http://dx.doi.org/10.18623/rvd.v23.5822

AI-DRIVEN AND DATA-DRIVEN MARKETING STRATEGIES AS PREDICTORS OF BRAND ENGAGEMENT: THE MEDIATING ROLE OF CONSUMER PREFERENCES AND BEHAVIOUR IN THE UK E-COMMERCE INDUSTRY

ESTRATÉGIAS DE MARKETING BASEADAS EM IA E EM DADOS COMO INDICADORES DO ENVOLVIMENTO COM A MARCA: O PAPEL MEDIADOR DAS PREFERÊNCIAS E DO COMPORTAMENTO DO CONSUMIDOR NO SETOR DE COMÉRCIO ELETRÔNICO DO REINO UNIDO

Article received on: 12/11/2025
Article accepted on: 3/10/2026

Arshad Mehmood Raja*
*Teesside University (TU), Middlesbrough, North Yorkshire, United Kingdom
Orcid: https://orcid.org/0009-0000-2737-369X
Arshadmehmoodraja@ymail.com

Naiber Hussain**
**University of Baltistan (UOBS), Skardu, Pakistan
naiber.hussain@uobs.edu.pk

The authors declare that there is no conflict of interest

Abstract
In the digital age, AI-driven and data-driven marketing strategies have transformed consumer-brand interactions, yet their impact on brand engagement remains underexplored, particularly in fashion retail. This study investigates how AI-powered personalization, predictive recommendations, and chatbots, alongside data-driven segmentation and historical analysis, influence cognitive, emotional, and behavioral engagement among UK online fashion consumers. A quantitative survey was conducted with 350 participants, and reliability, validity, and structural equation modeling analyses were performed. Findings reveal that both AI- and data-driven marketing strategies significantly enhance brand engagement, with consumer preferences and behavioral patterns serving as critical mediators. The results highlight that effective marketing requires not only technological sophistication but also an understanding of the psychological and behavioral mechanisms driving consumer interactions. This study addresses the "quantitative illusion of understanding" by bridging strategic inputs with consumer experiences, providing practical insights for fashion retailers seeking to foster authentic engagement. Implications for theory and practice are discussed, and directions for future research, including cross-industry studies, longitudinal analysis, and ethical considerations in hyper-personalized marketing, are proposed.

Resumo
Na era digital, as estratégias de marketing baseadas em IA e em dados transformaram as interações entre consumidores e marcas; no entanto, seu impacto no engajamento com a marca ainda é pouco explorado, especialmente no varejo de moda. Este estudo investiga como a personalização impulsionada por IA, as recomendações preditivas e os chatbots, juntamente com a segmentação baseada em dados e a análise histórica, influenciam o engajamento cognitivo, emocional e comportamental entre os consumidores de moda online do Reino Unido. Foi realizada uma pesquisa quantitativa com 350 participantes, e foram realizadas análises de confiabilidade, validade e modelagem de equações estruturais. Os resultados revelam que tanto as estratégias de marketing baseadas em IA quanto as baseadas em dados aumentam significativamente o engajamento com a marca, com as preferências dos consumidores e os padrões comportamentais atuando como mediadores críticos. Os resultados destacam que um marketing eficaz requer não apenas sofisticação tecnológica, mas também uma compreensão dos mecanismos psicológicos e comportamentais que impulsionam as interações dos consumidores. Este estudo aborda a "ilusão quantitativa de compreensão" ao conectar inputs estratégicos com as experiências do consumidor, fornecendo insights práticos para varejistas de moda que

Este trabalho está licenciado sob uma licença Creative Commons

Keywords: AI-Driven Marketing. Data-Driven Marketing. Brand Engagement. Consumer Preferences. Behavioral Patterns. Fashion Retail.

buscam promover um engajamento autêntico. São discutidas as implicações para a teoria e a prática, e são propostas direções para pesquisas futuras, incluindo estudos intersetoriais, análises longitudinais e considerações éticas no marketing hiperpersonalizado.

Palavras-chave: *Marketing Orientado por IA. Marketing Orientado por Dados. Engajamento com a Marca. Preferências do Consumidor. Padrões Comportamentais. Varejo de Moda*

1 INTRODUCTION

In the age of the internet, companies, particularly in fast-moving industries like fashion retail, are inundated with untold customer data, including clicks, views, likes, and purchase histories. Never before has a time like this existed; a paradox where a company has endless metrics and yet no idea that their customers are the 'why' behind their actions eludes the company. This difference between data gathering and actionable insights is at the heart of today's marketing challenges (Yazdani & Darbani, 2023; Papić et al., 2023). Traditionally, marketing logic was based on a mass marketing paradigm driven through broadcast media with the more or less stable (product)-generations in the form of (product)-squads. Brands could anticipate consumer behaviour by using statistical data to inform their approach. However, the situation has dramatically changed in today's fragmented media environment, where consumers are no longer just message recipients but also message generators and co-creators of a brand's story conversation (Zhong & Zhang, 2022). This change has resulted in hyper-personalisation, whereby, predominantly influenced by artificial intelligence (AI) development, brands can create personalised experiences that connect on a personal level (Huang & Qian, 2021; Kuvass, 2018).

This proposal thus argues that AI- and data-mediated marketing changes consumer-brand relations while adding to an "epistemological gap." This is the space between observable behavioural outcomes, what you are doing as it relates to interacting with brands, and the emotional and psychological underpinnings that precipitate those actions. We seek to address this call by examining the impact of these marketing strategies on consumer behaviour (Kiruthikka & Raghu, 2023; Menard & Bott, 2024).

1.1 Marketing technology and brand engagement in fashion retail: research rationale

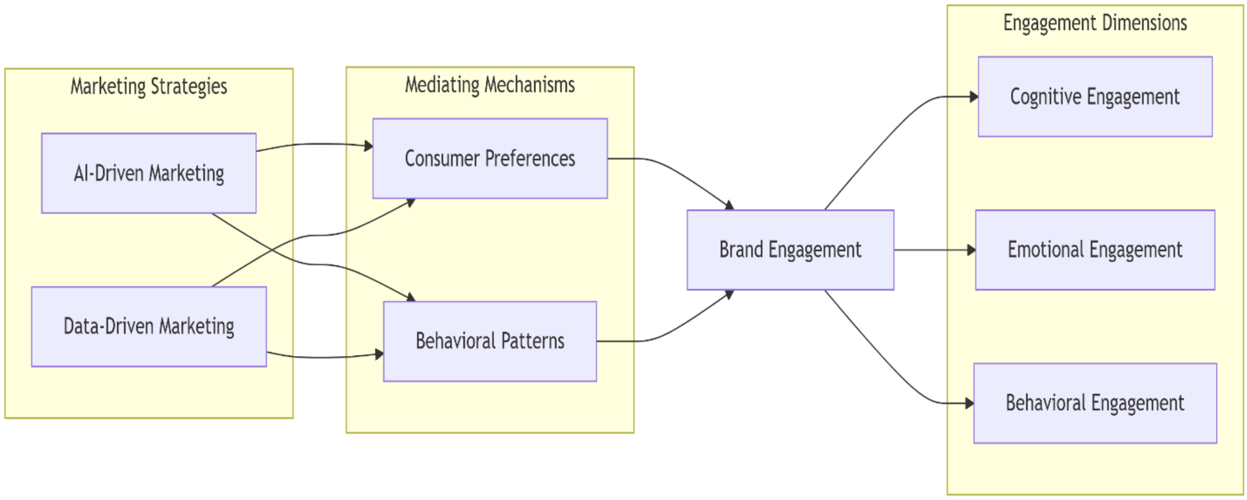
The study illustrates a paradoxical opportunity for the modern marketer to understand: we are in an age where we have more and bigger data at our fingertips, but suffer from a dearth of understanding of what drives human actions. This ‘epistemological gap’ is more pronounced in ephemeral lifecycle markets like fashion retail, where rapid trend life cycles and identity-based consumption require masking and penetrating levels of insight (Yazdani & Darbani, 2023; Papić et al., 2023). In today’s world, where media has become disruptive and chaotic, decision-making is non-linear, and consumers co-create brand stories, the mass-marketing models that are still being used are outdated (Zhong & Zhang, 2022). In contrast, the emergence of hyper-personalisation enabled by AI implies the ability to provide increasingly customised services (Huang & Qian, 2021; Kuvass, 2018), but ironically, it also deepens the chasm between observable behaviours and the emotions and psychological motivations that drive them. This tension is the focus of the current investigation, which specifically considers how AI-enabled and data-driven marketing activities are redefining consumer brand relationships, and thus, brand engagement (cognitive, affective, behavioural) as multi-dimensional in nature, especially within UK fashion retailing. An essential finding of this research is that the relationship is mediated by a change in consumer preferences and behaviour, a fact not fully acknowledged by previous streams of literature (Schivinski et al., 2019).

