The Effect of Automated vs Non-Automated Advertising on Customer Response to Social Media Ads: The Mediator Role of Perceived Personalisation

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Table of Contents

Abstract

The way advertising content is produced, tailored, and distributed has changed dramatically because of the rapid development of artificial intelligence (AI) in digital marketing, especially on social media platforms. AI-generated advertising raises questions about customer trust, perceived manipulation, and emotional discomfort, even though it has advantages, including improved targeting precision and real-time optimisation. These issues are consistent with the personalisation paradox, which holds that emotions of creepiness can coexist with enhanced relevance brought about by personalisation. Even though AI advertising is becoming increasingly popular, little empirical research has been done on how consumers react to and perceive ads produced by AI as opposed to those developed by humans. To address this gap, this study looks at how perceived personalisation, relevance, and creepiness influence consumer engagement (clicks, likes, comments, and shares) and ad avoidance. It also investigates how business experience, being part of a moderated mediation model, influences perceptions of personalisation.

A conceptual model that accounts for the direct and indirect impacts of AI-generated advertising on consumer behaviour is tested in this study using a quantitative experimental approach. Three advertising conditions, AI-generated personalised ads, AI-generated non-personalised ads, and human-created non-personalised ads were used in a between-subjects online experiment. A structured survey was used to gather information from a sample of n = 150 participants. The study tested the hypothesised links between ad type, perceived personalisation, relevance, creepiness, and behavioural effects by evaluating the measurement and structural models using Partial Least Squares Structural Equation Modelling (PLS-SEM).

The findings indicate that, when compared to non-AI (human-generated) content, AI-generated advertisements did not significantly increase perceived personalisation, indicating that algorithmic targeting by itself does not necessarily provide improved customer perceptions. However, perceived personalisation had a significant impact on both creepiness and relevancy, demonstrating the dual nature of personalised advertising. The personalisation paradox is reflected in this dynamic: while personalised content might increase engagement potential, it can also cause psychological discomfort if it is viewed as being overly intrusive. Additionally, perceptions of personalisation were not

significantly moderated by business experience, casting doubt on the idea that exposure to digital marketing in the workplace automatically results in positive assessments of AI-driven content. This thesis makes theoretical contributions by extending the SNS-Post Processing Framework to AI-generated advertising contexts, providing insights into how cognitive and affective responses to personalisation influence behavioural outcomes. Additionally, it also contributes to the limited empirical research on ad avoidance as a defensive mechanism triggered by AI-driven targeting. To promote customer trust and engagement, the study offers practical advice to digital platforms and advertisers on how to strike a balance between AI automation, human creativity, ethical transparency, and emotional resonance.

List of Figures

List of Tables

List of Appendices

Attestation of Authorship

I hereby declare that this submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person (except where explicitly defined in the acknowledgements), nor used artificial intelligence tools or generative artificial intelligence tools (unless it is clearly stated, and referenced, along with the purpose of use), nor material which to a substantial extent has been submitted for the award of any other degree or diploma of a university or other institution of higher learning.

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Signature Date

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Chapter 1: Introduction

1.1 Background

The advertising landscape and the way brands interact with consumers have undergone tremendous change because of the emergence of digital media. Digital media, sometimes known as "new media," includes content that is disseminated in digital formats, such as audio, video, and interactive platforms (Ming et al., 2007). Compared to 2018, when digital formats accounted for less than half of total spending, global advertising spending on digital platforms jumped dramatically to US$790 billion in 2024, or 72.7% of all ad expenditure globally (Datareportal, 2025). Interestingly, spending on digital ads has more than doubled since 2019 and is expected to expand at a rate of 10.3% per year from 2023 to 2024 (Datareportal, 2025). These rapid transformations in digital media form the foundational context for examining consumer interaction with AI-driven advertising. Furthermore, these numbers highlight how digital advertising is strategically prioritised in brand communication.

A major contributor to this evolution in digital advertising is the growing use of artificial intelligence (AI), particularly in social media contexts. Programmatic, interactive, and AI-powered advertising exemplify this evolution by moving away from conventional, one-way communication and toward consumer-centric, highly data-driven strategies that prioritise accuracy, speed, and real-time interaction (Coffin, 2022; Ford et al., 2023; Gao et al., 2023; Zhang & Zhang). The incorporation of artificial intelligence (AI), which enables scalable personalisation and predictive targeting across platforms, is the most disruptive factor among these advancements (Coffin, 2022; Gao et al., 2023; Raji et al., 2024). Digital advertising has changed because of the extensive application of AI, especially in social media settings. In addition to being places for online interaction, platforms like Facebook, Instagram, and TikTok are now the main hubs for advertising campaigns that make use of real-time behavioural data and dynamic personalisation (Datareportal, 2025; Rodgers & Nguyen, 2022). This highlights the increasing convergence between AI capabilities and personalised advertising delivery. One noteworthy development is AI-generated advertising, which uses algorithms, natural language processing, and real-time behavioural data to automatically create and optimise content, in contrast to traditional human-created ads (Arbaiza et al., 2024; Gu et al., 2024). When compared to non-automated formats, these features have the potential to increase user engagement and relevancy.

However, little is known about the moral and psychological ramifications of these developments (Ford et al., 2023). The growing reliance on algorithmic decision-making has raised concerns about customer trust, apparent manipulation, and the overall user experience. This study aims to improve knowledge of how AI-generated advertising affects consumer views and behaviours on social media platforms, which is in line with these ongoing discussions. The sections that follow examine how AI, which is already a major component of contemporary advertising, impacts not only operational effectiveness but also the perceptual, ethical, and emotional aspects of customer engagement.

1.2 Problem Statement

Digital advertising's rapid adoption of artificial intelligence (AI) has completely changed the way content is produced, tailored, and distributed (Arango et al., 2023). Little is known about how customers react psychologically and behaviourally to AI-generated advertising in comparison to conventional non-AI (human-created) content, despite the fact that AI makes hyper-personalisation, predictive targeting, and real-time optimisation possible (Gao et al., 2023). Instead of examining the emotional, cognitive, and behavioural aspects of consumer responses, existing research has primarily concentrated on the technological aspects of AI, such as increasing targeting efficiency or campaign performance (Rodgers & Nguyen, 2022; Wu & Jing Wen, 2021). This highlights a lack of attention to consumer experience, specifically how audiences feel and react.

The "personalisation paradox" is a crucial problem in AI-driven advertising. Although personalisation is meant to increase ad relevance, it can also make people feel uneasy, manipulated, or "creepy" when they believe their personal information is being misused or overused (Abbas, 2024; De Keyzer et al., 2024). The privacy-calculus theory (Lee & Cranage, 2011; Martin & Murphy, 2017) offers a theoretical framework for comprehending how customers balance privacy concerns with apparent benefits, but its applicability to AI-generated advertising remains poorly understood. The effects of personalisation on engagement behaviours (such as clicks, likes, shares, and comments) and ad avoidance when the material is produced by artificial intelligence (AI) rather than humans are not well-supported by empirical data (De Keyzer et al., 2024). Furthermore, individual characteristics like digital literacy, business experience, or an entrepreneurial mindset may affect how customers perceive personalisation, understand AI-generated advertisements, and form resistance or trust. For instance, because they understand the

workings of algorithmic personalisation, entrepreneurs and tech-savvy people might be more critical of it; nevertheless, this possible moderating influence has not been fully explored (Hardcastle et al., 2025; Raji et al., 2024).

Considering these discrepancies, empirical research is required that considers perceived personalisation, relevance, and creepiness as mediators of consumer engagement and ad avoidance in addition to comparing AI-generated and non-AI-generated advertising. This research attempts to fill these gaps by offering theoretical and practical perspectives on the advantages and disadvantages of AI-powered personalisation in social media marketing.

This study uses consistent terminology to differentiate between the two types of advertising evaluated to preserve clarity throughout the thesis. Ad creatives created with artificial intelligence systems that automatically create, modify, or optimize message content based on data-driven algorithms are referred to as "AI-generated advertising." Without direct human authorship of the final text, these advertisements rely on machine learning techniques to customize language, structure, and framing. On the other hand, "human-created advertising," also known as "non-AI advertising," refers to ad creatives that a human marketer manually develops without the aid of automated content creation tools. The distinction in this study focuses on the source of creative production rather than the delivery mechanism, even though both types may be distributed through digital platforms that employ algorithmic targeting.

1.3 Research Objectives and Research Questions

Defining research objectives is crucial for guiding inquiry and ensuring alignment with the research problem. The primary aim of this study is to examine how consumers respond behaviourally to AI-generated versus non-AI-generated advertisements, with a focus on the psychological constructs of perceived personalisation, relevance, and creepiness, which are known to influence engagement (clicks, likes, comments, shares) and ad avoidance. The study further investigates the role of business experience as a potential moderator mediation in shaping these perceptions.

In line with this aim, the research objectives are to:

1) Evaluate behavioural responses (engagement and ad avoidance) elicited by AI-generated versus non-AI-generated advertisements.
2) Examine the mediating role of perceived personalisation and its effects on perceived relevance and creepiness (i.e., the personalisation paradox).
3) Investigate how business experience influences perceptions of personalisation in AI-generated advertising, treating business experience as a segmentation factor and exploring moderated mediation; and
4) Test a conceptual model that integrates these constructs and explores their interrelationships.

To achieve these objectives, the study addresses the following main research questions and sub-questions:

- Main Research Question:
  How do consumers respond behaviourally to AI-generated versus non-AI-generated advertisements?

- Sub-Questions:
  RQ1: How do AI-generated advertisements, compared to human-created advertisements, influence consumer responses through perceived personalisation?
  RQ2: How does business experience influence consumers' perceptions of AI-generated advertisements in terms of personalisation?

When taken as a whole, these objectives allow for a more thorough investigation of the complex impacts of AI-driven advertising and provide a foundation for both theoretical and practical contributions.

1.4 Research Design

To clearly test the effects of AI-generated advertising on consumer behaviour, a structured and measurable experimental approach was essential. This thesis adopts a quantitative experimental research design to examine how AI-generated advertising influences consumer perceptions and behavioural responses, with particular focus on the constructs of perceived personalisation, relevance, creepiness, engagement, and ad avoidance. The

study also investigates the moderating role of business experience and the mediating influence of perceived personalisation within the conceptual model developed in Chapter 2. Building on this framework, the experimental stimuli were deliberately varied to isolate the effects of AI versus human-generated ads. The research design involved a between-subjects online experiment with three advertisement conditions, (1) AI-generated personalised advertisement, (2) AI-generated non-personalised advertisement, and (3) human-created non-personalised advertisement. Participants (n = 150) were recruited via MTurk and randomly assigned to one of the three conditions. This approach ensured a wide demographic reach, including respondents with varying degrees of digital literacy and business experience. Each participant viewed a designated social media advertisement and then completed a structured survey designed to measure their perceptions and behavioural intentions. The survey items were adapted from validated scales in existing literature to ensure reliability and construct validity. The data were analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM) with SmartPLS and SPSS. This ensured consistency and allowed for comparative analysis with prior advertising and consumer perception studies. This approach enabled the evaluation of both the measurement model (assessing reliability, convergent validity, and discriminant validity) and the structural model (testing direct, indirect, and moderating effects). Specifically, the analysis examined the hypothesised relationships between AI ad type, perceived personalisation, perceived relevance, perceived creepiness, and the outcome variables of engagement and ad avoidance. Ethical considerations, including informed consent, data confidentiality, and adherence to research ethics protocols, were addressed throughout the study.

1.5 Significance of the Study

This work contributes to the theoretical discussion of digital advertising by addressing emerging concerns about how AI may influence user behaviours and views. This study advances the academic understanding of AI-generated advertising by integrating the SNS-Post Processing Framework (Wagner et al., 2017) with constructs such as perceived personalisation, relevance, and creepiness. Furthermore, this study expands on the personalisation paradox (de Groot, 2022) by empirically analysing these dimensions and showing how personalisation can both raise ad relevance and engagement and cause discomfort or be viewed as intrusive. This contrast offers a sophisticated theoretical

viewpoint on the ways in which algorithmic advertising affects consumer behaviour. Additionally, the study explores business experience as a moderated mediation factor, which is largely absent in existing literature. This study emphasises the significance of individual traits in perceiving AI-driven content by examining how entrepreneurial attitude and digital familiarity impact perceptions of personalisation. These frameworks help explain not only what consumers think about AI advertising, but why they think and act the way they do in its presence.

Practically speaking, marketers are increasingly faced with the challenge of balancing technological innovation with user acceptance, making it essential to understand the emotional and behavioural responses AI ads provoke. The results emphasise how crucial it is to strike a balance between algorithmic accuracy and emotional resonance, transparency, and authenticity. Marketers can maximise engagement behaviours (clicks, likes, comments, shares) and decrease ad avoidance by using these insights. The research also highlights the ethical challenges surrounding AI personalisation, particularly those pertaining to privacy, trust, and apparent manipulation. Because of this, companies can create consumer-focused tactics that blend AI automation with imaginative narrative, guaranteeing that ads continue to be successful without sacrificing customer convenience or brand confidence. These insights can inform the design of ad campaigns that are both high-performing and respectful of consumer boundaries.

This study makes a methodological contribution by employing a quantitative experimental design to compare AI-generated and non-AI-generated advertisements in a controlled setting. Strong empirical evidence on the interactions between perceived personalisation, relevance, creepiness, engagement, and ad avoidance in the context of social media advertising is provided using validated measurement scales. A thorough examination of customer answers is provided using Partial Least Squares Structural Equation Modelling (PLS-SEM), which permits the investigation of direct, mediating, and moderating effects. This method not only increases the dependability of the findings but also offers a reproducible framework for further studies looking into the efficacy of AI advertising.

