUI) with AI-generated content (AIGC). Customizing both the visual UI layout and textual product descriptions for specific customer segments significantly improves conversion rates over traditional rule-based segmentation.	Notes that current literature heavily overlooks the synergy between UI design and content personalization. Further research is required to optimize behavior-based clustering prompts for AIGC tools (like ChatGPT) to avoid repetitive outputs.
Yin et al., (2025)	The impact of AI-personalized recommendations on clicking intentions: Evidence from Chinese e-commerce.	Journal of Theoretical and Applied Electronic Commerce Research	Mixed methods (Grounded Theory interviews with 30 consumers; structural equation modeling on 1097 survey responses).	Finds that relevance, inspiration, and insightful experiences generated by AI significantly promote clicking intention. Immersive digital experiences and high technology acceptance act as the primary mediators driving these clicks.	Discovers a severe negative moderating effect: if consumers perceive a high degree of information privacy infringement, the positive impact of the immersive AI experience on their clicking intention is drastically weakened or negated entirely.
Abrokvab-Larbi and Awuku-Larbi, (2024)	The impact of artificial intelligence in marketing on the performance of business organizations: evidence from SMEs in an emerging economy.	Journal of Entrepreneurship in Emerging Economies	Quantitative empirical study focused on SMEs in Ghana.	Empirically demonstrates that adopting AI marketing tools significantly enhances financial performance, customer retention, and internal business processes. Specifically identifies the integration of the Internet of Things (IoT), collaborative decision-making systems, and hyper-personalization as the primary strategic drivers of this performance boost.	Focuses exclusively on small and medium-sized enterprises (SMEs) within a developing economy context. Explicitly calls for comparative quantitative studies between emerging markets and fully developed digital economies to validate the universality of these performance metrics.
Al-Bdour et al.,(2024)	The role of marketing artificial intelligence in enhancing sustainable financial performance of medium-sized enterprises through customer engagement and data	Sustainability	Quantitative study utilizing Structural Equation Modeling (SEM).	Reveals that AI technology adoption leads to a 42.5% enhancement in sustainable financial performance. Critically, it proves this effect is not direct; it is strictly mediated by a 50% increase in customer engagement and a 76% improvement in the speed of data-driven decision-making.	Fails to establish a direct, isolated correlation between AI marketing and long-term financial performance without the presence of the mediating variables. Indicates a pressing need for longitudinal studies measuring AI's direct financial ROI over extended periods.

Khan et al., (2025)	How artificial intelligence and big data are shaping hyper-personalized marketing campaigns in e-commerce.	Regional Lens	Analytical framework / Empirical evaluation.	Details the strategic transition from basic demographic segmentation to algorithmic "hyper-personalization." Demonstrates that merging Big Data with AI predictive recommendation engines and real-time behavioral tracking fundamentally optimizes campaign targeting, heavily influencing consumer purchase decisions and building competitive advantage.	The scope is heavily restricted to the e-commerce sector. The authors acknowledge that scaling hyper-personalization requires strict strategic and ethical governance (e.g., algorithmic transparency) to prevent the erosion of consumer trust, an area requiring deeper behavioral investigation.
Konodromos, (2026)	AI-Driven Personalization in Marketing Administration: Qualitative Insights from European Professionals	Administrative Sciences	Qualitative study (Interpretive phenomenology and Actor-Network Theory). Semi-structured interviews with 36 senior European executives.	Identifies an ambivalent human-AI co-agency where AI acts as a "co-strategist" influencing budgets. Proposes the AI-MARC (Agency, Infrastructure, Responsibility, Capability) framework to manage the severe infrastructural challenges of integrating AI with legacy systems while navigating strict GDPR/EU AI Act regulations.	Addresses a specific geographical and regulatory boundary (Europe/GDPR). Highlights a critical gap regarding how to foster equitable networks that align rapid algorithmic innovation with fairness, accountability, and the redefinition of hybrid socio-technical professional identities.
Mukhopadhyay et al., (2024)	Developing artificial intelligence enabled Marketing 4.0 framework: an Industry 4.0 perspective.	Qualitative Market Research	Qualitative framework development (In-depth interviews with industry experts).	Constructs a validated theoretical framework establishing that AI integration elevates marketing performance primarily through four strategic pillars: advanced personalization, sustained consumer engagement, marketing automation, and broader organizational strategic alignment within the Industry 4.0 paradigm.	Primarily qualitative and exploratory in its methodology. While it provides a strong theoretical framework, it lacks the hard quantitative data required to measure the exact percentage of efficiency gained through automated AI marketing versus traditional human-led marketing efforts.