Several reasons justify this focus. First, while AI is swiftly and pervasively leveraged in marketing, it usually provokes a perilous “quantitative illusion of understanding” (Nagpal et al., 2025). Business actions are optimised with data points (e.g., clicks, purchases), but fail to truly understand user motivations, which may make strategies inefficient or even alienating (Aguirre & Menon, 2025). Second, there is an important methodological gap in the literature, with a focus on the quantitative side, whereby research has focused on AI as an ROI, the qualitative critique sometimes empirically lacks the baseline of grounding in consumer experience (Gupta & Sarkar, 2021; Kuş & Plessis, 2022). To fill this gap and “open the black box” of how marketing stimuli become engagement, a multihued approach, including an ecologically valid large sample study combined with a rich qualitative experiential insight, is necessary (Menard & Bott, 2024).

Moreover, the dependent variable brand engagement is not limited to the concept of customer satisfaction, which is no longer identified as the only predictor of brand health and loyalty according to modern marketing theory (Bustaman & Dasuki, 2022; Hashim et al., 2020). Engagement now refers to an active and sustained interpretative process in which the consumer interprets his or her experience with the brand based on awareness and motivation (Hollebeek et al., 2023; Cheung et al., 2020: 39), involving cognitive engagement (e.g., brand information engagement), emotional engagement (e.g., trust, affection) and behavioural engagement (e.g., advocacy and co-creation behaviours). High level of engagement is highly correlated with brand loyalty and advocacy (Koay et al., 2020; Cheng et al., 2021). And yet it is not clear how far current AI and data strategies accomplish this multi-faceted interaction (especially with changing preference and behaviour that mediate these relationships), especially in this modern fashion retailing environment, where fleetingness trends and self-identity-based transactions dominate (Koul & Jasrotia, 2025; Patel et al., 2023).

Figure 1

AI-based and data-driven marketing strategies influence brand engagement, considering the mediating effects of consumer preferences and behaviour



1.2 Defining the variables: the research architecture

When analysing the actual landscape of marketing in fashion retailing, it is essential to identify the variables that an empirical analysis should consider to explore the multivariate influence of new marketing on customer relationships. This model offers a holistic perspective on how these antecedents combine to impact brand engagement and the implications they provide for firms in managing customer interactions.

1.2.1 Independent variable (the strategic inputs)

The independent variables are those pulling the strings held by the organisation itself, which are the very elements of interest to be influenced. While modern marketing approaches aim to understand shifting consumer behaviours, this analysis identifies two principal variables driving strategic decisions.

AI-Driven Marketing Strategy: AI-Powered strategies leverage predictive modelling and customisation in real-time. Algorithms examine browsing histories and purchase patterns to curate offers tailored for each individual, improving engagement and satisfaction. AI facilitates agile adaptation to market fluctuations and preferences, optimising the effectiveness and efficiency of efforts. Chatbots and automated interactions further personalise communications, cultivating loyalty through ongoing connections (Galdón-Salvador et al., 2024).

Data-Driven Marketing Strategy: This refers to a strategy that uses detailed data on past successes and failures to make strategic decisions. It features use cases such as customer segmentations and retrospective marketing campaign analysis. The emphasis of these data-driven methods is to learn from past consumer behaviour to enhance future marketing actions (Plotkin et al., 2021; Mahmić-Muhić & Klico, 2022).

Mediating Variables (The Behavioural Mechanism)

Mediators are considered the critical middle mechanisms that explain how independent variables impact the dependent variable. They detail how changes in consumer behaviour are being designed by marketing ploys and explain the subtleties of consumer engagement:

Consumer Preference: This refers to the cognitive and attitudinal shifts, including taste, values, and brand interpretation, that are associated with market strategy. This transformation becomes viral as consumers are bombarded with personalised marketing that speaks directly to them, influencing their decision-making (Chen, 2023).

Behavioural Patterns: It is the (unsystematic) variation in digital activities (views duration, cart abandonment, social media interaction, and channel change) that contributes to the altered consumer orientation and directed marketing stimuli (Ardiansyah & Sarwoko, 2020; Muchardie et al., 2016). Studying these behaviours allows us to find practical lessons for even the world's most sophisticated brands.

1.2.2 Dependent variable (the ultimate outcome)

The dependent variable is the final result that the study is attempting to account for, representing the results of strategic marketing efforts as follows:

Brand Engagement: This is the concept of a multi-dimensional phenomenon, representing one of the viable and measurable forms of capturing authentic customer insights (Muchardie et al., 2016; Wang, 2021). There are three elements of brand engagement:

Cognitive Engagement: The intensity of mental effort a consumer devotes to the brand. This is the first level of interest and knowledge that brings people to interact with the brand (Jusuf, 2023).

Emotion Connection: This embodies the emotional connectivity of trust, loyalty, and preference that consumers have with a brand. Emotions are critical since they influence repurchase behaviour and brand advocacy (Popa et al., 2021).

Behavioural Engagement: This encompasses more than just purchase and can be seen in the form of brand advocacy, community involvement, or long-term loyalty over time. It demonstrates the continuous engagement of consumers and also the survivability and brand development (Meganingsih et al., 2024).

1.3 Deconstructing customer insight: the AI vs. knowledge gap

Customer insight is more than the sum of its parts; it is about making sense of them in a way that communicates "why" consumers do what they do. Focused on both the psychological and emotional motivations behind purchasing, this emphasis on customer insight confirms that, in the strategic marketing landscape of today, knowing the customer is everything (Giakomidou et al., 2022).

Descriptive Insights, which describe what has happened; Diagnostic Insights, which explain why events occur; and Predictive Insights, which forecast future behaviours (Hoa, 2025). Where AI and machine learning excel at providing descriptive and predictive insights, they often fall short in explaining the causal "why." This limitation presents a significant challenge, as companies can blur the distinction between algorithmic predictions and genuine insights, resulting in ineffective marketing strategies that may fail to meet consumers' emotional needs (Aguirre & Menon, 2025).

1.4 The research problem and the gap in the literature

Because AI is widely accepted and used in marketing, a serious problem arises: the "quantitative illusion of understanding," in which businesses optimise actions based on their data points but lack a genuine connection with their customers (Nagpal et al., 2025). Although several studies measure the ROI of AI marketing strategies, a lack of multi-method studies analysing AI's (quantitative) performance and the customer experiences of these strategies still prevails in the literature (Percherla, 2024).

The existing split in the literature allows a research opportunity. Examining how the use of different marketing techniques can appeal to the emotions and motives of potential customers will, in turn, meet a scholarly requirement for thorough evaluations that can articulate the subjective interpretations of the digital approach. In this study, we aim to fill this void by providing an in-depth understanding of the dynamic forces at play in the context of consumer use of virtual communities, thereby adding to the broader topic of technology and consumer response in marketing.