1.6 Outline of the Thesis

This thesis is structured into five main chapters, each building on the previous, providing a coherent examination of how AI-generated advertising influences consumer perceptions and behavioural responses. Chapter 1 introduces the study by presenting the research background, the problem statement, research objectives, and research questions. It also outlines the research design and highlights the significance and contribution of the study. The chapter concludes with an outline of the thesis structure.

Chapter 2 provides a comprehensive review of the existing literature on digital and AI-generated advertising. It examines the evolution from traditional to AI-driven marketing approaches, with a focus on key constructs such as personalisation, perceived relevance, and creepiness, as well as theoretical frameworks like the SNS-Post Processing Framework and the personalisation paradox. This chapter concludes with the development of the conceptual model and hypotheses guiding the study.

Chapter 3 details the research design and methodology adopted to test the proposed model. It discusses the research paradigm, experimental design, participant selection, data collection procedures, and statistical analysis methods. The chapter also addresses ethical considerations relevant to the study.

Chapter 4 presents the results of the empirical analysis. This includes an evaluation of the measurement model, reliability and validity assessments, and the testing of hypotheses. The findings are reported with reference to consumer engagement behaviours (e.g., clicks, likes, shares, comments), ad avoidance, and the mediating and moderating effects explored in the study.

Chapter 5 discusses the research findings considering the existing literature and theoretical foundations. It outlines the theoretical and managerial implications of the results, highlights the study's limitations, and proposes directions for future research. The chapter concludes by summarising the overall contributions and significance of the study.

Chapter 2: Literature Review

2.1. Introduction

This chapter critically examines the evolution of advertising, focusing on the transition from non-AI and digital models to AI-powered systems. It explores the unique features of AI advertising, automation, personalisation, and real-time optimisation, and evaluates their dual role in enhancing engagement while raising concerns around intrusiveness, authenticity, and consumer trust. By comparing non-AI and AI-driven approaches, the review highlights how the increasing use of machine learning, predictive analytics, and generative AI is reshaping advertising strategies, while also presenting new ethical and psychological challenges for marketers.

In the framework of the experimental manipulation, this thesis makes a clear distinction between AI-generated advertising and human-created (non-AI) advertising to prevent terminology ambiguity. Ad creatives created with generative artificial intelligence tools, which automatically create message content based on algorithmic patterns rather than human authorship, are referred to in this study as "AI-generated advertising." On the other hand, ad creatives that a human marketer manually authors without the use of automated content-generation technologies are referred to as human-created advertising. Crucially, this distinction focuses on the source of the creative content rather than the distribution method: digital platforms that employ algorithmic optimization or programmatic systems may distribute both AI-generated and human-created advertisements. By separating the creative source from the more general AI-driven targeting procedures that are now typical in digital advertising, the study focuses its contribution on comprehending how consumers view AI-generated ad content itself.

To frame consumer responses, the SNS-Post Processing Framework is introduced as a lens for understanding how audiences cognitively and emotionally engage with AI-generated content on social media platforms. Building on this, the chapter discusses the personalisation paradox, which reflects the tension between relevance and perceived intrusion, and the privacy-calculus theory, which explains how consumers weigh the trade-offs between personalisation benefits and data privacy concerns. Special attention is given to the moderating role of customer segments, particularly entrepreneurs, whose digital literacy and strategic outlook shape their perceptions of AI-generated ads.

The review concludes by emphasising the constructs of perceived personalisation, relevance, and creepiness as key drivers of consumer engagement and ad avoidance. These insights lay the foundation for the conceptual model that underpins the hypotheses for this study and guides the empirical analysis presented in the following chapters.

2.2. Evolution of Advertising in the Digital Age

2.2.1 Non-AI vs digital advertising

Non-AI advertising is defined by the unidirectional dissemination of promotional messages via print newspapers, magazines, radio, television, and other mass media outlets (Chiguvi, 2022); whereas, digital advertising makes use of internet connectivity and cutting-edge technologies, including social media platforms, search engines, and programmatic systems, to provide more individualised, quantifiable, and targeted advertising experiences (Chiguvi, 2022; MacRury & Manika, 2025). In this regard, digital advertising represents a significant shift in communication logic, as it customises information to each user's interests and habits, enhancing customer engagement, allowing for data-driven modifications, and promoting two-way conversation (Chung et al., 2021). This contrast emphasises the paradigm shift in how brands approach consumer engagement in a digitally connected world. According to the concepts employed in this thesis, the differentiation under consideration here relates to the advertisement's creative source rather than the algorithmic delivery methods employed by digital platforms. This study focuses on whether customers react differently to message content created by AI vs content written by humans, even if most of the digital advertising today relies on machine-learning optimization.

With advanced technology, digital platforms provide many advantages to marketers, such as providing performance tracking, real-time feedback, and adaptive content distribution, which improve efficiency and campaign effectiveness (Chiguvi, 2022; Ezzahra et al., 2024). These capabilities not only enhance advertiser agility but also reshape consumer expectations of immediacy and relevance in brand interactions. Some researchers argue that this enhanced efficiency explains the declining relative effectiveness of non-AI advertising, particularly as digital adoption rises globally, especially among younger, tech-savvy consumers (Chung et al., 2021). However, it is important to note that while digital platforms advance targeting and responsiveness, they

do not inherently solve issues of message fatigue or trust erosion among users, an area where further inquiry is needed (Dong et al., 2024; Zhang & Zhang).

With the emergence of generative AI, the development of advertisements has transformed even further. Rodgers and Nguyen (2022) explained that the automatic purchase and sale of digital ad inventory using algorithms and real-time bidding systems, known as programmatic advertising, utilises audience data and contextual information to enhance ad placement, thereby boosting efficiency, improving targeting accuracy, and increasing return on investment. Extending this logic, AI-powered advertising represents a game-changer as AI systems can evaluate enormous amounts of customer data using machine learning and natural language processing to provide hyper-personalised messages that are in line with each person's tastes and actions (Gao et al., 2023; Rodgers & Nguyen, 2022). Real-time content adaptation is made possible by this dynamic capability, which modifies tone, timing, and placement to optimise relevance and user engagement, a benefit that distinguishes AI from earlier rule-based systems (Aarzoo & Lal, 2024; Gao et al., 2023). Because AI improves every stage of the campaign lifecycle, from planning and production to delivery and evaluation, it is radically changing advertising strategy (Huh et al., 2023; IoniȚĂ et al., 2025). In particular, the capacity of AI to glean actionable insights from massive datasets is one of its most important contributions, as it enables marketers to achieve more accurate audience segmentation and content personalisation (Aarzoo & Lal, 2024; Arbaiza et al., 2024; Rodgers & Nguyen, 2022). These insights, while promising, remain under-validated in longitudinal consumer outcome studies, indicating an important gap in the empirical literature.

Another important advantage of integrating AI is automation. For instance, AI solutions enable quicker campaign deployment and more effective use of resources by streamlining tasks like performance monitoring, optimisation, and creative development (Rodgers & Nguyen, 2022; Wu et al., 2022). This aligns with recent literature that highlights AI’s role in improving operational efficiency, although there is limited consensus on how this automation affects perceived authenticity of content (Arango et al., 2023; Mirek-Rogowska et al., 2024). AI can automate A/B testing, real-time bidding strategy adaptation, and creative format refinement based on engagement data (Gao et al., 2023; Häglund & Björklund, 2024; Huh et al., 2023). Furthermore, AI makes it possible to distribute material in real time, modifying ad content according to users' location, surfing habits, and contextual factors (Wu et al., 2022). According to IoniȚĂ et al. (2025),

user engagement and ad relevancy are raised by this dynamic modification, which reinforces earlier findings on real-time personalisation.

However, this evolving capability also raises concerns around ethical advertising practices in addition to operational benefits (Gao et al., 2023). These concerns are especially salient in the context of AI systems generating campaign assets independently, such as product descriptions, headlines, and graphic creatives, which speeds up production while preserving personalisation (Gao et al., 2023). While this may improve scalability, it also introduces questions around creativity, authenticity, and oversight, which have yet to be fully explored in existing scholarship (Arbaiza et al., 2024; Huh et al., 2023; MurÁR et al., 2024). Encouragingly, AI systems can assist in ensuring adherence to privacy laws when used within strong governance frameworks, guaranteeing that personalisation initiatives remain compliant with data protection standards (Rodgers & Nguyen, 2022). This consideration is particularly crucial as consumers grow increasingly conscious of and sensitive to the use of personal information in targeted advertising, making ethical implementation not just a regulatory obligation but a strategic imperative (de Groot, 2022; Raji et al., 2024).

In keeping with the terminology used throughout this thesis, this analysis focuses on the creative source, AI-generated vs human-created message content, rather than the algorithmic methods of ad delivery, which are prevalent on most digital platforms.

2.2.2 AI-generated advertising vs. non-AI (human-crafted) advertising

A major change in the advertising environment has been brought about by the rise of AI-generated advertising, which introduces new paradigms for message generation, targeting, and delivery (Ford et al., 2023). AI-generated advertising uses algorithms, natural language processing, and machine learning to automate and personalise content at scale, in contrast to non-AI or even basic digital advertising, which frequently depends on human intuition and static creative assets (Gu et al., 2024). This contrast illustrates the fundamental transformation underway, as AI systems shift the creative process from manual craftsmanship to automated personalisation (Arbaiza et al., 2024). Fundamentally, this method revolutionises the process of creating content by producing text, images, and even audio elements that are customised for particular audience segments at a size and pace that are not possible for human creatives alone (Arbaiza et al., 2024; Chung et al., 2021; Moro Visconti, 2024).This foundational transformation

directly informs the increasing emphasis on hyper-personalisation, explored in the next paragraph.

The ability of AI-generated advertising to be mass-personalised is one of its main strategic advantages. AI systems can dynamically personalise information for individual customers by identifying demographic characteristics, preferences, and behavioural patterns through real-time analysis of large datasets (Kunekar et al., 2024). This mirrors earlier advancements in programmatic advertising, though AI systems expand these capabilities significantly through predictive and generative modelling (Coffin, 2022). As a result, advertisers can improve the relevance of their messages, leading to higher engagement, click-through rates, and conversion results (Arbaiza et al., 2024). However, despite these measurable gains, it is worth noting that empirical studies directly linking AI-generated content with consumer sentiment remain limited, highlighting an area for future investigation (Arango et al., 2023; Gu et al., 2024). This limitation invites further inquiry into the broader impact of AI advertising, particularly in how it shapes creative decision-making and campaign agility.

Beyond its operational effectiveness, AI-generated advertising is changing how data and creativity are used in marketing (Huh et al., 2023). Marketers may make well-informed adjustments at every stage of the campaign lifecycle thanks to its ability to enable more flexible, agile campaigns that change in response to real-time user behaviour (Gu et al., 2024). This trend aligns with current discourse on the benefits of adaptive advertising systems (Arbaiza et al., 2024). Given the fragmented and transient nature of consumer attention in increasingly overloaded media settings, this responsiveness provides a competitive advantage (Olney et al., 1991). Yet, such real-time reactivity may also raise concerns around the consistency of brand identity and message control, which remain underexplored in current literature (De Keyzer et al., 2024; De Keyzer, Dens, et al., 2022).

The growing application of AI in advertising raises important ethical issues (Gao et al., 2023). Concerns about customer privacy, authenticity, and creative originality are at the centre of the ongoing debate about AI's impact on persuasive communication (Arbaiza et al., 2024; Ghufran & Ahmad, 2025; Li et al., 2024). Furthermore, these concerns are particularly relevant in contexts where consumers may not clearly distinguish between human- and AI-generated messages. As AI-generated content increasingly resembles human-written messages, concerns arise regarding transparency, consent, and the potential for algorithmic manipulation (Ford et al., 2023). Arbaiza et al. (2024) stress the

need for specific legal and ethical guidelines to ensure that the use of AI technology in advertising maintains consumer trust and complies with more general standards of responsible marketing. (Goktas & Grzybowski, 2025).

2.2.3 Key features of automated (AI-generated advertising: automation, personalisation, and real-time optimisation)

The three main characteristics of AI-generated advertising, automation, personalisation, and real-time optimisation, set it apart from conventional and manually managed digital campaigns (Ford et al., 2023). When combined, these capabilities completely change how advertisers carry out, modify, and assess their strategies in ever-changing media landscapes (van Noort et al., 2020). To understand the implications of this transformation, it is useful to unpack each feature individually, beginning with automation.

First, media planning, ad design, audience segmentation, and performance tracking are among the traditionally time-consuming steps in the advertising process that are streamlined by automation (Gao et al., 2023). This represents a significant shift from earlier digital approaches, which often required extensive manual input at each stage (Kunekar et al., 2024). AI-driven automation allows marketers to devote more time to strategic decision-making and innovative ideation by reducing the need for manual oversight (Rita et al., 2025; Tran, 2024). In large-scale, multi-platform campaigns where cost control, speed, and response are crucial, this operational efficiency is especially beneficial (Moro Visconti, 2024). However, it is worth noting that while automation improves workflow efficiency, it may also reduce human oversight in critical creative and ethical decision-making processes, an issue that remains underexamined in current research (Arbaiza et al., 2024).

Second, by providing highly relevant advertising content to specific customers based on contextual, demographic, and behavioural data, AI improves personalisation (De Keyzer et al., 2024). Delivering communications that connect on a personal level is made possible by AI systems' ability to recognise trends in customer behaviour and forecast preferences through sophisticated machine learning algorithms (Mirek-Rogowska et al., 2024; Yang & Hu, 2022). This finding is broadly consistent with previous literature on data-driven personalisation, but AI expands this functionality by incorporating predictive learning models (Hayes et al., 2021; Raji et al., 2024). Higher conversion rates may result from this customised communication, which also improves perceived ad relevance and boosts customer engagement (Arbaiza et al., 2024). Nevertheless, some scholars have

raised concerns that excessive personalisation, particularly when based on inferred data, could provoke discomfort or resistance among users, pointing to the need for boundary-setting in algorithmic targeting (de Groot, 2022).