Saura et al., (2024)	Is AI-based Digital Marketing ethical? Assessing a New Data Privacy Paradox	Journal of Innovation & Knowledge	Systematic Literature Review (SLR) & Multiple Correspondence Analysis (MCA) using HOMALS.	Identifies a critical disconnect: the most profitable AI actions (cross-device tracking, IoT, real-time surveillance) have the weakest links to ethical standards. Proposes "Data Dignity," treating user data as an extension of identity. Links behavioral analytics and the metaverse as high-risk areas currently operating without sufficient privacy-by-design frameworks.	Explicitly states that no significant relationship currently exists in literature between high-profit data-driven actions and ethical implementation. Highlights a massive gap in how "privacy-by-default" standards are applied to real-time behavioral monitoring.
Acatrinei et al. (2025)	Artificial intelligence in digital marketing: Enhancing consumer engagement and supporting sustainable behavior through social and mobile networks	Sustainability	Quantitative Survey (n = 1,097) & Structural Equation Modeling (SEM).	Demonstrates that "Perceived Risk" regarding data privacy is the primary inhibitor of AI acceptance. Finds that consumer engagement is not just a result of tech utility but is strictly mediated by organizational transparency; if the AI logic is opaque, engagement metrics drop regardless of personalization quality.	The study is geographically focused on specific European social and mobile network users. It calls for broader cross-cultural research to determine if privacy norms and "perceived risk" thresholds vary significantly in non-Western digital ecosystems.
Hermann, E. (2022)	Leveraging Artificial Intelligence in Marketing for Social Good—An Ethical Perspective	Journal of Business Ethics	Normative Ethical Analysis & Conceptual Review.	Critically analyzes the "Black Box" nature of marketing algorithms. Finds that AI-driven segmentation often leads to unintended price discrimination and the digital exclusion of marginalized groups. Argues that "algorithmic bias" creates long-term reputational risks that outweigh short-term efficiency gains.	Primarily a normative and conceptual piece. It lacks quantitative hard data from a corporate perspective on the specific "cost of ethical compliance" or metrics for measuring the trade-off between algorithmic efficiency and social fairness in real-time.
Mardiati et al. (2024)	Data security and privacy concerns of AI-driven marketing in the context of economics and business field: an exploration into possible solutions	Cogent Business & Management	Systematic Literature Review (SLR) & Thematic Analysis.	Identifies a specific "Privacy Paradox" where consumers demand the benefits of AI-driven personalization while simultaneously fearing data misuse. Highlights organizational threats including cyber-vulnerability of AI training sets and the risk of AI-driven misinformation eroding brand trust.	Argues that extant literature is over-focused on technical security and legal (GDPR) compliance, neglecting the specific economic consequences and market-wide impact of systemic consumer distrust caused by AI privacy breaches.
Morley et al. (2021)	From what to how: An initial review of publicly available AI ethics tools, methods and research to support actionable ethical AI	Science and Engineering Ethics	Qualitative Review & Framework Development.	Establishes a foundational governance framework for "Operationalising AI Ethics." Finds that most organizations treat ethics as a "compliance checklist" rather than a strategic design principle, leading to organizational friction when high-level regulations (like the EU AI Act) are enforced.	The framework is multidisciplinary and broad. There is a specific research gap in adapting these general AI ethics tools into the specific, high-velocity workflow of digital marketing agencies and small-to-medium enterprise (SME) marketing departments.
Boyari and Hashem, (2025)	The role of artificial intelligence in personalizing social media marketing strategies for enhanced customer experience.	Behavioral Sciences	Quantitative study (Online questionnaire of 893 consumers in the MENA region).	Confirms that AI significantly enhances social media marketing by optimizing influencer selection, automating real-time interactions, and offering hyper-personalized content. These tools directly increase brand awareness, elevate the e-customer experience, and drive purchase intentions.	Geographically limited to the MENA region. Explicitly calls for further longitudinal research to deepen the understanding of how these specific AI tools sustain consumer attention over time across different global demographics.