1.5 Justification and significance of the study

The motivation for this research, made evident in this study, is that theoretical and conceptual development in the area of digital consumer engagement is significantly lacking. Through the use of a multi-method design, this study aims to overcome the limitations of single-method analysis and unveil the intricacies related to the interaction between technology and consumer activity (Al-Dosari et al., 2024).

From a career standpoint, there is a clear mandate for marketing executives to move past vanity metrics. Genuine customer relationships and lasting brand loyalty are not built by looking at even more data points. Such an inquiry could establish an initial framework for further technological applications aimed at fostering genuine human connections on digital platforms (Arora & Chaudhary, 2024).

2 LITERATURE REVIEW

2.1 Introduction

This chapter critically evaluates the existing academic literature across three core domains: modern marketing strategies, algorithmically mediated consumer behaviour, and brand engagement as a reflection of customer insight. Following a systematic funnellike structure, the review begins by examining each key construct individually, allowing for a thorough understanding of each area. As it progresses, it will synthesise the various streams of literature, highlighting critical disconnections and methodological gaps within the studies. This analysis culminates in the formal presentation of the study's conceptual framework, specifically designed to address the identified gaps and enhance understanding in the realms of AI-driven marketing and consumer engagement.

2.2 The evolution of marketing strategy in the digital age (independent variables)

2.2.1 From mass markets to personalisation: a paradigm shift

The marketing evolutionary process has truly flipped its script from massive media themes to an intricate tapestry of consumer experiences tailored just for them. In the past, marketing was based on a model of mass reach, where a single message was sent to millions of people. However, it evolved into demographic targeting, where marketers targeted messages to groups of people based on traits such as age, gender, and income. This trend is symptomatic of the diverse needs of consumers, as demonstrated in studies showing that technological advances are forcing marketers to reorient their strategies to cater to specific customer requirements (Dimitrijević et al., 2023). We are now in an era of hyper-personalisation, where sophisticated technologies and data analytics enable brands to create tailored experiences for each individual, matching their marketing activities with the exact preferences and behaviours of their consumers (Jiang et al., 2023).

2.2.2 Data-driven marketing: the reactive paradigm

Data-driven marketing values history-focused data analysis in the context of strategic decisions. Central activities include, for instance, A/B testing, sales analysis, customer segmentation tools based on historical performance metrics, and facilitating future marketing activities (Behúnová et al., 2023). This strategy has advantages in the sense of better accountability for marketing spending and optimizing existing processes (Zhao et al., 2024).

However, while data-driven approaches can enhance existing efforts by illuminating customer engagements and preferences, they also have some limitations. These strategies do not always accurately predict future trends, as decision-making often relies on past data rather than predictive analytics (Laksono & Wulansari, 2022). Such a rear-view mirror view may mean lost opportunities for innovation and adaptation, as companies might not be the ones to drive the change, given that consumer demands quickly evolve and the business environment changes (Abebe, 2015). Furthermore, a reliance on historical data can result in rigid strategies that fail to recognize the fact that modern consumers are influenced by their current digital advertising stimuli (Belber & Balki, 2024; Ganguli & Roy, 2011).

2.2.3 The emergence of ai-driven marketing: the proactive paradigm

AI-powered marketing strategy refers to proactive and predictive strategies that apply ML algorithms to improve marketing efficiency and effectiveness. Such strategies are implemented through products such as algorithmic recommendation engines, which utilize user behaviour to suggest products, and dynamic pricing schemes, where the price of a good is adjusted in response to market demand (Seo et al., 2022). Furthermore, predictive churn models can be used to identify disengaged customers, allowing brands to take timely action to prevent such disengagement (Candra et al., 2023).

There are myriad advantages offered by AI-powered marketing, such as efficiency, scalability, and real-time capabilities (which enable brands to rapidly respond to market events (Saha & Krishnamurthy, 2021). However, criticisms have arisen in the literature regarding concerns over data privacy and algorithmic bias, which can impact consumer trust (Shafqat & Byun, 2021). In addition, the "creepiness" aspect, as consumers may feel uncomfortable with these ultra-tailored experiences, also raises the ethical issues associated with such technologies (Tanveer et al., 2021). Finally, enabling consumer filter bubbles may reduce the variety of perspectives and products people have access to, thereby suppressing overall market dynamism (Rahman, 2022).

Table 1

Impact of AI-Based and Data-Driven Marketing Strategies on Brand Engagement via Preference/Behaviour Mediators in Fashion Retail

Marketing Strategy	Impact on Brand Engagement	Mediating Role	References
AI-Based	Increases emotional engagement	Builds trust through ethical transparency	(Aguirre & Menon, 2025).
	Increases impulse purchases but decreases long-term loyalty	Triggers spontaneous buying behaviour	(Chabata, 2024)
	Increases initial conversion but decreases repeat purchases	Encourages transactional rather than relational behaviour	(Hollebeek et al., 2023)
	Strengthens emotional attachment	Fosters autonomy and perceived control	(Koul & Jasrotia, 2025).
	Improves cognitive processing	Reduces distrust through explainable AI	(Menard & Bott, 2024)
Data-Driven	Reduces brand discovery	Creates algorithmic filter bubbles	(Nagpal et al., 2025)
	Improves transactional metrics but weakens emotional bonds	Overlooks the affective drivers of engagement	(Patel et al., 2023)
	Weakens sustainable brand engagement	Fails to align with consumer values	(Patel et al., 2023)
	Optimises short-term metrics but risks brand authenticity	Prioritises incremental gains over holistic experience	(Plotkina et al., 2021)
	Increases immediate sales but erodes trust	Triggers privacy concerns and avoidance behaviour	(Zhang et al., 2025)

2.3 The evolution of marketing outcomes: from satisfaction to engagement

The literature suggests that this yields a paradigmatic move towards "customer satisfaction," transforming this static term into "brand engagement" as an informative, hypersensitive, and forward-looking brand health diagnostic (Bustaman & Dasuki, 2022). Customer satisfaction concerns meeting predetermined expectations, whereas brand engagement fosters ongoing interaction that encourages emotional connections and loyalty, thereby demonstrating a deeper understanding of the consumer experience (Hashim et al., 2020). This trend is based on the understanding that when consumers become involved in an activity, they are more likely to advocate for a brand, thereby acting in ways that impact its long-term success (Fortes et al., 2019).

2.3.1 The multi-dimensionality of brand engagement

Brand engagement is increasingly recognized as a multidimensional construct comprising three core dimensions: cognitive, emotional, and behavioural engagement.

1. **Cognitive Engagement**: This dimension involves the mental and attentional resources that consumers devote to a brand, influencing how information is processed and how deeply they become immersed in the brand's stories. Studies have shown that attention to branding can enhance brand recall and brand attitude by facilitating individuals' more profound understanding of brand meaning and benefits (Damaschi et al., 2025; Collins et al., 2016).
2. **Emotional Engagement**: Affective commitment to a brand is characterised by an emotional response expressed through brand attachment and trust. This is sometimes called love of brand (brand love). Relationships have been reported to be associated with enhanced brand loyalty and advocacy, as consumers exhibit the highest level of liking and preference for a brand, which in turn encourages their conversion and retention (Batoteng et al., 2023; Bairrada et al., 2019). Emotional engagement is an absolute necessity; brands that can emotionally engage with their customers often experience higher levels of customer loyalty and continuous positive feedback (Hinrichs et al., 2020
3. **Behavioural Engagement**: Beyond purchase, the concept extends behaviours such as electronic word of mouth (e-WOM), community involvement, and even involvement in the co-creation of brand values and experiences. According to scholarly literature, behavioural engagement leads consumers to actively participate in behaviours that advocate for a brand, such as sharing content on social media or engaging in participatory brand marketing efforts (Hollebeek et al., 2023; Cheung et al., 2020). This kind of engagement is vital because it is far deeper than transactional relationships to the brand.