Third, AI systems can dynamically modify campaign variables in response to changing consumer behaviour or market conditions thanks to real-time optimisation, which enables them to continuously monitor ad performance (Gao et al., 2023). This involves making real-time adjustments to bid tactics, audience targeting, and creative assets (Tang, 2024). In this way, AI's optimisation capabilities significantly surpass the reactive nature of earlier digital platforms (Gao et al., 2023). Campaigns can therefore be continuously improved to guarantee optimal relevance and effectiveness, enhancing user experience and return on investment (ROI) (Ford et al., 2023; Hassan et al., 2024). However, the increasing reliance on AI to make autonomous decisions in real time raises unresolved questions about accountability, particularly in cases of bias, misclassification, or unintended targeting outcomes (Goktas & Grzybowski, 2025).

In combination, these three features position AI-generated advertising as a highly adaptive, efficient, and impactful approach to modern marketing communication (Huh et al., 2023). They not only improve campaign performance but also elevate the strategic role of data in guiding creative and operational decisions (IoniȚĂ et al., 2025). Yet, while the technological promise is clear, further empirical research is needed to explore the long-term effects of such automation on consumer trust, brand perception, and ethical standards in digital marketing (Hassan et al., 2025).

2.2.4 Shifting consumer perceptions of AI-generated advertising

As the capabilities of AI in marketing continue to grow, so too do the ways consumers react to its presence in advertising. When it comes to perceived intelligence, emotional resonance, trust, and engagement, consumers' reactions to AI-generated advertising are very different from those to non-AI-generated (human-created) ads (Gu et al., 2024). These views have a direct impact on how successful advertising campaigns are, and they provide significant challenges for marketers looking to use AI in persuasive messaging (Wu et al., 2022; Wu & Jing Wen, 2021).

One of the first distinguishing elements in consumer perception involves how intelligent the advertisement appears. Gu et al. (2024) notes that customers frequently judge AI-generated advertisements by how clever or "technologically advanced" they

seem. Customers are more likely to view AI-generated information as competent, relevant, and able to satisfy their demands when they believe it to be intelligent (Gu et al., 2024; Wu & Jing Wen, 2021). This perceived technological sophistication is consistent with studies showing that system credibility and intelligence can foster user trust; however, the relationship remains context-dependent and is not always linear (AbouElgheit, 2024; Gu et al., 2024; Hassan et al., 2025). Increased acceptance and trust in the advertisement may result from this apparent ability (Gu et al., 2024) . On the other hand, non-AI advertising is not usually examined from a technical perspective, which means it may not elicit the same expectations or cognitive assessments (Wu & Jing Wen, 2021).

Despite these benefits, AI-generated advertising can also make people feel uneasy or uncomfortable, especially if the content lacks emotional depth or seems extremely artificial (Gu et al., 2024). According to Gu et al. (2024), this uneasiness might result from the idea that AI advertisements are invasive or impersonal, which can erode perceived authenticity and trust. This concern contrasts with the more familiar and emotionally grounded appeal of non-AI advertising (Dong et al., 2024). Comparatively speaking, non-AI advertisements typically benefit from well-established narrative patterns, recognisable tones, and emotional appeal, all of which raise consumer comfort and receptivity (Dong et al., 2024; Yoo & MacInnis, 2005).

Another area where differences show up is in emotional engagement. According to research, conventional ads' use of cultural cues and human storytelling makes them more effective in creating emotional connections with viewers (Gu et al., 2024). This is particularly evident in campaigns that rely on nostalgia, empathy, or social values (Aarzoo & Lal, 2024). On the other hand, some consumers believe AI-generated advertisements to be less sympathetic or emotionally relatable, which could reduce their persuasive power, especially in campaigns that depend on an affective connection (Wu et al., 2022). However, it is worth noting that this may also depend on the ad category, as transactional or informational ads may benefit more from AI’s efficiency than emotional resonance (Aarzoo & Lal, 2024; Wu et al., 2022).

Furthermore, customer preferences for non-AI versus AI-generated content vary depending on the situation. Some viewers may prefer AI-generated content due to its uniqueness, inventiveness, or novelty value, whereas others may consider human-generated ads to be more genuine and trustworthy (Gu et al., 2024). These conflicting

preferences suggest that audience reactions are not uniform and instead are shaped by contextual cues and individual predispositions (Menon et al., 2004; Uribe et al., 2022). These conflicting perspectives also highlight the importance of tailoring AI implementation to campaign objectives, as a one-size-fits-all approach may undermine advertising effectiveness (Gu et al., 2024).

Lastly, a key factor in determining how consumers interact with advertising is still trust. Reduced involvement and avoidance behaviour may result when AI-generated content arouses scepticism, whether as a result of its strange tone or a perceived lack of human purpose (Gu et al., 2024). This finding aligns with earlier work on the importance of authenticity in fostering consumer trust (Kelly et al., 2020; Yang & Hu, 2022). Because of their familiarity and perceived authenticity, non-AI ads frequently foster more predictable engagement outcomes and better baseline trust (Kelly et al., 2020; Yang & Hu, 2022).

In conclusion, the differences in how consumers react to non-AI and AI-generated advertising highlight important subtleties in how people perceive technological intelligence, emotional resonance, and brand legitimacy. Although AI-generated advertisements are responsive and scalable, their efficacy is frequently tempered by emotional attachment and trust assessments. These intricacies underscore the importance of grounding future work in a structured framework that can capture both affective and cognitive processes underlying consumer interaction. These concerns lay the foundation for the following section, which introduces the SNS-Post Processing Framework, an analytically based paradigm for comprehending user interaction with brand content on social networking platforms, especially in the context of AI-enabled communication.

2.3. Theoretical Foundations of Consumer Response to Social Media Advertising

Social media platforms, which provide previously unheard-of opportunities for real-time connection and consumer engagement, have become essential components of modern marketing communication strategies. Social networking sites (SNS), including Facebook, Instagram, LinkedIn, and X (previously Twitter), continue to be the most popular social media platforms worldwide. Facebook alone claimed to have about 3 billion active members as of 2024, highlighting the scope and impact of SNS platforms in the digital

ecosystem (Statista, 2025). These figures underline why social media is increasingly seen as an indispensable tool for global brand strategies. According to Corstjens (2012), social media has emerged as a key platform for consumer interaction and brand communication. Similarly, social media activity now makes up a significant portion of the promotional mix for the majority of contemporary firms, indicating a paradigm shift away from conventional one-way messaging, according to Mangold and Faulds (2009).

2.3.1 Overview of the SNS-Post Processing Framework

Wagner et al. (2017) developed the SNS-Post Processing Framework to better understand how users engage with brand content in social networking environments such as Facebook, Instagram, and X (formerly Twitter). By extending established information processing theories from non-AI advertising into the dynamic and interactive context of SNS platforms, the framework offers a structured model for analysing how consumers perceive, process, and respond to brand posts, including those featuring personalised or AI-generated content (De Keyzer et al., 2024). This represents a significant conceptual progression from static media models, as it captures the fluid interplay between user characteristics, message construction, and platform affordances (Angus et al., 2024). Its value lies in its ability to unpack the psychological and behavioural mechanisms that influence communication effectiveness in social media advertising, with particular attention to user antecedents, message decoding, and outcome-based responses (De Keyzer et al., 2024).

By classifying engagement into three main dimensions, antecedents, processing mechanisms, and consequences, the SNS-Post Processing Framework investigates how users interpret and react to brand postings on social networking sites (Wagner et al., 2017). These aspects are consistent with traditional models of information processing, but they are reframed for the highly customised and interactive digital world of social networking sites (Dae Hee et al., 2010; Koch et al., 2023; Yanping et al., 2024). However, although the framework offers a promising lens for analysis, its application to AI-generated content remains underexplored in current literature, raising questions about how newer forms of automated messaging alter user cognition and behaviour (Ford et al., 2023; Mirek-Rogowska et al., 2024).

Wagner et al. (2017), explain that the term "antecedents" describes the elements that influence a user's preparedness and capacity to comprehend social media material. These include opportunity (e.g., time spent online or platform familiarity), cognitive

ability (e.g., attention availability), and motivational factors (e.g., interest in the topic) (Wagner et al., 2017). This mirrors cognitive load theory but contextualises it within the fragmented and fast-paced attention environment typical of SNS usage (De Keyzer, Dens, et al., 2022; Fisher, 2024; Winter et al., 2021). According to Wagner et al. (2017), a user's level of engagement with a brand post is shaped by a range of antecedent conditions that influence their readiness and capacity to process content. The next stage, processing, is driven by the post's thematic appeal, such as emotional, informational, humorous, or interactive elements, which directly affect users' motivation and attention. These appeals determine whether users engage heuristically, making quick and intuitive judgments, or systematically, through deeper and more deliberate elaboration. This distinction is especially relevant in the context of AI-generated advertising, where variations in emotional resonance, novelty, or complexity may shift how the content is cognitively processed. The final stage in the framework involves the consequences of processing, which (Wagner et al., 2017) categorise into three key outcomes: brand attitude (i.e., changes in perception or affinity toward the brand), user interaction (e.g., likes, shares, and comments), and post attitude (i.e., the user's evaluation of the content itself). These dimensions enable a more nuanced understanding of both superficial engagement metrics and deeper cognitive-emotional responses. By encompassing these stages, the SNS-Post Processing Framework provides advertisers with a comprehensive tool for assessing how consumers interpret and react to brand messages, insights that are critical for predicting outcomes like brand loyalty and purchase intention.

Although robust in its structure, the model would benefit from further empirical validation in contexts where algorithmic content generation or hyper-personalisation is present. Nonetheless, the SNS-Post Processing Framework offers a thorough understanding of how people perceive, assess, and react to branded information in digital social networks by combining these elements.

2.3.1.1 Application of the framework in social media advertising

To understand how consumer responses can be better predicted and influenced in digital environments, the application of theoretical models is essential. The framework is quite useful for directing content production, targeting, and assessment tactics in contemporary social media advertising (Mangold & Faulds, 2009). Advertisers can create messages that align with audience expectations and cognitive states by understanding user motivation and capacity, which increases the possibility of engagement (De Keyzer et al., 2024;

Zheng et al., 2024). This insight extends traditional message design approaches by integrating psychological readiness with media dynamics (Shumanov et al., 2022). Such integration allows marketers to create more nuanced and contextually relevant advertising content. Building on this strategic alignment, the framework enables tailoring content based on user intent. For instance, marketers can adjust their post appeal by determining whether a person is looking for knowledge or entertainment (Wagner et al., 2017). The model's focus on post-level appeals provides helpful advice for optimising content. Depending on the medium, target audience, or campaign objective, strategic use of emotional, interactive, or informative appeals is possible (Nayak et al., 2024). This alignment improves the message's persuasiveness and relevance (Veloso et al., 2024). As such, appeal strategies become more than creative preferences; they become precision tools in campaign design.

However, one unresolved issue is the extent to which these appeal types interact with AI-generated content formats, particularly as algorithmic design may lack the subtlety of human emotional framing (Gu et al., 2024). The framework offers a diagnostic method for assessing the efficacy of advertising by classifying user responses, ranging from opinions about the post to assessments at the brand level (Zheng et al., 2024). This classification adds a critical layer of analytical clarity in an otherwise noisy and dynamic media environment. This diagnostic capability is consistent with recent calls for more granular, behavioural-level ad evaluation tools (Menon et al., 2004). Moreover, marketers can modify their tactics in real time by tracking users' transition from engagement to attitudinal change (Arbaiza et al., 2024; Subeh, 2024). Furthermore, advertisers can create material that appeals to both heuristic (quick, intuitive) and systematic (slow, deliberate) processing styles thanks to the framework's support for a dual-processing approach (Florenthal, 2019). This duality supports existing elaboration likelihood models but also adds depth by tying cognitive style directly to platform engagement metrics (Guo & Jiang, 2023; Koch et al., 2023; Yousaf et al., 2021). Thus, the model aligns well with diverse consumer processing tendencies, enhancing both theoretical robustness and practical relevance. In social media, where user attention varies quickly yet emotional triggers and cognitive clues continue to influence brand outcomes, this dual engagement approach is especially crucial (De Keyzer et al., 2024). Lastly, the framework helps leverage social capital by promoting user-generated content and community involvement (Surucu-Balci & Balci, 2023). This increases peer-to-peer impact and perceived authenticity by broadening the organic reach and credibility of branded messaging (Nayak et al., 2024).

In doing so, the framework reinforces the social dimensions of brand interaction, a core strength of SNS-based marketing. Despite this, more research is needed to explore how AI-generated brand content affects user motivation to co-create or endorse branded messages within social communities, particularly in contexts where content authenticity is scrutinised (van Noort et al., 2020). This indicates an important area for future empirical inquiry as AI continues to reshape content creation.

2.3.1.2 Relevance to AI-driven advertising and consumer interaction

To evaluate the intersection of automation and consumer engagement, it is essential to consider how AI complements existing theoretical models. The SNS-Post Processing Framework is especially useful for comprehending the ways in which platform dynamics and consumer psychology interact with AI-driven advertising (Wagner et al., 2017). By automating emotional resonance modelling, real-time response tracking, and content customisation, artificial intelligence improves each step of the framework (Arbaiza et al., 2024). This enhancement represents a substantial extension of the original model's capabilities, as AI enables the transition from descriptive observation to predictive optimisation (Carvalho Proença, 2024).