Nguyen, J. (2025)	Invisible Inequities: How Algorithmic Marketing Reinforces Bias	Open Journal of Business and Management	Systematic Literature Review (SLR) & Interdisciplinary Synthesis.	Documents how marketing AI reproduces structural inequities through "stereotyping" in training data and biased recommendation engines that marginalize minority groups. Reports measurable metrics such as Disparate Impact (DI=0.60), proving that AI reinforces societal inequities even without harmful intent.	Highlights a lack of "intersectional" research. Specifically notes that the compounded effects of race, gender, and socioeconomic status in algorithmic targeting are critically under-explored in current marketing scholarship.
Akter et al. (2022)	Algorithmic bias in machine learning-based marketing models	Journal of Business Research	Conceptual framework development and systematic synthesis of ML microfoundations.	Develops a comprehensive taxonomy of algorithmic bias, categorizing it into Data Bias (unrepresentative training sets), Design Bias (flawed objective functions), and Socio-cultural Bias (reflecting human prejudices). It establishes that bias in ML marketing models leads to systemic "devastating and asymmetrical" impacts on consumer segments, such as discriminatory pricing and exclusion from credit or opportunities.	Primarily theoretical and focused on establishing the microfoundations of bias. The authors explicitly call for empirical research into "Dynamic Managerial Capabilities" (DMC) to investigate how marketing managers can practically detect and mitigate these biases during the deployment phase.
Pantoni et al. (2021)	Consumers and Artificial Intelligence: An Experiential Perspective	Journal of Marketing	Conceptual review and framework development.	Examines how AI impacts the professional experience through four lenses: automation, augmentation, interaction, and personalization. It finds that marketers perceive AI as a powerful tool for efficiency but experience "psychological friction" when AI threatens their perceived creative autonomy.	Primarily conceptual in nature. The authors explicitly state that there is a critical need for large-scale field experiments to measure the long-term psychological impact of AI-human collaboration on marketing team morale and creative output.
Verma et al. (2021)	Artificial intelligence in marketing: Systematic review and future research direction	International Journal of Information Management Data Insights	Systematic Literature Review (SLR) using bibliometric and TCCM analysis.	Identifies that marketing professionals value AI for its data-crunching capabilities but identify significant barriers in "interpretability" (the black-box problem) and the high cost of skilled talent. It highlights a widespread perception that AI lacks the "socio-emotional" depth required for high-level creative strategy.	Points to a significant geographical bias in existing literature, which is heavily focused on North American and European markets. It calls for research into how practitioners in emerging economies perceive and adopt AI tools.
Ismail and Eid (2025)	Marketing professionals' adoption of artificial intelligence and its influence on marketing efficiency	Benchmarking: An International Journal	Dual-method: UTAUT2 model with PLS-SEM and fuzzy-set qualitative comparative analysis (fsQCA) on 353 professionals.	Demonstrates that "Technology Resistance" (TR) acts as the most significant moderating barrier. Finds that high adoption is driven by a configuration of "Hedonic Motivation" and "Price Value," whereas "Performance Expectancy" alone is insufficient to overcome organizational inertia.	Geographically limited to marketing professionals in Sri Lanka. The study calls for broader cross-cultural validation to determine if "Technology Resistance" patterns remain consistent in different global labor markets.
Mustaqeem, K. M. (2025)	The Impact of Generative AI on Digital Marketing Strategies: Evidence from Emerging Markets	International Journal of Research and Scientific Innovation	Mixed-methods (120 marketing experts + 12 senior executives).	Shows that 68% of businesses in emerging economies are now employing GenAI for automated content and personalized campaigns. Reports a 23% lift in interaction ratios and improved ROI for early adopters in these regions.	Highlights "High Deployment Costs" and "Workforce Shortage" as uniquely severe barriers in emerging markets compared to developed economies. Calls for more affordable technology and transparent regulatory engagements.
Kashif et al. (2026)	Using artificial intelligence in digital branding: a two-phase qualitative approach	Euro-Mediterranean Journal of Business	Two-phase qualitative study (SLR of 3,983 documents + 17 expert interviews).	Identifies a shift from fragmented AI tools to integrated platforms that connect content, analytics, and personalization into a single managed ecosystem. Proposes that AI's primary role in 2026 is fostering "meaningful connections" through immersive digital branding.	Highlights that while AI-driven personalization is maturing, there is a lack of a consolidated framework explaining its implications for core brand identity and long-term consumer-brand relationship sustainability.