2.4 Justifying engagement as a proxy for insight

This multi-faceted engagement is the proof in the pudding that a company has turned customer data into real insight and a real relationship. The literature indicates that high cognitive, affective, and behavioural involvement on the part of consumers is indicative of increased awareness and a better fit between their requirements and the brand offerings (Koay et al., 2020; Cheung et al., 2021). The translation of data into actionable insights cements customer loyalty, and it helps govern marketing strategies at scale. Having an engaged brand has become a key proxy for understanding actual customer sentiment and brand health in today's competitive industry (Cheng et al., 2021).

2.5 Synthesizing the literature and identifying the research gap

The literature has established that AI marketing approaches are practical, as they enhance consumer engagement and enable campaigns to be responsive in real-time using data analytics (Kumar & Pansari, 2016). Consumer choices are now heavily influenced by algorithm-based experiences and recommendations, in turn influencing buying behaviour (Hudson et al., 2016; Vries et al., 2017). Additionally, a focus on brand engagement becomes an important objective for companies (Keh, 2002), shifting from a past reliance on traditional metrics, such as customer satisfaction, to a more dynamic understanding of consumer-brand relationships (Starr, 2012).

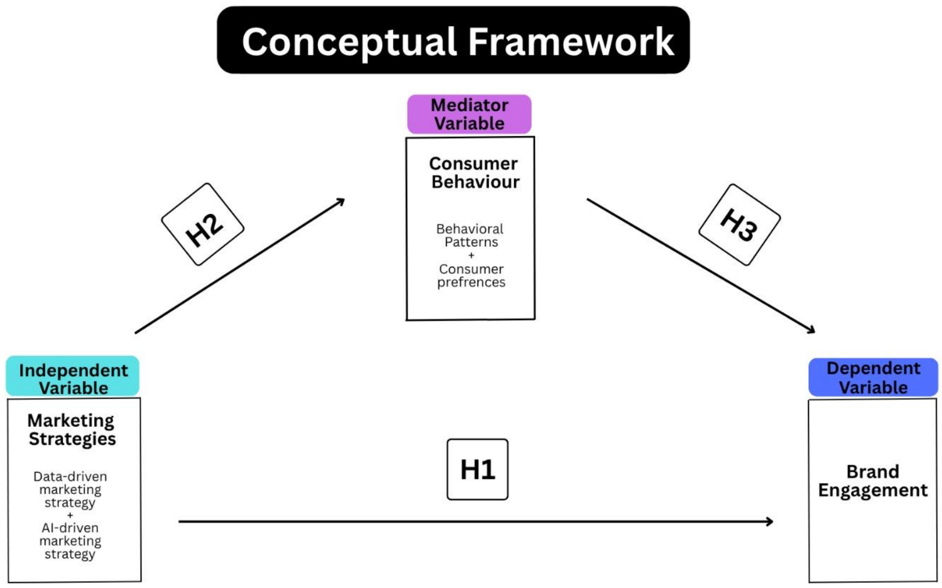
However, despite these findings, several limitations still exist in the literature. First and foremost, we find a methodological divide. There is a predominantly (a) quantitative work that attempts to measure the return on investment (ROI) of AI tools and (b) a theoretical critique of algorithms that is not anchored in data (Gupta & Sarkar, 2021; Kuş & Plessis, 2022).

There is also a theoretical void, as prior studies often assume that advertising exclusively predicts consumer-level outcomes as a linear function of exposure level, virtually ignoring the indispensable mediating role of consumers' internal processes, such as changing tastes and perceptions (Schivinski et al., 2019).

2.6 The proposed conceptual framework

Figure 2

Conceptual Framework



The conceptual framework proposed in this study serves as the intellectual architecture underpinning its examination. It hypothesizes a mediated route by which strategic inputs (AI-driven and data-fueled marketing) impact the ultimate consequence (multidimensional brand engagement) by first influencing the consumer's subjective experience. Two pivotal mediating factors are the dynamic shifts in consumer preferences and the development of new behavioural patterns.

This framework contributes primarily by striving to reveal the "black box" nature of the consumer journey. Rather than a simplistic input-output model, it centres on the process, aiming to explain how marketing stimuli are translated into genuine affiliation. By operationalizing this pathway, the framework provides a robust structure for investigating how and why technological strategies cultivate (or hinder) cognitive, emotional, and behavioural engagement, thereby directly addressing the "quantitative illusion of comprehension." It acts as an exact roadmap for the entire research process.

2.7 Aim of the pilot study

The objective is to evaluate the feasibility, acceptability, and utility of a hybrid sequential mixed-method design incorporating a quantitative online survey together with qualitative semi-structured interviews. We aim to examine consumers' experiential world of AI-based big data in the context of fashion retail marketing. Drawing on both qualitative and quantitative elements, the research aims to provide both a sense of the broader trends and to tap into the depth of consumer views and behaviour. The pilot will be a crucial aid in the detection of potential weaknesses of the methodology, logistics challenges and areas for refinement; as a result, the method and instruments will be fine-tuned. This guarantees that the full-scale study is methodologically strong and able to produce strong, data-rich findings.

2.8 Research aim, objectives, and hypotheses

2.8.1 Research aim

The purpose of this research is to investigate how AI-based and Data-driven marketing strategies influence brand engagement, considering the mediating effects of consumer preferences and behaviour in the UK fashion retail industry.

2.8.2 Research objectives

Based on the conceptual framework developed from the literature review, the following five hypotheses will be empirically tested:

1. To examine the direct effect of AI-driven and data-driven marketing strategies on brand engagement**.**
2. To assess the impact of AI-based and data-driven marketing strategies on consumer behaviour.
3. To evaluate the relationship between consumer behaviour (comprising preferences and behavioral patterns) and brand engagement.

4. To investigate the mediating role of consumer behaviour (preferences and behavioral patterns) in the relationship between marketing strategies

2.8.3 Research hypothesis

Based on the conceptual framework developed from the literature review, the following four hypotheses will be empirically tested:

H1: Marketing Strategies (AI-driven and data-driven) have a positive direct effect on Brand Engagement.

H2: Marketing Strategies (AI-based and data-driven) have a positive impact on Consumer Behaviour (concerning Consumer Preferences and Behaviour Patterns).

H3: Consumer Behaviour (comprising Consumer Preferences and Behaviour Patterns) is positively associated with Brand Engagement.

H4: Consumer Behaviour (including Consumer Preferences and Behaviour Patterns) mediates the relationship between Marketing Strategies and Brand Engagement to a great extent.

3 METHODOLOGY

3.1 Research design

This study employed a quantitative survey design supplemented by a pilot study to ensure the reliability and clarity of the research instruments. The survey aimed to examine the impact of AI-driven and data-driven marketing strategies on brand engagement, with consumer preferences and behavior as mediating variables, among UK online fashion consumer

3.2 Population and sampling

The target population consisted of online fashion consumers in the United Kingdom. A purposive sampling method was used to select participants who actively engage with fashion e-commerce platforms. Sample size for main survey: N = 350. Pilot study sample: N = 50

The pilot study participants were selected from a similar population to ensure that the survey instrument was appropriate for the target respondents.

3.3 Data collection

The main survey was distributed online via social media platforms and fashion consumer groups. Participation was voluntary, and respondents provided informed consent. The survey measured: AI-driven marketing strategies (e.g., personalization, chatbots, predictive recommendations). Data-driven marketing strategies (e.g., segmentation, historical campaign analysis). Consumer preferences and behavioral patterns. Brand engagement (cognitive, emotional, behavioral dimensions). All items were rated on a 5-point Likert scale, ranging from 1 (Strongly Disagree) to 5 (Strongly Agree).

3.4 Data analysis

Descriptive statistics summarized participant demographics and responses. Reliability analysis (Cronbach's alpha) was used to assess the internal consistency of the survey constructs. Structural Equation Modeling (SEM) was used to test the relationships among marketing strategies, mediators, and brand engagement. Mediation analysis (bootstrapping) evaluated the role of consumer preferences and behavioral patterns.