This predictive capability becomes increasingly relevant in data-saturated digital spaces. To influence antecedents and customise material to maximise engagement, artificial intelligence (AI) systems can examine user activity patterns to identify which posts are most likely to generate interaction (Arbaiza et al., 2024; Tran, 2024). AI offers the framework for large-scale monitoring and prediction of user motives and emotional states from the standpoint of data processing (Carvalho Proença, 2024; Li, 2019). In congested SNS environments, this facilitates the transmission of hyper-relevant and adaptive advertising, which is crucial (Rodgers & Nguyen, 2022). This aligns with recent scholarship emphasising the value of personalisation under high-choice digital conditions (Lee & Cranage, 2011; McKee et al., 2024). AI's ability to fine-tune message relevance also supports dynamic feedback mechanisms in SNS advertising. AI can also improve the congruence between post content and audience expectations by examining behavioural indications across platforms (Aarzoo & Lal, 2024). In this way, the framework is reinforced through feedback loops that allow for real-time adaptation based on implicit signals (Wagner et al., 2017). AI-generated content has the ability to process messages dynamically in response to user reactions, resulting in customized advertising journeys that align with various phases of the consumer decision-making process (Li, 2019). These

routes support the framework's focus on post-interaction outcomes at the brand level, indicating that, when used appropriately, AI can increase favourable brand sentiments(Wagner et al., 2017).

However, despite these operational benefits, the growing use of automation also brings up ethical issues, particularly regarding data protection, consent, and originality of material (Arbaiza et al., 2024; Ford et al., 2023). These concerns echo wider debates on algorithmic accountability and raise important questions about consumer autonomy in AI-mediated communication (Coffin, 2022; Hardcastle et al., 2025; Raji et al., 2024). Transparency and trust are crucial prerequisites for customer involvement as AI makes it harder to distinguish between human and machine-generated content (Hardcastle et al., 2025; Hassan et al., 2025; Raji et al., 2024). By including ethical design principles as part of the antecedent layer, the SNS-Post Processing Framework may take these factors into account and help ensure that the transmission of content doesn't compromise consumer welfare or brand credibility (De Keyzer et al., 2024; Nayak et al., 2024). In conclusion, by incorporating AI into the SNS-Post Processing Framework, marketers may improve targeting, responsiveness, and personalisation, all the while keeping a framework in place to assess user responses critically and respect moral principles in automated advertising settings.

2.3.2 Information processing in social media advertising contexts

Evaluating the efficacy of both AI-driven and non-AI advertising methods requires an understanding of how people interpret social media ads. This section builds on the SNS-Post Processing Framework by analysing the different cognitive and affective reactions of consumers to automated and non-automated advertisements, with particular emphasis on engagement, personalisation, and trust. Consumers' interpretations, evaluations, and emotional responses to brand messages are becoming increasingly complex as advertising technologies advance toward greater automation and real-time adaptation. This presents marketers with both strategic opportunities and moral dilemmas.

2.3.2.1 How users process Automation vs. Non-Automated Advertising

Artificial intelligence-powered automated advertising analyses customer data and dynamically customises messaging to enable real-time customisation (Ford et al., 2023). Because messages are seen as more timely and relevant, there is a greater chance that users will engage (Rodgers & Nguyen, 2022). AI can modify ad content to match user

tastes and behaviours through data-driven optimisation, resulting in a more streamlined and focused experience that encourages response and attention (Gao et al., 2023). On the other hand, non-automated advertising usually uses static, pre-defined content that isn't as adaptable as AI systems (IoniȚĂ et al., 2025). These advertisements are frequently shown according to general demographic standards rather than behavioural analysis, which limits their applicability and lowers the likelihood that they will resonate with specific consumers (Arbaiza et al., 2024). Lower engagement rates may come from consumers viewing non-automated advertisements as generic or less relevant (Guo & Jiang, 2023).

Campaign responsiveness is further improved by automated advertising's operational flexibility. According to Ford et al. (2023), AI systems are able to track user activity continually and make adjustments to creative content, targeting, and bidding methods in real time. Non-automated advertising, on the other hand, follows set campaign plans and provides less opportunity for real-time customisation or iterative improvement (Qin & Jiang, 2019). Automated advertising, however, also raises issues with privacy (Bleier & Eisenbeiss, 2015; Kim et al., 2019). Users' trust and willingness to participate may be weakened by the gathering and usage of personal data, which may cause anxiety or a sense of surveillance (Arbaiza et al., 2024). In contrast, non-automated advertisements usually use less precise targeting, which may make them appear to be less of a risk to user privacy (Malheiros et al., 2012). Furthermore, different measurement techniques also exist. Short-term interaction indicators, including click-through rates, dwell times, or engagement ratios, are commonly used to assess automated campaigns since they offer instant feedback for optimisation (Li, 2019). It is more challenging to evaluate the efficacy of non-automated ads in real time since they frequently rely on long-term metrics like brand lift or memory (Guo & Jiang, 2023).

2.3.2.2 Cognitive and affective responses to personalised advertising

Perceived as relevant and non-intrusive, personalised advertising improves cognitive and affective processing (De Keyzer et al., 2024; Maslowska et al., 2016). According to De Keyzer et al. (2024), when consumers believe advertisements are closely related to their wants or experiences, they are more likely to engage in meaningful evaluation. This suggests that relevance functions as a cognitive amplifier, encouraging deeper elaboration and recall (Tam & Ho, 2006; Van den Broeck et al., 2019).

However, psychological characteristics may mitigate the cognitive impact of personalisation (Maslowska et al., 2016; Pfiffelmann et al., 2020). People who are more self-aware or digitally literate, for example, could react to advertisements differently, either accepting them as effective filters of pertinent content or rejecting them as manipulative (Campbell et al., 2022). This introduces a user-level variability that complicates the assumed universality of personalisation effects and highlights the need for segmentation-based targeting strategies (Lee & Cranage, 2011; Zahirović et al., 2024).

Users' emotional moods have a big impact on how they react to personalised advertisements (Guo & Jiang, 2023). While negative emotional states may impede processing or cause resistance, positive emotional states can increase participation (De Keyzer et al., 2024; Yanping et al., 2024). While personalisation can increase positive emotions like curiosity, joy, or relevance, it can also cause discomfort if it is viewed as "creepy" or unduly intrusive, according to De Keyzer et al. (2024). In contrast to non-AI emotional appeal strategies, AI-generated content may lack emotional nuance, potentially triggering unease when personalisation feels algorithmically cold or overly precise (Gu et al., 2024; Wu et al., 2022). To ensure that material connects without crossing psychological boundaries, ad design must be emotionally calibrated, as this contradiction illustrates (Srivastava & Dorsch, 2020; Yoo & MacInnis, 2005).

The dual-process approach, which includes both systematic (deliberative) and heuristic (intuitive) thinking, emphasises the significance of striking a balance between rational and emotional appeals (Koch et al., 2023; Rhee & Choi, 2020). Both emotive resonance and cognitive elaboration must be taken into consideration in successful advertising campaigns, particularly when using personalisation (De Keyzer et al., 2024). In AI-driven environments, where human reactions can be instantaneous, emotional, and challenging to reverse, striking this balance is especially important (Ghufran & Ahmad, 2025; Ma et al., 2023). This reinforces the importance of integrating design-level sensitivity into automated content systems, particularly when scaling personalised messages across diverse audiences (Gao et al., 2023; Hardcastle et al., 2025; Li, 2016)

In this thesis, creepiness refers to the emotional discomfort consumers experience when an advertisement appears unusually tailored or overly familiar, intrusiveness refers to a feeling of unwelcome interruption during media use, and privacy concern relates to consumers' cognitive assessment of how their personal data may have been collected or used.

2.3.2.3 The role of engagement and trust in AI-driven ad effectiveness

As both results and facilitators of successful communication, engagement and trust are essential to the success of AI-driven advertising (Guo & Jiang, 2023; Wu et al., 2025). By delivering messages that feel timely, relevant, and personalised, artificial intelligence (AI) technologies greatly increase user engagement by enabling granular targeting and content adaptation based on real-time behavioural indications (Arbaiza et al., 2024). This reflects a growing consensus that relevance and immediacy are central to effective digital communication (Akdim & Casaló, 2023; Munsch, 2021).

AI technologies provide more engaging brand experiences and increased conversion rates when they are in line with user intent and preferences (Arbaiza et al., 2024; Yang & Hu, 2022). However, engagement on its own is insufficient (Hassan, 2024; Kelly et al., 2020). Consumer trust in the brand and the underlying technology is crucial to the long-term viability of AI-driven promotions (Hardcastle et al., 2025). Building and preserving this trust requires ethical algorithmic design and transparent data usage policies (Ford et al., 2023). This perspective aligns with broader scholarship emphasising the importance of algorithmic fairness and explainability in maintaining consumer confidence (Gu et al., 2024; Hassan et al., 2025; Lee et al., 2024). While perceived manipulation or a lack of openness can damage a brand's credibility, consumers who are aware of how and why their data is utilised are more inclined to accept personalisation and interact with content (Hardcastle et al., 2025; van Noort et al., 2020). This suggests that perceived control and transparency act as moderators in the engagement process (Kim et al., 2019; Lee et al., 2024). Customers' emotive disposition toward AI-generated advertisements is also influenced by trust (Gu et al., 2024). Personalised communications, however, can increase relevance, but if they come across as intrusive or manipulative, they may also cause resistance or scepticism (Arbaiza et al., 2024; Ford et al., 2023). This duality highlights a key tension in AI advertising: the same mechanisms that optimise content delivery can simultaneously provoke suspicion (Gao et al., 2023; Gu et al., 2024). This implies that ethical personalisation improves engagement results and brand loyalty by allowing users to maintain some control and comprehension of the process (Abbas, 2024; Hardcastle et al., 2025).

In conclusion, trust and engagement serve as key mediators in the success of AI-driven advertising, either enhancing or diminishing the efficacy of campaigns based on the integrity and experience of the exchange (Guo & Jiang, 2023; Wu et al., 2025).

Although AI makes it possible to convey messages with previously unheard-of precision, its effectiveness depends on user receptivity, which is influenced by views of relevance, fairness, and data transparency (Guo & Jiang, 2025; Mirek-Rogowska et al., 2024). Understanding these human reactions is essential for both responsible practice and strategic improvement as social media advertising depends more on algorithmic personalisation (De Keyzer, Van Noort, et al., 2022). As a result, the following chapter will focus on the function of personalisation in AI-generated advertising, critically analysing how customers perceive customised information and the circumstances in which it either strengthens or weakens marketing results.

2.4. Advertising Personalisation and Consumer Reactions

2.4.1 The strategic role of personalisation in digital advertising

The idea of personalised advertising is explained in this subsection, along with how AI enables dynamic targeting and how AI-generated personalisation differs from conventional techniques. The dual potential of customisation to increase engagement and raise privacy-related issues is emphasised (Hu & Wise, 2024; Raji et al., 2024).

To improve relevance and engagement, personalised advertising entails creating material that is in line with the unique traits, interests, and behaviours of each consumer (Hu & Wise, 2024; Segijn & van Ooijen, 2022). Advertisers can provide personalised offers, recommendations, and messages that more thoroughly connect with the recipient by using algorithmic analysis of user data (Gao et al., 2023; Hardcastle et al., 2025). This improves cognitive processing and decision-making (Tran et al., 2020). Furthermore, it has been demonstrated that by enhancing perceived ad relevance and utility, personalised campaigns raise purchase intent and brand engagement (Zhu & Kanjanamekanant, 2021). This aligns with a growing body of research highlighting the persuasive power of personalised content when tailored appropriately (De Keyzer et al., 2024; Guo & Jiang, 2023; Subeh, 2024). From a strategic standpoint, customisation increases return on ad spend, decreases wasted impressions, and increases cost efficiency by more accurately targeting segmented audiences than mass-market approaches (Hardcastle et al., 2025). As long as the use of data is viewed as morally righteous and open, it also increases brand legitimacy and perceived informativeness, which can fortify brand attitudes (Deng et al., 2019). However, in contrast to its performance benefits, too much customisation might

make people uneasy or suspicious, which emphasises how crucial it is to strike a balance between customer privacy and customisation (Hardcastle et al., 2025). In the end, whether personalisation increases or decreases the effectiveness of advertising depends on trust (Bleier & Eisenbeiss, 2015).

Advertisers can create highly targeted communications and categorise consumers into prediction groupings thanks to AI technology's exceptional ability to synthesise enormous volumes of contextual and behavioural data (Häglund & Björklund, 2024). AI improves audience insights and facilitates more in-depth personalisation tactics by identifying behavioural patterns and psychological characteristics in digital footprints (Aarzoo & Lal, 2024; Gao et al., 2023; Hensman et al., 2024). Furthermore, by evaluating media contexts, including emotion and content complexity, AI systems can improve contextual advertising by identifying the best places for ads (Hardcastle et al., 2025). This data-driven strategy guarantees that material is both pertinent and adaptable to changing consumer preferences (Subeh, 2024). AI models adjust their delivery of messages for optimal impact by continuously adapting to real-time interactions (Shumanov et al., 2022). However, despite these benefits, privacy-conscious design must balance personalisation (Hardcastle et al., 2025). When data collecting becomes opaque or overreaches users' private digital environments, ethical issues surface (Abbas, 2024). This tension remains a critical unresolved issue in AI-enabled targeting and highlights the need for transparent data governance (Arbaiza et al., 2024). To maintain consumer trust, marketers must manage this conflict by remaining transparent and avoiding intrusiveness (Li et al., 2024; Subeh, 2024).