Haleem et al., (2022)	Artificial intelligence (AI) applications in marketing: A systematic-review	Information and Learning Sciences	Systematic Literature Review (SLR) mapping the lifecycle of AI marketing tools.	Identifies that AI's primary value lies in its capacity to process "big data" to accurately predict customer churn, automate content creation, and manage programmatic advertising bidding. Concludes that companies implementing AI-based hyper-personalization reported up to a 30% improvement in customer purchase intentions.	As a broad macro-level systematic review, it categorizes tools but lacks micro-level primary empirical data. The authors highlight a need for targeted quantitative studies to measure the actual financial ROI and operational friction of deploying these specific AI tools in real-world corporate settings.
Peltier et al., (2023)	Artificial intelligence in interactive marketing: a conceptual framework and research agenda	Journal of Research in Interactive Marketing	Systematic Literature Review (SLR) and conceptual framework development.	Demonstrates that the true transformative power of AI lies in "Machine-to-Human" interactive learning. Finds that AI algorithms (specifically ML) continuously adapt without human intervention, significantly enhancing Service Dominant Logic (SDL) by actively co-creating value with the consumer in real-time.	Primarily conceptual. Points out that while interactive AI is widely discussed, empirical research measuring the exact parameters of "value-in-use" outcomes during live, automated machine-to-human engagements remains scarce.
Sullivan and Wambsu (2024)	Artificial intelligence and adaptive response to market changes: a strategy to enhance firm performance and innovation	Journal of Business Research	Quantitative empirical study utilizing structural modeling.	Proves that AI capabilities drastically reduce a firm's response time to market volatility. Identifies that integrating AI into marketing communication (e.g., dynamic search ads, algorithmic social media distribution) allows firms to transition from reactive strategies to predictive innovation, yielding a direct uplift in firm performance.	Focuses heavily on the structural and strategic output of the firm. Lacks an in-depth exploration of the "human capital" side—specifically, how the cognitive load on marketing teams shifts when algorithms autonomously execute rapid market responses.
Rameshu et al. (2025)	The Role of Artificial Intelligence in Transforming Digital Marketing Strategies	International Journal of Latest Technology in Engineering, Management & Applied Science (IJLTEMAS)	Mixed-method approach utilizing both primary and secondary data. Primary data was gathered via a structured questionnaire from 140 respondents (convenience sampling) and analyzed using Pearson correlation and regression analysis.	Demonstrates that AI significantly enhances personalization, with 63% of respondents agreeing it improves digital marketing. Chatbots and predictive analytics showed weak positive correlations with overall customer experience. Critically, trust remains a severe issue, as only 30% of consumers trust AI with their personal data. The regression analysis revealed that basic personalization efforts do not have a statistically meaningful impact on customer experience without transparent, ethical deployment and effective chatbot integration.	The sample size is restricted to 140 participants acquired via convenience sampling, meaning the findings lack broad statistical generalizability for the global market. The study relies entirely on self-reported data, which is susceptible to subjective bias. The authors explicitly call for future empirical research into "Hybrid Intelligence" and the fusion of AI with emerging technologies like AR, VR, and IoT to understand long-term customer engagement.
Omri et al., (2025)	The Role of Artificial Intelligence and Digital Solutions in Transforming Educational and Employment Access for Individuals With Disabilities	The British Journal of Sociology	Quantitative macro-level analysis utilizing panel data from 33 high-income countries (2010–2022). Employs a moderated moderation model via the Hayes PROCESS macro with bootstrapped confidence intervals.	Demonstrates a significant "moderated moderation" effect where AI and digitalization synergistically amplify the impact of education on employability for individuals with disabilities. AI acts as a critical moderator by creating adaptive learning environments and fostering technical skills, while broader digitalization provides the infrastructural foundation for equitable labor market inclusion.	Geographically restricted to high-income developed nations. The macro-level panel data approach fails to capture the micro-level, lived experiences of individuals interacting with specific AI accommodations. It explicitly highlights a need to investigate how these dynamics operate in developing economies where foundational digital infrastructure and adaptive technologies remain inaccessible.