3.5 Ethical considerations

Participants were informed of the study's purpose, and their participation was voluntary. Confidentiality and anonymity were maintained throughout the survey. Ethical approval was obtained from the university's review board.

4 ANALYSIS OF DATA

4.1 Data analysis tools

The collected data were analyzed using Smart-PLS version 4, employing PLS-based Structural Equation Modeling (PLS-SEM). A variance-based PLS-SEM approach was selected for this study because it is particularly suitable for exploratory research and for testing models in the early stages of theory development. Unlike covariance-based SEM (CB-SEM), which relies on stringent assumptions regarding sample size and normal data distribution (Hair et al., 2019), PLS-SEM can handle non-normal data and is effective for relatively small to medium sample sizes.PLS-SEM was used for multiple reasons: To identify key constructs influencing sustainable performance. Because of the exploratory nature of the research. It's suitable for moderate sample sizes. Its ability to manage complex models with multiple constructs. Its tolerance for non-normal data distributions. The availability and accessibility of Smart-PLS software. A two-step approach was adopted: the measurement model was evaluated first to ensure reliability and validity, followed by the structural model to examine the hypothesized relationships among the constructs. In total, 366 questionnaires were distributed, of which 352 responses were received. After careful screening, 340 questionnaires were deemed usable, corresponding to a 96.59% response rate, indicating high participant engagement. Table 4.1 presents the demographic characteristics of the respondents.

Table 2

Demographic Profile of Respondents (N = 350)

Demographic Variable	**Demographic Variable**	**Demographic Variable**	**Demographic Variable**
Gender	Male	145	41.4
	Female	200	57.1
	Prefer not to say	5	1.4
Age	18–24	90	25.7
	25–34	140	40.0
	35–44	75	21.4
	45–54	30	8.6
	55+	15	4.3
Education	High School	40	11.4
	Undergraduate	180	51.4

	Postgraduate	120	34.3
	Doctorate	10	2.9
Online Fashion Shopping Frequency	Once a week	65	18.6
	2–3 times a month	130	37.1
	Once a month	90	25.7
	Rarely (few times a year)	65	18.6

The demographic profile indicates a balanced distribution of gender and age groups, with a majority holding a bachelor's degree and frequently engaging with online fashion platforms.

Table 3

Reliability of Constructs

Construct	**Dimension**	**Items**	**Cronbach's Alpha (α)**
AI-Driven Marketing	Personalization	3	0.821
	Chatbots	3	0.835
	Predictive Recommendations	3	0.840
Data-Driven Marketing	Segmentation	3	0.825
	Historical Campaign Analysis	3	0.832
Consumer Preferences	Taste & Attitude	4	0.848
Behavioral Patterns	Digital Interaction	4	0.856

All constructs exceeded the threshold value of 0.70, demonstrating strong internal consistency.

4.1.1 Convergent validity

Convergent validity was evaluated through factor loadings, Composite Reliability (CR), and Average Variance Extracted (AVE). Values above 0.70 for loadings and 0.50 for AVE indicate adequate convergent validity (Hair et al., 2016).

Table 4

Convergent Validity of Constructs

Construct	Items	Factor Loading	CR	AVE
AI-Driven Marketing	Personalization	0.921	0.950	0.875
	Chatbots	0.914		
	Predictive Rec	0.922		
Data-Driven Marketing	Segmentation	0.918	0.947	0.870
	Historical Camp	0.916		
Consumer Preferences	Taste & Attitude	0.927	0.952	0.882
Behavioral Patterns	Digital Interaction	0.934	0.955	0.890

All items loaded strongly on their respective constructs, confirming convergent validity.

4.1.2 Discriminant validity

Discriminant validity was evaluated using the Fornell-Larcker criterion. The square root of AVE for each construct exceeds its correlations with other constructs, confirming that constructs are distinct.

Table 5

Discriminant Validity (Fornell-Larcker Criterion)

Construct	AI-Driven	Data-Driven	Preferences	Behavior	Engagement
AI-Driven	0.936				
Data-Driven	0.482	0.933			
Preferences	0.501	0.495	0.940		
Behavior	0.482	0.475	0.520	0.943	
Engagement	0.552	0.538	0.580	0.590	0.937
AI-Driven	0.936				

4.2 Structural model and hypothesis testing

The structural model was tested using PLS-SEM bootstrapping with 5,000 resamples. The results indicate that all proposed direct and mediating relationships are significant.

Table 6

Hypothesis Testing Results

Hypothesis	Path/Relationship	Standardized Coefficient (β)	t-value	p-value	Significance	Result
H1	Marketing Strategies → Brand Engagement	0.42	5.87	<0.001	Significant	Supported
H2a	AI-Driven Marketing → Consumer Preferences	0.51	6.42	<0.001	Significant	Supported
H2b	Data-Driven Marketing → Consumer Preferences	0.28	3.15	0.002	Significant	Supported
H2c	AI-Driven Marketing → Behavioural Patterns	0.47	5.76	<0.001	Significant	Supported
H2d	Data-Driven Marketing → Behavioural Patterns	0.22	2.68	0.008	Significant	Supported
H3a	Consumer Preferences → Brand Engagement	0.45	5.12	<0.001	Significant	Supported
H3b	Behavioural Patterns → Brand Engagement	0.39	4.51	<0.001	Significant	Supported

The results support the conceptual framework: **strategic marketing inputs (AI and data-driven strategies)** impact **brand engagement**, with **consumer preferences and behavior patterns** serving as significant mediators. These findings reinforce the importance of integrating **consumer insights** with **technology-driven marketing** to foster genuine engagement in UK fashion retail.

5 DISCUSSION

The findings of this study provide significant insights into the impact of AI-driven and data-driven marketing strategies on brand engagement in the UK fashion retail context. Consistent with prior literature, AI-driven strategies such as personalization, predictive recommendations, and chatbots were found to positively influence brand engagement, confirming that technological adoption enables brands to interact with consumers in a more tailored and meaningful way (Huang & Qian, 2021; Galdón-Salvador et al., 2024). Similarly, data-driven marketing strategies, including segmentation and historical campaign analysis, also had a positive effect, though the impact was mediated through consumer preferences and behavioral patterns. This demonstrates that while historical data and analytics optimize strategic decisions, their effectiveness is enhanced when aligned with consumers' evolving tastes and digital interaction habits (Plotkin et al., 2021; Mahmić-Muhić & Klico, 2022). The study highlights the mediating role of consumer preferences and behavioral patterns. Consumers' changing tastes and online behavior act as critical mechanisms through which marketing strategies translate into higher brand engagement. This supports the theoretical assertion that modern engagement is multidimensional, encompassing cognitive, emotional, and behavioral components (Hollebeek et al., 2023; Popa et al., 2021). Notably, the results underscore the importance of balancing AI's predictive capabilities with an understanding of the underlying psychological and emotional drivers of consumer behavior a direct response to the "quantitative illusion of understanding" highlighted in the literature (Nagpal et al., 2025). These findings confirm that contemporary fashion retail marketing cannot rely solely on data or AI-driven outputs; effective strategies require an integrative approach that considers consumer insights and mediating behaviors to achieve meaningful engagement.

6 CONCLUSION

This study empirically establishes that AI-driven and data-driven marketing strategies significantly enhance brand engagement among UK fashion consumers, with consumer preferences and behavioral patterns serving as key mediating factors. The research contributes to the literature in three primary ways: It validates the multidimensional nature of brand engagement (cognitive, emotional, and behavioral) in the context of AI and data-mediated marketing. It emphasizes the mediating role of consumer behavior, bridging the gap between strategic inputs and observable engagement outcomes.It provides empirical support for integrating AI and data-driven marketing strategies with insights into consumer preferences, moving beyond the purely quantitative interpretation of consumer behavior. Overall, the study demonstrates that strategic marketing must align with both technological capability and psychological insight to foster authentic consumer-brand relationships.