The speed, scalability, and capacity of AI-generated advertising to dynamically create content in response to user behaviour set it apart from conventional methods (Gao et al., 2023; Gu et al., 2024). AI can automatically change headlines, images, and calls-to-action in real time based on detailed user signals, in contrast to non-AI tailored advertising, which depends on predetermined audience segmentation and human-curated messaging (Guo & Jiang, 2025). This flexibility enables advertisers to react quickly to changes in customer intent and enhances engagement results (Arbaiza et al., 2024). Additionally, compared to static, human-curated advertisements, AI systems offer more precise targeting, which frequently results in higher click-through and conversion rates (Hardcastle et al., 2025). However, while this heightened precision provides short-term gains, it may also increase consumer apprehension about surveillance and manipulation (Campbell et al., 2022). Increased accuracy might also heighten worries about data abuse

and spying, especially if personalisation is seen as intrusive (Abbas, 2024). Because they use more comprehensive targeting criteria and pose fewer privacy problems, traditional approaches, despite being less flexible, are frequently regarded as more reliable (Malheiros et al., 2012). Therefore, it is essential to strike a balance between ethical protections and the level of customisation to maximise results in both formats (Raji et al., 2024).

To conclude, AI-generated advertising offers major strategic advantages over non-AI customised techniques in terms of adaptability, efficiency, and targeted precision (Ford et al., 2023; Gu et al., 2024). These advantages do have some drawbacks, too, as greater personalisation could heighten customer worries about data privacy, manipulation, and spying (Hillqvist & Johnsson Östergren, 2020; Rhee & Choi, 2020). According to the comparative research, artificial intelligence (AI) creates new conflicts between value generation and user discomfort, even as it improves message relevancy and engagement (Gu et al., 2024; Mirek-Rogowska et al., 2024). The personalisation paradox, a phenomenon in which the very technologies that improve participation also create resistance, is centred on these contradictions (Lee & Cranage, 2011). To comprehend this paradox's significance for AI-powered advertising campaigns, the following section will examine it in greater detail using both theoretical and empirical data.

2.4.2 The personalisation paradox and consumer discomfort

This section explores the ways in which personalisation can influence both favourable and unfavourable user experiences, highlighting the importance of moral boundaries, openness, and user agency. It provides empirical data and theoretical ideas that highlight the conflicting impacts of customisation in AI-generated advertising.

The contradictory phenomena known as the "personalisation paradox" occur when consumers feel more engaged by personalisation, but they also become more resistant or uncomfortable when they feel like they have less control or are being invaded (de Groot, 2022). Personalised advertising improves relevance and perceived value by customising material to each user's interests and behaviours, which in turn boosts user engagement (Abbas, 2024; Lee & Cranage, 2011). However, these advantages do come at the expense of higher data usage, which raises privacy and surveillance concerns (Martin & Murphy, 2017). This duality reveals an underlying tension in the user experience, where consumers frequently struggle to balance their desire for personalised experiences with their concerns about the amount of data being gathered in order to

provide them (Gutierrez et al., 2019). This paradox highlights a delicate trade-off: the same mechanisms that increase the efficacy of advertisements can also cause avoidance and erode confidence (de Groot, 2022). In response to these competing pressures, researchers suggest proactive transparency and privacy-enhancing features that allow users to modify personalised settings in order to lessen these consequences (Abbas, 2024). Sustaining positive user perceptions requires striking a balance between ethical duty and value creation (Hallam & Zanella, 2017; Hassan et al., 2025).

A sensation of surveillance and loss of autonomy may result from over-personalisation, which can cause unease by indicating that users are being watched carefully (Lee et al., 2022). Ads that seem overly precise, particularly when done without express consent, might come across as intrusive, which can result in negative emotional responses and a decline in interest (Segijn & van Ooijen, 2022). In many cases, defensive actions, such as ad avoidance or a drop in trust, are frequently prompted by this perceived invasion of privacy (Ghanbarpour et al., 2022; Lee et al., 2024; Pfiffelmann et al., 2020). These advertisements are sometimes interpreted by consumers as “creepy” or manipulative, particularly when algorithms predict demands that the user has not stated (Wu & Jing Wen, 2021). In addition to decreasing ad efficacy, personalisation can harm a brand's reputation when it goes too far and is viewed as intrusive (de Groot, 2022; De Keyzer et al., 2024). This underscores the importance of user-centric design and highlights the ethical boundaries necessary in algorithmic advertising (Rodgers & Nguyen, 2022).

According to empirical research, personalisation can exacerbate privacy problems even when it boosts ad relevancy (Bleier & Eisenbeiss, 2015; Malheiros et al., 2012). Lee and Cranage (2011) showed that even while consumers recognise the functional advantage, their sense of privacy breach increases when they perceive ad customisation based on past activities without explicit authorisation. Similarly, Facebook users linked tailored ads to greater brand relevance, but this effect was lessened when the ads were also seen as intrusive, according to (Maslowska et al., 2016). Consumer reactions to highly tailored advertising are mixed, as evidenced by De Keyzer, Dens, et al. (2022) identification of both cognitive appreciation and emotional discomfort. These results highlight the necessity of developing personalisation tactics that minimise apparent overreach while maximising relevance (Lee & Cranage, 2011; Maslowska et al., 2016). Taken together, these empirical data demonstrate the delicate balance between the benefits of personalisation and the psychological discomfort it might cause when viewed

as intrusive (De Keyzer, Dens, et al., 2022; Pfiffelmann et al., 2020). Marketers are challenged by the personalisation paradox to design compelling and morally sound customised experiences (de Groot, 2022).

To deepen this understanding, the privacy-calculus hypothesis is examined in the following section, offering a framework for understanding how customers weigh the perceived benefits of personalisation against its potential privacy risks.

2.4.3 Privacy-Calculus Theory and trade-offs in personal ads.

This section examines how customers weigh trade-offs, how the privacy calculus functions in AI contexts, and what elements affect trust in tailored ad environments.

According to the privacy-calculus theory, people weigh the subjective advantages and disadvantages of disclosing personal information when making logical decisions about it (de Groot, 2022; Hardcastle et al., 2025). Users balance the danger of data misuse or surveillance against the enhanced relevance and usefulness of tailored messaging in the context of AI advertising (Li et al., 2024). This balancing act is increasingly relevant in digital ecosystems where algorithmic targeting has become both ubiquitous and opaque (Gao et al., 2023; Hardcastle et al., 2025; Zhang & Zhang). Users are more likely to react favourably to tailored advertising if they believe the advantages, like time savings, ease, or better product discovery, outweigh the drawbacks (Subeh, 2024). However, in contrast, users might opt out, decrease participation, or form a negative impression of the brand if data methods seem opaque or overbearing (Hardcastle et al., 2025). Therefore, to preserve trust, marketers need to enhance perceived value while limiting perceived risk (Khamitov et al., 2024).

Consumers evaluate personalisation along a spectrum of risk-benefit trade-offs, often influenced by perceived intrusiveness, transparency, and control (Jin-Myong & Jong-Youn, 2017). Segijn and van Ooijen (2022) also note that when users perceive personalised ads as saving time or reducing irrelevant exposure, they may tolerate some data usage. However, if ads are perceived as invasive, emotional discomfort and avoidance behaviours often follow (Lee et al., 2022). This duality illustrates how personalisation strategies must not only provide functional value but also respect emotional boundaries (De Keyzer, Dens, et al., 2022; Maslowska et al., 2016). Therefore, successful personalization tactics need to control the acceptability threshold, providing value without provoking psychological opposition (De Keyzer, Dens, et al., 2022; Kim &

Jeong, 2023). Hu and Wise (2024) found that by offering user education, transparent data rules, and opt-in controls, businesses may help consumers retain their sense of agency and become more responsive to tailored advertising.

One of the most important moderators in the personalisation equation is trust (Bleier & Eisenbeiss, 2015). According to (Li et al., 2024), user trust in AI systems is directly impacted by transparency in the collection, processing, and application of consumer data. This trust becomes particularly fragile when automated decisions are made without a clear explanation or consumer awareness (Sargın, 2024). Perceived intrusiveness, targeted precision, and user control also affect trust (Hardcastle et al., 2025; Raji et al., 2024). Companies can increase the efficacy and moral standing of their AI advertising campaigns by giving consumers the ability to control their personalised settings and by exhibiting acceptable data practices (Guo & Jiang, 2025).

In conclusion, views of ethical integrity, transparency, and control influence consumer trust in AI-driven advertising in addition to the precision and applicability of personalisation (Arbaiza et al., 2024; Gao et al., 2023; Raji et al., 2024). This trust, which mediates the trade-offs consumers make between convenience and data risk, is essential to the success of AI-powered advertising (Ford et al., 2023; Hassan et al., 2025). Yet, designing for trust remains an ongoing challenge, especially when user expectations outpace institutional safeguards (Hassan et al., 2025). Building on these observations, the following section focuses on the hypothesis development from personalisation AI-generated advertising and its effects to the role of business experience in shaping ad perceptions.

2.5. Personalisation AI-Generated Advertising and Its Effects

Consumer responses to AI-driven advertising are significantly influenced by perceived personalisation. Perceived personalisation refers to the consumer's subjective perception that a message is specially designed for them, as opposed to actual personalisation, which is based on objective behavioural data (Hu & Wise, 2024). This distinction is crucial; perceived personalisation reflects the consumer's subjective sense that an ad is tailored for them, whereas actual personalisation is grounded in data-driven targeting controlled by the advertiser (De Keyzer et al., 2024; Li, 2016). While actual personalisation can be objectively measured, such as through targeting a user based on prior brand interactions,

it is ultimately perceived personalisation that drives behavioural outcomes such as ad engagement, click-through rates (CTR), and conversion intent (De Keyzer, Dens, et al., 2022). Therefore, perceived personalisation operates as a psychological filter that influences how consumers evaluate relevance, often independently of the underlying algorithmic accuracy. Supporting this, De Keyzer et al. (2024) argue that unless a user feels the message aligns with their preferences, even data-backed targeting may fail to trigger engagement. In line with prior studies on advertising effectiveness, engagement outcomes, such as attitude toward the ad, brand attitude, and behavioural intention, are more strongly linked to perceptions than actual message tailoring (Choi & Kim, 2022; Maslowska et al., 2016).

In this context, AI personalisation enhances ad effectiveness by increasing perceived relevance through real-time behavioural analysis, thereby encouraging attention, elaboration, and user interaction (Hu & Wise, 2024; Raji et al., 2024). However, in contrast, the same mechanisms that drive personalisation can raise privacy concerns, particularly when users sense their autonomy is compromised or feel that they are under surveillance (De Keyzer et al., 2024). While personalised content can improve brand engagement, it may also provoke discomfort, resistance, or avoidance if perceived as overly invasive or manipulative (Hu & Wise, 2024). Indeed, perceived personalisation influences both affective and behavioural engagement metrics such as CTR, viewing duration, and emotional response (Subeh, 2024). High CTRs and longer watch times signal immediate attention and deeper processing, while positive emotional reactions such as joy or inspiration contribute to favourable brand attitudes and stronger consumer-brand ties (Yoo & MacInnis, 2005).

However, as De Keyzer et al. (2024) caution, the effectiveness of these outcomes depends on user choice and perceived control, critical factors that mediate engagement. Therefore, the ability of personalised content to produce conversions hinges not just on relevance, but on balancing that relevance with ethical design. As studies have shown, excessive targeting can backfire, leading to ad avoidance and brand distrust (Maslowska et al., 2016). Consequently, ethical AI personalisation must be grounded in privacy, transparency, and user autonomy (Hardcastle et al., 2025; Lee et al., 2024). Strategies such as user control over data, humanised messaging, and context-sensitive ad delivery have been shown to mitigate psychological resistance and improve acceptance (Dwivedi et al., 2021; Guo & Jiang, 2025).

Complementing these efforts, machine learning enhances perceived relevance through predictive analytics, audience segmentation, real-time adaptation, and iterative feedback loops (Chen et al., 2023; Choi & Kim, 2022). This capability enables the delivery of timely, meaningful content that aligns with evolving consumer expectations (Guo & Jiang, 2025; van Noort et al., 2020). However, this strength can also become a vulnerability; technical precision, when not calibrated to user comfort or social norms, can be interpreted as intrusive or manipulative (Campbell et al., 2022; Henkens et al., 2021).

> *H1*: (a) Due to the mediating effect of perceived personalisation, AI-generated ads, compared to human-created ads, will lead to (b) higher perceived relevance and (c) greater perceived creepiness.

Relevance in AI-personalised advertising is a psychological doorway to engagement, trust, and enduring loyalty rather than just a technological result (Harmata & Kondak, 2024). A key factor in determining how customers engage with AI-personalised advertising is perceived relevance, which affects how they perceive and respond to brand messaging (De Keyzer et al., 2024). According to Tam and Ho (2006), perceived relevance is defined as the degree to which customers feel that a message or marketing communication fits with their own requirements, values, or interests. This alignment encourages attention, processing depth, and emotional resonance, thereby improving the efficacy of digital marketing (Abhiseka et al., 2024; Buvár & Gáti, 2023; Munsch, 2021).

In support of this, Bleier and Eisenbeiss (2015) discovered that consumers were more likely to act in a brand-consistent manner and develop positive brand perceptions when they were exposed to product recommendations that were deemed relevant. Similarly, de Groot (2022) found that perceived relevance strengthened consumer-brand interactions by raising the perceived authenticity of the communication. The importance of relevance in creating brand meaning is reaffirmed by these investigations. However, this is contrasted by findings from Niu et al. (2021), who suggest that achieving relevance through intrusive data collection may reduce brand trust and provoke ad avoidance. This suggests that although perceived relevance typically improves brand engagement, the way in which personalisation is implemented determines how effective it is.