Brocato & Davis (2025)	Transforming marketing creative capacities: the role of artificial intelligence in minimizing cognitive load and enhancing task performance	European Journal of Marketing	Two quantitative experimental studies. Study 1 utilized 250 undergraduate students, while Study 2 utilized 200 marketing professionals via Prolific. Manipulated AI assistance (presence/absence) and task complexity (low/high) to measure impacts on cognitive load and performance.	Empirically proves that AI assistance significantly reduces both cognitive load and perceived task difficulty, with these benefits amplifying as task complexity increases. Demonstrates that AI acts as an extension of the marketer's cognitive capacity, freeing up mental resources and allowing professionals to achieve higher-quality task performance and faster completion times for complex marketing strategies.	The experimental, controlled nature of the studies may lack full ecological validity compared to chaotic, real-world agency environments. The study relies heavily on subjective self-reporting for cognitive load. It explicitly calls for future research utilizing objective physiological measures (e.g., eye-tracking) and longitudinal studies to determine if long-term AI reliance degrades inherent human creative skills.
Trinh et al., (2025)	A Systematic Review of Artificial Intelligence Integration in Modern Marketing Strategies: Evaluating Consumer Engagement, Ethical Challenges, and Performance Outcomes	Sustainability (MDPI)	Systematic Literature Review (SLR) utilizing the PRISMA framework to analyze recent peer-reviewed literature on AI marketing integration.	Synthesizes AI's impact across three core dimensions: technical execution (hyper-personalization, NLP chatbots), business value (enhanced ROI and predictive lead scoring), and socio-technical impacts. Confirms that AI successfully shifts marketing from reactive to proactive forecasting. However, it highlights a severe "privacy paradox," where consumers demand extreme personalization but actively resist the algorithmic surveillance required to achieve it.	Identifies a pronounced geographical and cultural bias in existing literature, noting that the vast majority of empirical data is derived from Western, developed economies. Explicitly calls for longitudinal, cross-cultural studies. Furthermore, it highlights a critical lack of empirical research testing "Explainable AI" (XAI) as a practical mechanism to mitigate "black-box" distrust among consumers.
Chishty et al. (2025)	The Utilisation of Artificial Intelligence in the Export Performance of MNCs: The Role of Cultural Distance	Administrative Sciences (MDPI)	Quantitative empirical study grounded in the Resource-Based View (RBV). Utilized Structural Equation Modeling (SEM) to analyze survey data from 449 Indian multinational exporters across diverse industries.	Empirically proves that AI capabilities significantly boost export intensity, trade expansion, and market penetration, particularly in regions with high institutional uncertainty. Crucially, it identifies "cultural distance" as a major positive moderator: AI-driven analytics amplify a firm's ability to navigate foreign language barriers, predict localized consumer preferences, and adapt to complex international regulatory environments.	The sample is exclusively restricted to Indian multinational corporations (MNCs) operating as exporters. While it provides a robust framework for emerging markets, the findings lack generalizability. It highlights a critical need for comparative studies to test whether the moderating effect of "cultural distance" operates identically for MNCs originating from fully developed digital economies.
Mogaji & Sivrajah (2020)	The implications of artificial intelligence on the digital marketing of financial services to vulnerable customers	Australasian Marketing Journal	Conceptual review and theoretical framework development based on a critical synthesis of existing multidisciplinary literature.	Demonstrates that while AI offers financial institutions enhanced targeting capabilities, it simultaneously creates new forms of digital vulnerability (data, technical, spatial). Algorithms can inadvertently or intentionally profile and exploit vulnerable customers (e.g., the elderly, low-income, or digitally illiterate) leading to financial exclusion, predatory pricing, and unfair credit scoring. Proposes a framework for ethical, transparent AI deployment.	The paper is entirely conceptual and lacks primary empirical data to measure these effects in the real world. The authors explicitly call for future qualitative and quantitative empirical research to test their theoretical propositions and to actively measure the psychological and financial impact of AI algorithms on specific vulnerable cohorts across different countries.
Gomes et al., (2025)	Anthropomorphism in artificial intelligence: a game-changer for brand marketing	Future Business Journal	Quantitative empirical study. Data collected via a structured questionnaire from 1,319 participants and analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM).	Demonstrates that integrating anthropomorphic traits (e.g., human-like tone, expressions, and personality) into AI chatbots profoundly transforms digital interactions. Anthropomorphism significantly boosts customer satisfaction, trust, and brand loyalty. Crucially, it identifies that "customer engagement" acts as a powerful mediator: the human-like design of the AI does not directly drive sales on its own, but rather fosters deep psychological engagement, which in turn significantly positively influences purchasing decision-making.	The study relies on cross-sectional data, capturing consumer perceptions at a single point in time. While it proves the mediating power of engagement, it lacks a longitudinal perspective to determine if the positive effects of AI anthropomorphism degrade over time as the "novelty" wears off. Additionally, the study notes that despite high engagement potential, overall consumer adoption of chatbots remains structurally low, indicating a gap between theoretical engagement and actual market utilization.