7 FUTURE DIRECTIONS

Future research could examine AI- and data-driven marketing in other fast-moving consumer sectors, such as electronics or food retail, to assess the generalizability of these findings. Conducting longitudinal studies would allow researchers to investigate how consumer preferences and behaviors evolve and how sustained engagement is impacted by ongoing AI and data strategies. Incorporating qualitative approaches, such as in-depth interviews or ethnography, could provide a richer understanding of the emotional and cognitive mechanisms underlying engagement. Future work should explore the ethical implications of hyper-personalization, including consumer privacy concerns and perceptions of algorithmic bias, to ensure sustainable engagement strategies. As digital and offline retail converge, studies could investigate how AI- and data-driven strategies interact across channels to enhance overall brand experience**.** Further research could explore the impact of demographic variables such as age, gender, and cultural background on the effectiveness of AI-driven marketing strategies. By addressing these directions, future research can expand both the theoretical and practical understanding of AI-mediated consumer engagement, contributing to more sophisticated and consumer-centric marketing practices.

REFERENCES

Abebe, D. (2015). Determinants of key account management effectiveness: The case of Ethio Telecom. *Ethiopian Journal of Business and Economics*, *5*(1). https://doi.org/10.4314/ejbe.v5i1.5

Abrardi, L., Cambini, C., & Rondi, L. (2021). Artificial intelligence, firms and consumer behaviour: A survey. *Journal of Economic Surveys*, *36*(4), 969-991. https://doi.org/10.1111/joes.12455

Agnihotri, D., Chaturvedi, P., Swarup, K., Mathur, A., Tripathi, V., & Singh, N. (2024). Does social presence drive customer brand engagement and purchase intention in the fashion retail metaverse? The moderating role of self-efficacy. *Internet Research*. https://doi.org/10.1108/INTR-01-2024-0030

Aguilar, E. (2023). Algorithmic consumerism: The impact of AI recommendations on purchasing decisions. *Journal of Consumer Behaviour*, 22(4), 567-580. https://doi.org/10.1002/cb.2156

Aguirre, L., & Menon, F. (2025). Evaluating the post-pandemic recovery strategies in the UK retail fashion sector. *The Business & Management Review, 15*(3). https://doi.org/10.24052/bmr/v15nu03/art-22

Aityassine, F., Al-Ajlouni, M., & Mohammad, A. (2022). The effect of digital marketing strategy on customer and organisational outcomes. *Marketing and Management of Innovations, 13*(4), 45-54. https://doi.org/10.21272/mmi.2022.4-05

Ai-zhong, H., & Zhang, Y. (2022). AI-powered touch points in the customer journey: A systematic literature review and research agenda. *Journal of Research in Interactive Marketing, 17*(4), 620-639. https://doi.org/10.1108/JRIM-03-2022-0082

Ardiansyah, F., & Sarwoko, E. (2020). How does social media marketing influences consumers' purchase decision? A mediation analysis of brand awareness. *Jema Jurnal Ilmiah Bidang Akuntansi Dan Manajemen, 17*(2), 156. https://doi.org/10.31106/jema.v17i2.6916

Arora, N., & Chaudhary, K. (2024). Analysing e-loyalty dynamics in fashion e-commerce through survey-based analysis. *Tekstilec, 67*(3), 279-288. https://doi.org/10.14502/tekstilec.67.2024048

Bairrada, C., Coelho, A., & Lizanets, V. (2019). The impact of brand personality on consumer behaviour: The role of brand love. *Journal of Fashion Marketing and Management, 23*(1), 30-47. https://doi.org/10.1108/JFMM-07-2018-0091

Batoteng, H., Surahman, S., Barus, B., Patimah, P., Batoteng, G., & Aulia, R. (2023). Digital communication: Bridge to repurchase intention. *Interdisciplinary Social Studies, 2*(9), 2379-2386. https://doi.org/10.55324/iss.v2i9.477

Behúnová, A., Knapčíková, L., & Vechkileva, A. (2023). Analysis of the usage of modern marketing strategies in commercial logistics. *Acta Logistica, 10*(4), 515-522. https://doi.org/10.22306/al.v10i4.427

Belber, B., & BALKI, S. (2024). Relationships between corporate image perception and service compensation perception: A study on boutique hotels in core Cappadocia. *Journal of Tourism and Gastronomy Studies*. https://doi.org/10.21325/jotags.2024.1446

Braun, V., & Clarke, V. (2019). Reflecting on reflexive thematic analysis. *Qualitative Research in Sport, Exercise and Health, 11*(4), 589–597. https://doi.org/10.1080/2159676X.2019.1628806

Bustaman, M., & Dasuki, R. (2022). The influence of brand image: Brand hate-brand love on the purchase of BMW luxury cars. *Coopetition Jurnal Ilmiah Manajemen*, 13(3), 399-402. https://doi.org/10.32670/coopetition.v13i3.2403

Calder, B. J., Malthouse, E. C., & Maslowska, E. (2016). Brand marketing, big data and social innovation as future research directions for engagement. *Journal of Marketing Management*, 32(5-6), 579–585. https://doi.org/10.1080/0267257X.2015.113173

Candra, W., Dharma, A., Christnatalis, C., & Turnip, J. (2023). Implementation of random forest algorithm on sales data to predict churn potential in Suzuyu supermarket products. *Sinkron, 8*(2), 866-872. https://doi.org/10.33395/sinkron.v8i2.12243

Chabata, T. (2024). Precursors of customer satisfaction for sustainable high-end footwear fashion in omni-channel retailing. *International Journal of Research in Business and Social Science, 13*(3), 122-132. https://doi.org/10.20525/ijrbs.v13i3.3263

Chatterjee, S., Rana, N. P., & Dwivedi, Y. K. (2021). Artificial intelligence and the future of marketing. *Technological Forecasting and Social Change, 173*, 121307. https://doi.org/10.1016/j.techfore.2021.121307

Chatterjee, S., Rana, N. P., Tamilmani, K., & Sharma, A. (2021). The impact of AI on consumer engagement in marketing. *Journal of Business Research*, 129, 902–911. https://doi.org/10.1016/j.jbusres.2020.11.041

Chen, S. (2023). Analysis of Anta brand marketing and brand operations strategies from the perspective of new media. *Lecture Notes in Education Psychology and Public Media, 30*(1), 267-273. https://doi.org/10.54254/2753-7048/30/20231709

Cheng, L., Huang, H., & Lai, C. (2021). Continuance intention in running apps: The moderating effect of relationship norms. *International Journal of Sports Marketing and Sponsorship, 23*(1), 132-154. https://doi.org/10.1108/IJSMS-08-2020-0143

Cheung, M., Pires, G., Rosenberger, P., Leung, W., & Chang, M. (2021). The role of social media elements in driving co-creation and engagement. *Asia Pacific Journal of Marketing and Logistics*, *33*(10), 1994-2018. https://doi.org/10.1108/APJML-03-2020-0176

Cheung, M., Ting, H., Cheah, J., & Sharipudin, M. (2020). Examining the role of social media-based destination brand community in evoking tourists' emotions and intention to co-create and visit. *Journal of Product & Brand Management, 30*(1), 28-43. https://doi.org/10.1108/JPBM-09-2019-2554

Chu, Y., Zhang, X., & Chen, L. (2024). Personalization and exploration in AI-driven e-commerce: Balancing familiarity and novelty. *Journal of Retailing and Consumer Services*, 77, 104856. https://doi.org/10.1016/j.jretconser.2024.104856