While the literature affirms that relevance enhances cognitive, affective, and behavioural aspects of brand engagement, it also reveals unresolved questions around the role of contextual moderators such as data transparency, personalisation frequency, and consumer privacy expectations (De Keyzer et al., 2024). Ads produced by AI have the power to profoundly affect consumer-brand interactions in both positive and negative ways (Wu et al., 2025). Furthermore, when these advertisements are viewed as knowledgeable, entertaining, or competent, they can promote trust and engagement (Kelly et al., 2020). For example, AbouElgheit (2024) and Gu et al. (2024) argue that AI-generated material perceived as high in expertise may enhance consumer perceptions of brand credibility. This perception, when reinforced through relevance, contributes to deeper trust and brand attachment. Moreover, Gu et al. (2024) found that dynamic, interactive, or creatively generated AI ads often increase customer attention and foster emotional bonds, particularly when aligned with personal interests and values. However, the benefits of AI personalisation are not universal. AbouElgheit (2024) and Gu et al. (2024) also highlight how content that appears overly artificial or intrusive may evoke scepticism and alienate consumers. This so-called “uncanny valley” effect creates a psychological dissonance that undermines emotional connection and encourages avoidance (Chang et al., 2023; Gutuleac et al., 2024). Therefore, while AI-generated advertising can enrich consumer-brand bonds through personalised, engaging content, its effectiveness depends on maintaining a delicate balance between innovation and psychological comfort.

Deeper, more meaningful interactions with customers are fostered by artificial intelligence (AI) personalisation, which has become a major factor in long-term brand loyalty. According to Terason et al. (2025), customer satisfaction, emotional engagement, and long-term commitment are all raised by personalised interactions, particularly those made possible by service-oriented and interactive digital touchpoints. Similarly, Subeh (2024) found that alignment between AI-driven personalisation and consumer preferences strengthens emotional ties and brand loyalty over time. These findings collectively suggest that sustained relevance leads to trust and retention. However, scholars also warn that the emotional benefits of personalisation are contingent on ethical and transparent practices (De Keyzer, Dens, et al., 2022; Tam & Ho, 2006). According to (Subeh, 2024), the very relationship that personalisation aims to strengthen may be compromised if the data practices supporting it feel invasive or opaque. This remains a critical tension, as brands must balance algorithmic sophistication with emotional legitimacy (Hardcastle et

al., 2025; Yang & Hu, 2022). Thus, while AI personalisation has significant potential to enhance loyalty, its success depends on a user-centric design approach that aligns with consumer expectations (Hassan et al., 2025). Brands that strike this balance are more likely to cultivate loyal followings grounded in perceived relevance, emotional resonance, and trust (De Keyzer, Dens, et al., 2022; Terason et al., 2025). When relevance is strong, a thorough picture of how consumers react to AI-personalised advertising can be obtained by combining cognitive, emotional, and behavioural engagement measures (Arbaiza et al., 2024; Guo & Jiang, 2023). Nevertheless, not every individualised experience yields favourable outcomes, as personalisation may cause resistance or disengagement if it deviates from user expectations or crosses psychological lines (Kim & Jeong, 2023).

> *H2*: Perceived relevance will (a) increase brand engagement by increasing click intention, like intention, comment intention, and share intention, but (b) reduce ad avoidance.

Perceived creepiness plays a critical role in shaping consumer reactions to AI-personalised advertising, particularly when the experience of personalisation crosses psychological boundaries (De Keyzer, Van Noort, et al., 2022). Defined by McAndrew and Koehnke (2016) as a state of anxiety induced by ambiguous threats and a lack of control, perceived creepiness often emerges when consumers sense that their personal space is being invaded by overly intrusive AI practices. This discomfort is frequently triggered by perceived violations of privacy through behavioural tracking and data harvesting, which consumers may interpret as being conducted without clear consent (Li et al., 2024). The so-called “creepiness factor,” as described by Malheiros et al. (2012), reflects the unsettling feeling that a brand is prying into aspects of one’s personal life that should remain private. Empirical studies show that the unauthorised collection or usage of data exacerbates this feeling, especially when ads appear too humanlike or persistently repetitive, factors that increase emotional unease (Li et al., 2024). These effects underscore a complex relationship between relevance, intrusiveness, and brand attitude, wherein highly personalised content may simultaneously enhance ad effectiveness while provoking psychological discomfort (De Keyzer et al., 2024; Niu et al., 2021).

In this light, perceived creepiness becomes a double-edged sword, capable of derailing otherwise engaging campaigns if not ethically managed. While relevant and well-targeted ads can elicit positive reactions and boost brand favourability (Bleier &

Eisenbeiss, 2015; de Groot, 2022), they may also erode trust if perceived as manipulative or violating personal boundaries (Segijn & van Ooijen, 2022). This trade-off highlights the necessity of understanding individual thresholds for personalisation and ensuring emotional calibration within ad design (van Doorn & Hoekstra, 2013). As such, marketers must tread carefully to avoid the tipping point where perceived relevance becomes perceived intrusion (De Keyzer, Van Noort, et al., 2022; McKee et al., 2024). Moreover, research reveals that excessive personalisation can trigger emotional resistance and avoidance behaviour, particularly when AI systems over-target users, collect data non-transparently, or generate content that misaligns with the user's identity or self-concept (Hardcastle et al., 2025; Shumanov et al., 2022). These concerns are exacerbated by the "black box" nature of AI algorithms, which can create perceptions of manipulation and ethical ambiguity due to their lack of explainability (Toti & Steils, 2024). Resistance may also stem from algorithmic bias, identity misalignment, and repeated ad exposure, all of which reduce perceived autonomy and authenticity (Benlian et al., 2020; Van den Broeck et al., 2019). In this context, transparency emerges as a crucial moderator of perceived creepiness. By openly disclosing data practices, offering opt-in controls, and simplifying privacy policies, brands can mitigate consumer apprehension and foster trust (Li et al., 2024). However, this must be done with caution, as revealing certain techniques, such as third-party data brokering, may ironically heighten discomfort or suspicion (Ghanbarpour et al., 2022). Thus, transparency should not be viewed merely as a regulatory obligation but as a consumer-centric strategy that reinforces autonomy, fairness, and ethical data use.

In sum, perceived creepiness reflects a pivotal point where AI personalisation either fosters engagement or triggers resistance (AbouElgheit, 2024; Lee et al., 2024). Its presence underscores the need for ethically balanced, emotionally intelligent advertising design, where relevance is maximised without sacrificing consumer trust (Rodgers & Nguyen, 2022).

> *H3*: Perceived creepiness will (a) reduce brand engagement by decreasing click intention, like intention, comment intention, and share intention, but (b) increase ad avoidance.

2.6. The Moderating Role of Business Experience in AI-Personalised Advertising

Although AI-generated advertising enables large-scale personalisation, consumer responses are far from uniform. One particularly relevant individual-level factor shaping these responses is business experience, a form of domain-specific knowledge that influences how consumers interpret, evaluate, and react to personalised advertising. Entrepreneurial and business-experienced individuals who frequently engage with digital marketing tools, data analytics, and customer segmentation strategies are more likely to understand the mechanisms underlying AI-generated content (Barbosa et al., 2024). This greater digital literacy equips them to detect personalisation cues more easily, especially when ads reflect behavioural targeting or strategic message tailoring. As a result, even when exposed to the same AI-generated content, business-savvy individuals may perceive the ads as more personalised than their less-experienced counterparts.

This heightened perception of personalisation can be attributed to several psychological and strategic factors. First, these individuals are often early adopters of AI technologies, not only in their businesses but also in their personal digital ecosystems (Ford et al., 2023; Huh et al., 2023). Their familiarity with customer analytics, CRM systems, and algorithmic targeting increases cognitive fluency, making them more receptive to message customisation. Second, they tend to approach content from a goal-oriented and analytical perspective, aligning advertising value with performance metrics such as relevance, return on investment (ROI), and engagement efficiency (Arbaiza et al., 2024; Coffin, 2022). This means that when AI-generated content appears smart, data-driven, or responsive, it may be interpreted as strategically sound and highly personalised. However, this greater fluency also brings more critical scrutiny. Individuals with business experience are more likely to assess the ethics and transparency of AI usage in advertising (Raji et al., 2024). If personalisation appears manipulative or lacks authenticity, they may respond with heightened scepticism. Thus, their perceptions are not just more attuned, but also more nuanced, balancing appreciation of AI's efficiency with sensitivity to overreach or data misuse.

From a theoretical standpoint, this suggests that business experience may moderate the relationship between ad type (AI vs. non-AI) and perceived personalisation. In turn, perceived personalisation has been shown to mediate the relationship between ad type and consumer outcomes such as engagement, relevance, and avoidance. Therefore, the indirect effect of ad type on outcomes, through perceived personalisation, may be stronger or weaker depending on the level of business experience. This moderated mediation model reflects the reality that personalised advertising does not function in a

cognitive vacuum; its effectiveness depends not only on the content itself but also on who is processing it. Business-experienced individuals, as a key psychographic segment, thus play a pivotal role in determining how personalised AI content is perceived and acted upon.

> *H4*: Business experience moderates the indirect effect of ad type on consumer outcomes (engagement and ad avoidance) via perceived personalisation, such that the indirect effect is stronger among individuals with higher business experience.

2.7. Conceptual Model

This study proposes a conceptual framework integrating three key psychological mechanisms, perceived personalisation, perceived relevance, and perceived creepiness, to explain how consumers respond to AI-generated versus human-created advertising. Prior research suggests that while personalised ads can increase consumer engagement and positive brand attitudes, they may also provoke discomfort when the targeting appears overly intrusive (De Keyzer et al., 2024; Li et al., 2024). This dual effect, often referred to as the personalisation paradox, forms the theoretical foundation for this model.

The framework includes four main hypotheses, illustrated in Figure 1. Together, they explore both the direct and indirect effects of AI-generated advertising on consumer outcomes.

- H1 posits that AI-generated advertising, compared to human-created ads, will lead to differences in perceived personalisation, which in turn influences both relevance and creepiness. Specifically, perceived personalisation is expected to mediate the effects of ad type on these psychological responses, reflecting the ambivalent impact of personalised communication.
- H2 proposes that perceived relevance will lead to (a) increased consumer engagement (e.g., clicks, likes, comments, shares) and (b) reduced ad avoidance, consistent with literature linking perceived relevance to attentional and behavioural outcomes.
- H3 argues that perceived creepiness will result in (a) decreased engagement and (b) increased ad avoidance, reflecting consumer defence mechanisms when personalisation is perceived as unsettling or invasive.

- H4 introduces business experience as a moderating variable. Specifically, it predicts that individuals with greater business or marketing experience will be more likely to perceive AI-generated ads as personalised due to their familiarity with digital targeting strategies. Furthermore, business experience is expected to moderate the indirect effect of ad type on behavioural outcomes (engagement and avoidance) via perceived personalisation, consistent with a moderated mediation structure.

This integrated model provides a basis for examining how consumers process and react to AI-generated advertising, depending not only on content features but also on individual experience and expectations (see Figure 1). It enables the empirical testing of both mediating pathways and moderating influences and highlights the trade-offs between innovation and emotional comfort in digital communication.

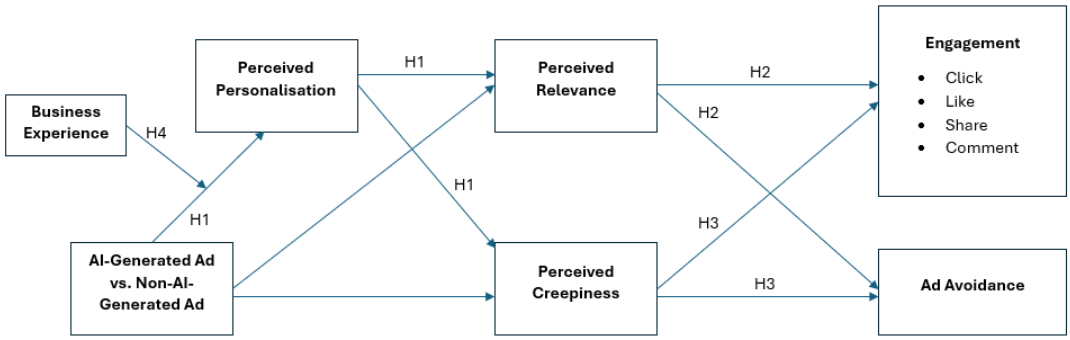


Figure 1 Research Model

2.8. Chapter Conclusion

This chapter has examined the evolution of advertising, highlighting the shift from non-AI approaches to highly dynamic, AI-powered systems characterised by automation, personalisation, and real-time optimisation. While AI-driven advertising offers unprecedented precision and operational efficiency, the literature underscores its dual nature, enhancing engagement and relevance on one hand, while risking intrusiveness, perceived manipulation, and trust erosion on the other. These tensions are encapsulated in the personalisation paradox, which reveals how the same mechanisms that increase ad effectiveness can also provoke consumer discomfort and avoidance.

The chapter further explored cognitive and affective consumer responses, drawing on the SNS-Post Processing Framework to explain how audiences process AI-generated versus human-crafted content on social media. Core constructs such as perceived personalisation, relevance, and creepiness emerged as central determinants of engagement, brand attitude, and ad avoidance. Additionally, the review highlighted the privacy-calculus theory as a useful framework for understanding how consumers balance perceived benefits against privacy risks, particularly in AI-mediated advertising environments.

Importantly, the chapter recognised that consumer responses are not uniform but are moderated by demographic and psychographic factors, notably entrepreneurial experience, which influences perceptions of authenticity, utility, and ethical design. By synthesising these insights, this literature review identifies critical gaps in empirical research, particularly regarding the long-term effects of AI-driven advertising on trust and brand loyalty, while laying a robust theoretical foundation for this study's conceptual model and hypotheses. This model, introduced at the end of this chapter, integrates the identified constructs and moderating variables to guide the empirical investigation that follows. Building on this foundation, Chapter 3 details the research design and methodology, explaining how these constructs are operationalised and measured. It discusses the experimental design, participant selection, data collection process, and statistical techniques used to empirically examine the relationships proposed in the conceptual model.