Islam et al. (2024)	Transforming Digital Marketing with Generative AI	Computers (MDPI)	Conceptual framework development (MARK-GEN) combined with qualitative validation through two practical case studies within the fashion industry (e.g., image-based virtual try-on models).	Introduces MARK-GEN, a structured, iterative conceptual framework designed to help businesses integrate Generative AI into their marketing workflows. The fashion industry case studies demonstrate that deploying GenAI effectively overcomes the creative bottlenecks of manual content generation, allowing brands to produce highly compelling, unique, and tailored visual marketing materials at an unprecedented scale.	The MARK-GEN framework is explicitly conceptual and flexible, lacking a rigid implementation sequence. Furthermore, the empirical validation is strictly confined to the fashion retail sector. The study highlights a critical need for future quantitative research across diverse industries (e.g., B2B, finance, services) to statistically measure the financial ROI and operational efficiency gained from this framework.

Behara et al. (2024)	Transforming customer engagement with artificial intelligence E-marketing: an E-retailer perspective in the era of retail 4.0	Marketing Intelligence & Planning	Quantitative methodology utilizing Covariance-based Structural Equation Modelling (CB-SEM). Primary data was gathered via surveys from 305 e-retailer customers in India.	Demonstrates that AI-driven e-marketing (AIeMktg) significantly enhances customer engagement (CE) by allowing retailers to predict demands and deliver hyper-personalized, location-based messages. Automation, error minimization, and decision-making capabilities positively influence the adoption of AIeMktg. Furthermore, customer commitment acts as a critical moderator; highly committed customers experience deeper engagement through AI interactions.	The study is geographically limited to a relatively small sample (305 participants) from a single developing country, India, which restricts global generalizability. It restricts its scope to self-efficacy factors, ignoring broader social marketing theories. Crucially, the model does not account for "Explainable AI" (XAI), treating deep learning algorithms as a "black box" that customers cannot interpret, potentially impacting trust.
Ziakis & Vlachopoulou (2023)	Artificial Intelligence in Digital Marketing: Insights from a Comprehensive Review	Information (MDPI)	Systematic literature review (SLR) guided by the PRISMA framework, combined with a comprehensive bibliometric analysis (using R Studio and Biblioshiny) of 211 relevant articles published between 2015 and 2023.	Identified seven dominant thematic clusters shaping the landscape: AI/ML Algorithms, Social Media, Consumer Behavior, E-Commerce, Digital Advertising, Budget Optimization, and Competitive Strategies. Concludes that AI/ML algorithms serve as the foundational "bedrock" of modern digital marketing, shifting the entire ecosystem toward data-driven decision-making, precise consumer targeting, and efficient resource allocation.	Acknowledges the risk of rapid obsolescence of insights due to the fast-paced evolution of AI technologies, as well as potential biases in bibliometric source selection. Explicitly calls for longitudinal studies focusing on AI ethics, data privacy, and consumer consent, alongside interdisciplinary research integrating AI with neuroscience to better understand user engagement.
Ntapias (2023)	Artificial intelligence in digital marketing: Descriptive analysis of companies' artificial intelligence strategies with random sampling	Ekileşim	Descriptive analysis utilizing a random sampling of five leading global corporations (JP Morgan Chase, Starbucks, Amazon, Unilever, Alibaba) with annual revenues exceeding \$10 million.	Demonstrates that integrating AI into marketing strategies directly correlates with significant revenue growth and enhanced customer acquisition. Specific findings include Amazon boosting recommendation accuracy by 50%, Unilever saving 50,000 hours in AI-driven recruitment and discovering new product flavors via social listening, and Alibaba achieving a 52.09% revenue increase through AI-optimized customer recommendation systems.	The methodology is heavily restricted to a descriptive analysis of five mega-corporations using publicly available revenue data. This restricts generalizability to small and medium-sized enterprises (SMEs) that lack similar capital. Furthermore, by focusing exclusively on successful implementations the study exhibits survivorship bias and lacks a quantitative assessment of the operational costs or failure rates associated with AI integration.