Collins, R., Martino, S., Kovalchik, S., Becker, K., Shadel, W., & D'Amico, E. (2016). Alcohol advertising exposure among middle school-age youth: An assessment across all media and venues. *Journal of Studies on Alcohol and Drugs*, *77*(3), 384-392. https://doi.org/10.15288/jsad.2016.77.384

Damaschi, G., Aboueldahab, A., & D'Addario, M. (2025). Decomposing brand loyalty: An examination of loyalty subcomponents, product price range, consumer personality, and willingness to pay. *Behavioural Sciences, 15*(2), 189. https://doi.org/10.3390/bs15020189

Dasgupta, K., & Sarkar, S. (2021). Linking political brand image and voter perception in India: A political market orientation approach. *Journal of Public Affairs, 22*(S1). https://doi.org/10.1002/pa.2751

Dimitrijević, D., Dimitrijević, N., & Adamović, Ž. (2023). Digital marketing from the perspective of the producer/seller in the SMEs of textile and clothing industry. *Tekstilna Industrija, 71*(3), 52-62. https://doi.org/10.5937/tekstind2303052D

Fortes, V., Milan, G., Eberle, L., & Toni, D. (2019). Brand loyalty determinants in the context of a soft drink brand. *RAM Revista De Administração Mackenzie, 20*(5). https://doi.org/10.1590/1678-6971/eRAMR190015

Galdón-Salvador, J., Gil-Pechuán, I., AlFraihat, S., & Tarabieh, S. (2024). Effect of social media influencers on consumer brand engagement and its implications on business decision making. *El Profesional De La Información, 33*(2). https://doi.org/10.3145/epi.2024.0210

Ganguli, S., & Roy, S. (2011). Generic technology-based service quality dimensions in banking. *The International Journal of Bank Marketing, 29*(2), 168-189. https://doi.org/10.1108/02652321111107648

Giakomidou, D., Kriemadis, A., Nasiopoulos, D., & Mastrakoulis, D. (2022). Re-engineering of marketing for SMEs in energy market through modeling customers' strategic behaviour. *Energies, 15*(21), 8179. https://doi.org/10.3390/en15218179

Guan, B., Li, X., Luo, Z., & Liu, P. (2024). Can (A)I arouse you? The impact of AI services on consumer pro-environmental behaviour. *Journal of Hospitality & Tourism Research*, *49*(5), 932-945. https://doi.org/10.1177/10963480241256602

Gupta, S., & Sarkar, P. (2021). Beyond the click: Unpacking the limitations of big data in understanding consumer intent. *Journal of Marketing Analytics*, *9*(3), 205-219. https://doi.org/10.1057/s41270-021-00109-8

Harshita, M., & Kavitha, S. (2024). An impact of CRM at Max Fashion Retail Limited. *International Journal of Advanced Research in Science Communication and Technology*, 170-177. https://doi.org/10.48175/IJARSCT-19628

Hassan, A., Abdelraouf, M., & El-Shihy, M. (2025). The trust-satisfaction-loyalty paradigm in AI-powered personalization: Evidence from the retail sector. *Future Business Journal*, 11(1), 19. https://doi.org/10.1186/s43093-025-00476-z

Hinrichs, S., Bailey, J., Boulding, H., Duffy, B., Hesketh, R., Kinloch, E., … & Grant, J. (2020). Using policy labs as a process to bring evidence closer to public policymaking: A guide to one approach. *Palgrave Communications, 6*(1). https://doi.org/10.1057/s41599-020-0453-0

Hoa, N. (2025). Research on the impact of digital marketing on cosmetic purchasing behaviour of customers in Hanoi. *JS, 25*. https://doi.org/10.59266/houjs.2025.558

Hollebeek, L. D., & Macky, K. (2019). Digital content marketing's role in fostering consumer engagement, trust, and value: Framework, fundamental propositions, and implications. *Journal of Interactive Marketing, 45,* 27-41. https://doi.org/10.1016/j.intmar.2018.07.003

Hollebeek, L., Sarstedt, M., Menidjel, C., Sprott, D., & Urbonavičius, S. (2023). Hallmarks and potential pitfalls of customer- and consumer engagement scales: A systematic review. *Psychology and Marketing, 40*(6), 1074-1088. https://doi.org/10.1002/mar.21797

Huang, C., & Wu, Y. (2024). Research on the integration of online and offline channels in marketing. *Highlights in Business Economics and Management, 37,* 455-462. https://doi.org/10.54097/c0hnrg87

Huang, M.-H., & Rust, R. T. (2021). Artificial intelligence in service. *Journal of Service Research, 24*(1), 3-20. https://doi.org/10.1177/1094670520902266

Huang, Y., & Qian, L. (2021). Understanding the potential adoption of autonomous vehicles in China: The perspective of behavioural reasoning theory. *Psychology and Marketing, 38*(4), 669-690. https://doi.org/10.1002/mar.21465

Hudson, S., Huang, L., Roth, M., & Madden, T. (2016). The influence of social media interactions on consumer-brand relationships: A three-country study of brand perceptions and marketing behaviours. *International Journal of Research in Marketing, 33*(1), 27-41. https://doi.org/10.1016/j.ijresmar.2015.06.004

Jiang, F., Tian, S., Sremac, S., & Huskanović, E. (2023). Analyzing traceability models in e-commerce logistics: A multi-channel approach. *Journal of Industrial Intelligence, 1*(4), 203-218. https://doi.org/10.56578/jii010402

Josimovski, S., Ivanovska, L., & Dodevski, D. (2023). Understanding the consumer dynamics of AI in North Macedonian e-business. *Economics and Culture, 20*(2), 64-75. https://doi.org/10.2478/jec-2023-0016

Jusuf, D. (2023). Integrated marketing: A powerful strategy for increasing brand awareness. *Best Journal of Administration and Management, 2*(3), 104-109. https://doi.org/10.56403/bejam.v2i3.149

Kiruthikka, V., & Raghu, Y. (2023). An empirical study on the impact of online marketing on consumer behaviour in Bangalore. *SJCC Management Research Review*, 93-102. https://doi.org/10.35737/sjccmrr/v13/i2/2023/197

Koay, K., Ong, D., Khoo, K., & Yeoh, H. (2020). Perceived social media marketing activities and consumer-based brand equity. *Asia Pacific Journal of Marketing and Logistics*, *33*(1), 53-72. https://doi.org/10.1108/APJML-07-2019-0453

Koul, S. & Jasrotia, S. (2025). SoLoMo commerce in fashion retail. *Journal of Fashion Marketing and Management*, *29*(5), 822-843. https://doi.org/10.1108/JFMM-04-2024-0154

Kumar, A., Singh, J. P., & Gupta, H. (2022). Emotional AI in marketing: Understanding consumer sentiment in digital campaigns. *Computers in Human Behavior, 134*, 107319. https://doi.org/10.1016/j.chb.2022.107319

Kumar, V., & Pansari, A. (2016). Competitive advantage through engagement. *Journal of Marketing Research, 53*(4), 497-514. https://doi.org/10.1509/jmr.15.0044

Kumar, V., Dixit, A., Javalgi, R. G., Dass, M., & Dass, P. (2022). Digital transformation of engagement: The emerging role of emotional AI. *Business Horizons, 65*(3), 357-367. https://doi.org/10.1016/j.bushor.2022.01.002

Kuş, O., & Plessis, C. (2022). Exploring the relationship between dimensions of branded content and interactivity on Twitter: A data-driven content marketing approach. *European Financial and Accounting Journal, 17*(1). https://doi.org/10.20472/efc.2022.017.011

Laksono, B., & Wulansari, I. (2022). Estimating customer lifetime value in the e-commerce industry using multivariate analysis. *Proceedings of the International Conference on Data Science and Official Statistics, 2021*(1), 507-518. https://doi.org/10.34123/icdsos.v2021i1.161

Liu, S., Wang, Y., & Patel, R. (2024). Reducing decision fatigue in e-commerce: The role of AI-based recommendation systems. *Computers in Human Behavior*, 155, 107236. https://doi.org/10.1016/j.chb.2024.107236