Chapter 3: Research Design and Methodology

3.1. Introduction

With a focus on perceived personalization, relevance, and creepiness as mediators influencing brand engagement and ad avoidance, this chapter describes the research design and methodological procedures used to investigate differences in consumer responses to AI-generated versus human-created social media advertisements. Using a between-subjects experimental design and an online Qualtrics survey, the study takes a quantitative, causal-explanatory method, grounded in a post-positivist paradigm with objectivist ontology and positivist epistemology. Using Amazon Mechanical Turk, participants were chosen at random from three ad conditions according to their experience or interest in entrepreneurship. After analysing the data using SPSS for factor, reliability, and descriptive analysis, SmartPLS 4.1's Partial Least Squares Structural Equation Modelling (PLS-SEM) was used to evaluate the constructs' psychometric validity, test direct and indirect path effects, and investigate moderating factors like business experience. To ensure a thorough and morally sound investigation of how ad format and personalization affect digital consumer behaviour, the chapter is organized to explain the philosophical foundations of the study, justify the methodological decisions, describe the experimental and sampling procedures, describe the measurement tools, and outline the ethical safeguards put in place.

3.2. Research Paradigm

The framework that directs researchers as they plan and build a research endeavour is known as the research paradigm (Gray, 2018). Determining a suitable research paradigm is crucial because it will direct the study's activities, including conceptualizing and planning the study, creating a plan for gathering data, and analysing and interpreting the data to support or refute the suggested theories, all of which are necessary to produce the intended research results (Levers, 2013).

Ontology, epistemology, and paradigm are the proper terms to use when developing a research project. Understanding the nature of reality, or simply "what is reality," is the focus of ontology; understanding "what is acceptable knowledge" is the goal of epistemology; and knowing "what approach to use to get knowledge" is the focus

of paradigm (Gray, 2018; Wilson, 2010). Exploring the effects of AI use on online social media advertising in promoting a business is the main goal of the research topic for this study. Therefore, addressing this topic is the main goal of the study's ontology, epistemology, paradigm, and methodology decisions. In the lines that follow, each of these options will be discussed in more detail.

Since the goal of the study was to identify the causal structures and quantifiable relationships that underpin consumer reactions to AI-generated advertising, the study first adopts an objectivist ontology in line with the larger tradition of realism (Creswell, 2018). According to Levers (2013), this position makes the assumption that reality, including concepts like perceived creepiness, relevance, or behavioural engagement, exists apart from personal ideas and values. The realist presumption that information on the efficacy of advertising may be objectively researched and generalized was supported by the operationalization of these latent constructs through verified survey items and quantitative analysis modelling. Therefore, the observed events are positioned as discoverable truths about the digital advertising environment by the research design.

Second, the epistemological method is based on positivist empiricism, which uses rigorous measurement and hypothesis testing to find objective information about customer behaviour (Gray, 2018). By using well-known measuring scales and statistical methods like SmartPLS for path modelling and SPSS for validation, this work seeks to reduce researcher bias in accordance with an objectivist epistemology. According to this perspective, truths can be discovered through scientific research since reality exists apart from human consciousness (Levers, 2013). The study supports the idea that reliable insights come from systematic, repeatable data collection and analysis since customer responses to AI advertising can be measured using behavioural intention metrics (such as clicks, comments, likes, and shares).

Third, the post-positivist paradigm, which is especially suitable for behavioural and advertising research containing intricate psychological concepts, is where this study is situated. The post-positivist paradigm acknowledges that knowledge is imperfect, probabilistic, and influenced by contextual circumstances, in contrast to rigorous positivism, which holds that there is perfect objectivity and ultimate truth (Creswell, 2018). The study noted that not all associations were significant and that consumer responses may differ depending on segment characteristics like company experience, even as it worked to statistically validate theories about AI influence, creepiness,

relevance, and personalisation. This is consistent with post-positivism's view that reality can only ever be roughly represented (Levers, 2013). The findings thus complement the paradigm's emphasis on evidence, falsifiability, and structured inquiry because they are evidence-based generalisations rather than universal laws (Gray, 2018). Additionally, the study advances our knowledge of how consumers interpret and process AI-driven advertisements, which is consistent with post-positivism's goal of employing solid empirical evidence to explain human behaviour (Kankam, 2019).

3.3 Research Methodology

A study's organisation and execution are guided by the research methodology, which includes the research approach, data gathering techniques, and data analysis procedures (Creswell, 2018). To comprehensively investigate how consumers react to AI-generated advertising along dimensions such as perceived personalisation, perceived relevance, and perceived creepiness, a quantitative research approach was used in this study. The objective was to assess the impact of AI advertising on a range of behavioural and attitudinal outcomes, such as ad avoidance and engagement metrics (click, like, comment, share), and to test hypothesised relationships empirically.

The goal of quantitative research is to measure and explain relationships between variables objectively. By using validated tools and statistical methodologies, it minimises researcher bias and adheres to systematic, repeatable procedures (Mertler & Charles, 2005). This method worked well for the current study since it made it easier to evaluate causal hypotheses, allowed for moderation and mediation analysis, and made it possible to extrapolate results outside of the sample. Researchers can evaluate patterns and verify theoretical predictions in a thorough and transparent way by using quantitative approaches, which convert responses into numerical values and use statistical models (Creswell, 2018).

Participants (who were recruited using MTurk) were randomly exposed to either AI-generated or non-AI-generated social media adverts as part of the study's experimental survey design housed on Qualtrics. The survey used Likert-scale tools that have been validated in the literature to measure a variety of consumer perceptions and behavioural intentions. This architecture made it possible to assess the measurement and structural models using regression-based modelling with SPSS and SmartPLS, as well as between-

group comparisons. Multi-item scales with proven validity and reliability were used to operationalise key constructs.

In line with best standards in quantitative research, the study adopted structured sampling processes to recruit a varied sample of persons aged 18 and above and collected data anonymously to ensure ethical integrity. Reliability testing (Cronbach's alpha and Composite Reliability), convergent and discriminant validity (via AVE and correlation matrices), descriptive statistics, and hypothesis testing utilising path modelling approaches were among the steps in the data analysis process (Edmonds & Kennedy, 2013; Wilson, 2010).

All things considered, a quantitative approach was in line with the goals of the study, allowing for the use of statistical analysis based on hypotheses to investigate how AI-driven personalisation and perceived relevance affect user engagement while taking into consideration factors like ad avoidance and business experience. The conclusions are supported by the method's inherent objectivity and replicability, which also enable possible generalisation to larger online customer populations.

3.4 Sampling and Data Collection

The purpose of this study was to test the validity of the conceptual model. To streamline the research process, the questionnaire was developed using Qualtrics, a web-based survey platform, and distributed via Amazon Mechanical Turk (MTurk), a crowdsourcing website. MTurk is widely recognised as an effective tool for collecting consumer insights, enabling rapid access to a large and diverse sample (Daly & Nataraajan, 2015; Keith et al., 2017). The use of MTurk ensured an anonymous and randomised sample, as participants did not reveal any identifying information. Each participant received US$2 as compensation for completing the survey and was informed that participation would take approximately 10 to 15 minutes. Data collection was conducted in a single wave, between July 7 and July 8, 2025.

Eligible respondents included individuals aged 18 and over, residing in the United States, who either had business experience or aspired to gain it. A screening question was included at the start of the survey to ensure alignment with the target sample: “Which of the following best characterises your current business experience?” Participants who

selected “I am not interested in starting a business” were directed to the end of the survey and excluded from further participation. Those who selected either “I am interested in starting a business but have not yet started” or “I am currently running or managing my own business” were permitted to proceed (**Table *1***). Participants under 18 were automatically screened out.

Additionally, a quota was established on Qualtrics to obtain a total of 150 valid responses, ensuring a balanced sample across the experimental conditions (AI-generated vs. human-created ads, and experienced vs. aspiring business participants). Fifty participants (both experienced and aspiring business participants) were exposed to an online course advertisement created by a human, fifty aspiring business participants viewed an online course ad generated by AI (ChatGPT), and fifty experienced business participants viewed an online course ad generated by AI (ChatGPT) (**Appendix D**). The AI-generated ads were tailored based on the participants' level of business experience. This study's experimental modification was restricted to text-based advertisement content; the stimuli did not contain any dynamic or visual components. This method was selected to keep control over unrelated variables while isolating the impact of the message source (AI-generated vs. human-created). There was no missing data in the final dataset, as all survey items were set as mandatory within the Qualtrics platform.

Several screening and quality-control methods were used to guarantee the validity and quality of the data. Initially, a screening question at the beginning of the survey confirmed that participants were either aspiring or seasoned business owners and that they were at least 18 years old. Participants who did not fit these requirements were immediately disqualified from the study. To detect inattentive respondents, the survey also included attention-check items. Participants who failed these tests were eliminated from the dataset. By keeping an eye on MTurk Worker IDs, duplicate entries were avoided, and responses that showed indicators of poor engagement, like irregular response patterns or unreasonably quick completion times, were eliminated. When combined, these processes made sure that only dependable, high-quality answers were kept for examination.

Table 1. *Participant Profile*

Profile	Statement
Aspiring Entrepreneur	I am interested in starting a business.
Experienced Entrepreneur	I am currently running or managing my own business.

Note. "Aspiring entrepreneurs" are actively planning or getting ready to start an online business, whereas "experienced entrepreneurs" are people who currently run an online business (such as e-commerce, consulting, or digital products).

Participants were invited to complete an online questionnaire designed to assess their perceptions and behavioural responses to AI-generated versus non-AI-generated Facebook advertisements. The survey included items measuring perceived personalisation, perceived relevance, perceived creepiness, ad avoidance, and engagement behaviours, alongside demographic variables such as age, gender, and business experience. All items were adapted from previously validated instruments to align with the context of the present experimental study (see **Table *2***). Participants rated their responses on a 7-point Likert scale ranging from 1 – “Strongly Disagree” to 7 – “Strongly Agree,” or on a semantic differential scale where appropriate.

Table 2. *Item Measurements*

Constructs and Items	
Perceived Personalisation (adapted from De Keyzer, Dens, et al. (2022))	
A.1	I believe this ad is customised to my characteristics
Perceived Relevance (adapted from De Keyzer, Dens, et al. (2022))	
B.1	For me, this Facebook advertisement by LIM is not important/important
B.2	For me, this Facebook advertisement by LIM is not relevant/relevant
B.3	For me, this Facebook advertisement by LIM is meaningless/meaningful
Perceived Creepiness (adapted from De Keyzer, Van Noort, et al. (2022))	
C.1	To what extent do you think the advertisement by LIM was creepy
C.2	To what extent do you think the advertisement by LIM was disturbing
C.3	To what extent do you think the advertisement by LIM was worrying
Ad Avoidance (adapted from De Keyzer, Van Noort, et al. (2022))	
D.1	I want to resist the advertisement
D.2	I want to dismiss the content of the advertisement
D.3	I want to avoid this kind of advertisement
Engagement (adapted from Buzeta et al. (2024))	
E.1	I would click the advertisement to obtain more information
E.2	I would click like this Facebook advertisement
E3.	I would share this Facebook advertisement
E4.	I would comment on this Facebook advertisement

To measure perceived personalisation, one item was adapted from De Keyzer, Dens, et al. (2022): "I believe this ad is customised to my characteristics." This item captured participants' perception of whether the ad content was tailored to them personally. Perceived relevance was assessed using a 3-item semantic differential scale, also adapted from De Keyzer, Dens, et al. (2022). Participants were asked to rate the advertisement on dimensions such as importance, relevance, and meaning, e.g., "For me, this Facebook advertisement by LIM is meaningless/meaningful." To evaluate perceived creepiness, a 3-item scale adapted from (De Keyzer, Van Noort, et al., 2022) was used. Participants rated the ad on how creepy, disturbing, and worrying they found it (e.g., "To what extent do you think the advertisement by LIM was creepy?"). Ad avoidance was assessed with three items adapted from (De Keyzer, Van Noort, et al., 2022), such as "I want to avoid this kind of advertisement" and "I want to resist the advertisement," measuring psychological and behavioural intent to disengage from the ad. To capture

engagement behaviours, four items adapted from Buzeta et al. (2024) asked participants how likely they were to engage with the advertisement by clicking, liking, sharing, or commenting (e.g., “I would click the advertisement to obtain more information”).

3.5. Data Analysis

IBM SPSS Statistics Software (Version 30) and SmartPLS 4.1 were used to analyse the legitimate data collected from research participants. Using SPSS, preliminary results were obtained through reliability analysis, confirmatory factor analysis, and initial descriptive analysis to collect demographic characteristics of the sample. The associations between the variables in the study were then tested using structural mediation modelling with SmartPLS.

3.5.1 Data preparation by SPSS

Following the collection of research participant data, the data was downloaded in a table-structured manner from Qualtrics, containing numerical values for each response. Before the file was uploaded into IBM SPSS Statistics Software, the data was cleansed. The data was cleaned by ensuring correct age and codes were formatted, as well as removing all blank data rows, ensuring no missing data. Every scale item from the survey was labelled and coded in SPSS. To ascertain the sample's characteristics, a basic demographic analysis was first conducted for each profile group. The mean values and standard deviations of every survey item were then summarised using an initial descriptive analysis. Descriptive statistics, as noted by Gavin (2008), offer a useful synopsis that makes it possible to compare population subgroups and constructs of interest.