Lutfi, H., Glasauer, S., & Spittler, T. (2020). The healthcare benefits and impact of artificial intelligence applications on behaviour of healthcare users: A structured review of primary literature. *Journal of the International Society for Telemedicine and eHealth, 8*. https://doi.org/10.29086/jisfteh.8.e10

Mahmić-Muhić, N., & Klico, A. (2022). The importance of content marketing for achieving customer brand engagement. *Bh Ekonomski Forum, 16*(1), 131-150. https://doi.org/10.5937/bhekofor2201131m

McLean, G., & Osei-Frimpong, K. (2019). Hey Alexa … examine the variables influencing the use of artificial intelligent in-home voice assistants. *Computers in Human Behaviour, 99*, 28-37. https://doi.org/10.1016/j.chb.2019.05.009

Meganingsih, F., Wisesa, A., & Fachira, I. (2024). Enhancing Nogi Livin's brand awareness: A customer decision journey perspective through social media. *International Journal of Current Science Research and Review, 7*(6). https://doi.org/10.47191/ijcsrr/v7-i6-38

Menard, P. & Bott, G. (2024). AI misuse and privacy concerns. *Information Systems Journal*, *35*(1), 322-367. https://doi.org/10.1111/isj.12544

Mogaji, E., Soetan, T., & Kieu, T. (2020). The implications of artificial intelligence on the digital marketing of financial services to vulnerable customers. *Australasian Marketing Journal* (Amj), *29*(3), 235-242. https://doi.org/10.1016/j.ausmj.2020.05.003

Muchardie, B., Yudiana, N., & Gunawan, A. (2016). Effect of social media marketing on customer engagement and its impact on brand loyalty in Caring Colours Cosmetics, Martha Tilaar. *Binus Business Review, 7*(1), 83. https://doi.org/10.21512/bbr.v7i1.1458

Nagpal, T., Jangam, A., Purushothaman, A., & Kumar, S. (2025). A study on the effect of augmented reality in enhancing customer engagement in the fashion retail industry. *International Journal of Scientific Research in Engineering and Management*, *9*(4), 1-9. https://doi.org/10.55041/ijsrem44207

Noranee, S. and Othman, A. (2023). Understanding consumer sentiments: exploring the role of artificial intelligence in marketing. *Jmm17 Jurnal Ilmu Ekonomi Dan Manajemen*, *10*(1), 15-23. https://doi.org/10.30996/jmm17.v10i1.8690

Papić, T., Mihajlović, A., & Gajić, J. (2023). Advanced technologies as a framework for sustainable marketing campaigns (AI application in neuromarketing). *SINTEZA 2023*, 180-184. https://doi.org/10.15308/sinteza-2023-180-184

Rahman, F. (2022). Kernel k-mace: Hypercube unsupervised clustering method (Doctoral dissertation). Ryerson University. https://doi.org/10.32920/ryerson.14661465

Rahwan, I., Cebrián, M., Obradovich, N., Bongard, J., Bonnefon, J., Breazeal, C., … & Wellman, M. (2019). Machine behaviour. *Nature, 568*(7753), 477-486. https://doi.org/10.1038/s41586-019-1138-y

Saha, A., & Krishnamurthy, A. (2021). Efficient and optimal algorithms for contextual dueling bandits under realizability. *arXiv*. https://doi.org/10.48550/arXiv.2111.12306

Schivinski, B., Muntinga, D., Pontes, H., & Łukasik, P. (2019). Influencing COBRAs: The effects of brand equity on the consumer's propensity to engage with brand-related content on social media. *Journal of Strategic Marketing, 29*(1), 1-23. https://doi.org/10.1080/0965254X.2019.1572641

Seo, D., Choi, S., & Yoo, Y. (2022). Prevention of customer churn due to issuance of real-time coupons based on deep learning. *Research Square*. https://doi.org/10.21203/rs.3.rs-1384946/v1

Starr, M. (2012). Qualitative and mixed-methods research in economics: Surprising growth, promising future. *Journal of Economic Surveys, 28*(2), 238-264. https://doi.org/10.1111/joes.12004

Tanveer, J., Haider, A., Ali, R., & Kim, A. (2021). Machine learning for physical layer in 5G and beyond wireless networks: A survey. *Electronics, 11*(1), 121. https://doi.org/10.3390/electronics11010121

TechRadar. (2024). Consumers warming up to AI assistants: 38% cite time-saving benefits. Retrieved from https://www.techradar.com/pro/consumers-are-warming-up-to-ai-assistants-survey-finds-1-3-of-us-would-allow-ai-to-make-purchases

Timoshenko, A., & Hauser, J. R. (2019). Identifying customer needs from user-generated content. *Marketing Science*, *38*(1), 1–20. https://doi.org/10.1287/mksc.2018.1125

Vasileiou, K., Barnett, J., Thorpe, S. J., & Young, T. (2018). Characterising and justifying sample size sufficiency in interview-based studies: systematic analysis of qualitative health research over a 15-year period. *BMC Medical Research Methodology, 18*(1). https://doi.org/10.1186/s12874-018-0594-7

Verhoef, P. C., Broekhuizen, T., Bart, Y., Bhattacharya, A., Dong, J. Q., Fabian, N., & Haenlein, M. (2021). Digital transformation and customer experience: A research agenda. *Journal of Business Research, 122*, 889–901. https://doi.org/10.1016/j.jbusres.2020.06.003

Vogue Business. (2024). Unfolding AI: New worlds of fashion personalization. Retrieved from https://www.voguebusiness.com/technology/unfolding-ai-new-worlds-of-fashion-google-white-paper

Vries, L., Gensler, S., & Leeflang, P. (2017). Effects of traditional advertising and social messages on brand-building metrics and customer acquisition. *Journal of Marketing, 81*(5), 1-15. https://doi.org/10.1509/jm.15.0178

Wang, C. (2021). New frontiers and future directions in interactive marketing: Inaugural editorial. *Journal of Research in Interactive Marketing, 15*(1), 1-9. https://doi.org/10.1108/JRIM-03-2021-270

Wedel, M., & Kannan, P. K. (2016). Marketing analytics for data-rich environments. *Journal of Marketing*, 80(6), 97–121. https://doi.org/10.1509/jm.15.0413

Wolff, J., Pauling, J., Keck, A., & Baumbach, J. (2020). Systematic review of economic impact studies of artificial intelligence in health care. *Journal of Medical Internet Research, 22*(2), e16866. https://doi.org/10.2196/16866

Yazdani, A., & Darbani, S. (2023). The impact of AI on trends, design, and consumer behaviour. *Aitechbesosci, 1*(4), 4-10. https://doi.org/10.61838/kman.aitech.1.4.2

Yunus, R. M. (2023). Understanding business marketing strategy and its influence on consumer behaviour: a qualitative analysis. Ilomata *International Journal of Management*, *4*(1), 47-57. https://doi.org/10.52728/ijjm.v4i1.673

Zhong, L., & Zhang, W. (2022). Consumer empowerment in social media: A framework and research agenda. *Journal of Interactive Marketing*, 57(1), 1-15. https://doi.org/10.1016/j.intmar.2021.06.001

Authors' Contribution

All authors contributed equally to the development of this article.

Data availability

All datasets relevant to this study's findings are fully available within the article.

How to cite this article (APA)

Raja, A. M., & Hussain, N. (2026). AI DRIVEN AND DATA DRIVEN MARKETING STRATEGIES AS PREDICTORS OF BRAND ENGAGEMENT: THE MEDIATING ROLE OF CONSUMER PREFERENCES AND BEHAVIOUR IN THE UK E COMMERCE INDUSTRY. *Veredas Do Direito*, 23(6), e235822. https://doi.org/10.18623/rvd.v23.5822