The current study adhered to the guidelines provided by Hair Jr et al. (2014), which recommends a two-step measurement-model analysis to guarantee that all constructs were measured correctly. This analysis consists of evaluating the reliability of all measures by looking at their Cronbach's alpha values and testing the validity of all measures using confirmatory factor analysis (CFA). The internal consistency of each scale item was first confirmed by testing each construct using confirmatory factor analysis (CFA) (Hancock & Mueller, 2001). In order to ascertain whether the model fits the current study conditions well, CFA analyses the link between latent variables, often referred to as the constructs, and the measurements or observed variables (Roos & Bauldry, 2022). Therefore, it is essential to assess the factor loadings derived from the CFA analysis to comprehend the

relationship between each observed variable and the latent variable. Low factor loadings suggest that the observed variable is not an effective way to measure a latent variable, whereas higher loadings show that the observed variable has a large influence on the hidden variable (Roos & Bauldry, 2022). For a value to be considered consistent, it must be more than 0.50 (Hancock & Mueller, 2001).

To ascertain whether each scale might be regarded as a valid measure for the study, reliability analysis was used in the following phase (Pallant, 2010). To put it simply, the research tool needs to be dependable so that the outcomes of a repeat experiment conducted under the same circumstances should be reasonably comparable to those of the initial test (Field, 2018). Cronbach's alpha is the most often used measure of the scale's internal consistency (Pallant, 2010). For a scale to be considered reliable and its items consistent, its Cronbach's alpha coefficient should ideally be at least 0.70 (Hair, 2010). Hinton (2004) state that "high reliability" is defined as values between 0.70 and 0.90, while "excellent reliability" is defined as values 0.90 and higher.

3.5.2 Model testing by using SmartPLS.

Using the SmartPLS 4.1 software, Partial Least Squares Structural Equation Modelling (PLS-SEM) was used to examine the survey data. Because of its ability to analyse complex research models with mediating and moderating variables, PLS-SEM was chosen. This is especially true for studies with non-normal data distributions, smaller sample sizes (between 100 and 200), and predictive goals (Chin, 1998; Haenlein & Kaplan, 2004; Hoyle, 1995). This approach made it possible to evaluate the hypotheses that were put forth, assess the constructs' psychometric qualities, and investigate the direct and indirect connections between the structural model's latent variables.

The final cleaned dataset from the structured online experiment was imported into a new SmartPLS 4.1 project to start the data analysis. Perceived personalization, perceived relevance, perceived creepiness, ad avoidance, and engagement (click, like, comment, share) are examples of latent constructs that were added to the structural model based on the conceptual framework previously described in this thesis. These constructs were then connected based on the hypothesized relationships. In accordance with Hair et al. (2011), the PLS-SEM path modelling approach was used to compute t-statistics and p-values for hypothesis testing utilizing the path weighting scheme with 5,000 bootstrap samples and a significance level of 0.05. Variance Inflation Factor (VIF) values were analysed in SmartPLS to evaluate multicollinearity among the predictor variables. All the

VIF values were below the widely recognized cutoff point of five, suggesting that the predictor variables each made a distinct contribution to the explanation of variance in the endogenous constructs and that multicollinearity was not an issue in the measurement or structural models.

T-statistics are used in this study to determine whether the route coefficients deviate considerably from zero; values greater than ±1.96 are considered statistically significant at the 95% confidence level (Field, 2018). Accordingly, p-values indicate the likelihood that the observed outcomes were the result of chance; statistically significant effects are indicated by values less than 0.05 (Field, 2018).

Several validation tests were carried out to assess the measurement model. First, the validity of the constructs was confirmed using Confirmatory Factor Analysis (CFA). Item dependability was indicated by factor loadings greater than 0.70 (Hair, 2010). Convergent validity was evaluated using Average Variance Extracted (AVE); values greater than 0.50 suggest that the construct explains a greater proportion of variance than measurement error (Bagozzi & Yi, 1988). The Fornell-Larcker criterion, which compares the square root of each concept's AVE with its inter-construct correlations to verify that each construct is empirically unique, was used to assess discriminant validity (Chin, 1998; Fornell & Larcker, 1981). Additionally, Cronbach's alpha and Composite Reliability (CR) were calculated to determine internal consistency reliability, and both values exceeded the 0.70 criterion (Fornell & Larcker, 1981; Hair, 2010). Because all item loadings surpassed 0.70 and the measure showed adequate convergent validity, the Perceived Relevance construct was kept even though its Cronbach's alpha was marginally below the traditional 0.70 standard. However, this moderate reliability implies that future study on the scale might benefit from improvement or retesting. Lastly, these variables were included as control variables in the structural model to account for potential variance attributable to individual characteristics. This was done because previous research has demonstrated the impact of demographic factors, such as gender, age, and business experience, on consumer responses to advertising (Davvetas et al., 2022; Lavuri et al., 2022).

To minimize respondent burden and preserve a brief survey, the study used a single-item measure for the engagement construct (click, like, comment, share). Although reliability assessment may be limited by single-item measures, its application is appropriate for specific and easily comprehensible behavioural phenomena. This trade-

off is recognized, and multi-item engagement measures could be useful in future research to improve measurement accuracy and dependability.

To determine if business experience mitigated the impact of ad type on perceived personalization, the moderated mediation hypothesis (H4) necessitated the development of an interaction term between ad type and company experience. The two-stage method used in SmartPLS to generate this interaction term involved first estimating the latent variable scores and then multiplying them to create the interaction construct. Indirect effects flowed through perceived relevance, perceived creepiness, engagement, and ad avoidance. The moderation was examined on the pathway from ad type to perceived personalization. The modelling process adhered to suggested PLS-SEM procedures and enabled reliable estimation of the conditional associations even though the interaction effect was not statistically significant.

The study satisfied the suggested minimal criteria for identifying small-to-moderate interaction effects in PLS-SEM due to the total sample size of 150 participants. The sample size was adequate for estimating interaction terms using the two-stage approach and offers an acceptable foundation for evaluating the non-significant moderation impact shown in this study, even though moderation usually requires larger samples than mediation.

The journey from ad type to perceived personalization is where the moderating effect enters the structural model. To determine whether seasoned business owners see AI-generated versus human-created advertisements differently from aspiring business owners, business experience was modelled as a moderator on this relationship. Through the mediators of perceived personalization, perceived relevance, and perceived creepiness, this regulated pathway then indirectly affects the downstream outcomes of engagement and ad avoidance. It is easier to differentiate the moderated mediation structure from the direct mediation effects examined in previous hypotheses when this position in the model is made clear.

3.6. Ethical Considerations

According to Creswell and Creswell (2017), ethical issues are crucial for any kind of research involving human subjects. This study complies with the ethical guidelines set

forth by the Auckland University of Technology Ethics Committee (AUTEC) and is consistent with the more general social science research values of respect, integrity, and participant protection. Care has been taken to ensure informed permission, protect data security, and preserve anonymity because the study involves human participants answering simulated ads in an online survey environment.

The study's design places a high priority on confidentiality and anonymity. Amazon Mechanical Turk (MTurk) is used to gather all participant responses anonymously; no personally identifiable information (PII) is ever recorded. Only randomly allocated MTurk Worker IDs are used to identify participants; these IDs are not connected to survey answers at the time of data collection or analysis. All information will be safely kept on AUT's OneDrive platform, which is password-protected and only the supervisory team and researcher can access it, to preserve confidentiality. The dataset will be kept for six years before being irreversibly erased using safe data disposal techniques in accordance with AUTEC's data retention policy.

The MTurk survey interface has an electronic procedure for obtaining informed consent. Prior to starting the survey, participants get an information sheet explaining the type of the commercial content they will be exposed to, the research's goal, the estimated time needed, and how their data will be handled. The entire poll is only accessible to those who check a consent box, indicating their voluntary agreement to participate. To reinforce autonomy and voluntary involvement, participants are also made aware of their right to resign from the study at any time before final submission without incurring penalties.

Participants receive fair compensation in accordance with MTurk norms and ethical criteria for participating in online research to guarantee ethical compensation. To assure fair participation free from compulsion, each respondent is paid USD $2 for their time, which corresponds to the study's expected 10-minute duration.

The study design also considers psychological safety and participant well-being. There is nothing sensitive, gory, or upsetting in the marketing stimuli, which are typical of social media content. Since the study is deemed low-risk, no additional intervention or follow-up assistance is required. The survey does, however, end with a debriefing message that thanks participants for their participation and explains the study's academic goal.

Lastly, by guaranteeing inclusive methods, fair treatment of all participants, and open communication throughout the research process, this study upholds the Treaty of Waitangi's tenets of partnership, protection, and participation. The study is culturally sensitive and does not particularly target Māori or other ethnic groups, but it is designed to avoid any practices or content that could be seen as disrespectful or exclusionary. By taking these precautions, the study upholds the highest ethical standards and guarantees that each participant is treated fairly, with respect, and with dignity at every stage of the research process.

3.7. Chapter Conclusion

The research methodology used to examine how consumers react to social media ads produced by AI as opposed to humans is described in this chapter. Using a quantitative, causal-explanatory methodology, the study employs a post-positivist paradigm based on positivist epistemology and objectivist ontology to investigate how ad type affects perceived personalization, perceived relevance, and perceived creepiness, mediators that affect brand engagement, and ad avoidance. An online Qualtrics survey was used to establish a between-subjects experimental design, and Amazon Mechanical Turk was used to recruit participants. Participants filled out validated Likert-scale measures after being randomly assigned to one of three ad conditions. Partial Least Squares Structural Equation Modelling (PLS-SEM) in SmartPLS 4.1 was used to assess the hypothesised paths, mediators, moderators (perceived personalisation), and outcome variables after the data had been analysed using SPSS for preliminary reliability and CFA. Strict adherence to ethical standards was maintained, including informed permission, data anonymization, safe storage, AUTEC approval, and equitable participant pay. Validity, dependability, and the possibility of extrapolating results to larger digital consumer contexts are all guaranteed by the methodology. Chapter 4 reports the outcomes of the statistical tests, including reliability and validity assessments, descriptive statistics, and hypothesis testing. This chapter links directly back to the research questions, providing quantitative evidence that addresses the theoretical and empirical gaps identified in Chapter 2.

Chapter 4: Findings

4.1. Introduction

The findings of the statistical analysis are presented here to test the previously suggested hypotheses. The impact of AI on online social media ads for business promotion was examined using SPSS Version 30 and SmartPLS 4.0 statistical software, with perceived personalisation serving as a mediating variable.

4.2. Sample

In total, 150 people completed the questionnaire; the participants who are interested in starting a business but have not yet started (n = 67) and the participants who are currently running or managing their own business (n = 83). **Table *3*** displays the sample's demographic characteristics.

Table 3. *Respondent's Profile*

Demographics	**Frequency (n=150)**	**%**
Gender		
Male	48	32
Female	102	68
Business Experience		
Interested in starting a business but have not yet started	67	44.7
Currently running or managing my own business	83	55.3

Note. Age was collected as a continuous variable. Participants ranged from 24 to 60 years old (M = 34.19, SD = 7.45)

Table *3* indicates that the ages of the participants ranged from 24 to 60 years (M = 34.19, SD = 7.45). 68% (n = 102) of the 150 respondents identified as female, and 32 percent (n = 48) as male. 44.7% (n = 67) of respondents said they were interested in starting a business but had not yet done so, while 55.3% (n = 83) said they were actively managing or operating their own company.

Despite having both male and female participants, there was a clear gender disparity in the sample, with a greater percentage of female respondents. Online survey platforms like MTurk, where female participation rates are often greater, frequently exhibit this discrepancy. Gender was incorporated as a control variable in the structural model to take into consideration any impact of gender on the major constructs. The findings showed that the associations between ad type, perceived personalization, perceived relevance, perceived creepiness, engagement, and ad avoidance were not significantly impacted by gender. As a result, even when the imbalance is recognized, the validity of the results does not seem to be compromised.

4.3. Data Examination

SPSS Version 30 and SmartPLS 4.0 statistical software were utilised to accomplish the study's goals and test the hypotheses that were put forth. Descriptive analysis was performed using SPSS to provide a preliminary analysis of the data and determine the sample's demographic characteristics. Additionally, the data set was tested using reliability analysis and confirmatory factor analysis. Confirmatory factor analysis was used with SmartPLS to demonstrate the validity of each construct, and Cronbach's alpha and composite reliability (CR) indices were used to assess the constructs' reliability. The research hypotheses were then tested using structural equation modelling. The next sections provide more information on the procedures followed to perform the data examination.

4.3.1 Missing data

The data set was moved to SPSS for preliminary cleaning and descriptive analysis when the experiment's Qualtrics quota was reached. To ensure that there was no missing data for the analysis of the measurement variables, it is crucial to remember that each item on Qualtrics was made mandatory for research participants to complete before they could proceed with the survey. As a result, the data set was suitable for further study.

4.3.2 Initial analysis on SPSS

To comprehend the overall construction of the nine questions, SPSS was used to evaluate confirmatory factor analysis (CFA). The purpose of this phase was to verify that every item was loaded into the appropriate structures. On SmartPLS, a more thorough analysis

was conducted based on each condition. Ad avoidance, perceived creepiness, and perceived relevancy were the three initial constructs. Given that their factor loadings were more than 0.50, the results demonstrated that the items were loaded in their own constructions (**Table *4***). According to Hair (2010), this indicates that the items met the acceptable convergent validity threshold. The internal consistency of the measures was then evaluated for each construct using Cronbach's alpha coefficients. Hair (2010) state that to demonstrate that a concept has a satisfactory degree of internal consistency, the coefficient needs to be more than 0.70. The analysis's findings, including factor loadings, mean values, standard deviations, and Cronbach's α for every item, are displayed in **Table *4***.

The first construct related to an individual's perceived relevance in assessing if a social media advertisement is relevant, important, and meaningful (De Keyzer, Dens, et al., 2022). Factor loading of each item was 0.821, 0.727, and 0.814, with Cronbach's α of 0.688. This construct's Cronbach's α result is marginally below 0.7 and is kept in as a "grey area" for further testing on SmartPLS. The second construct is related to perceived creepiness and, in particular, to the extent that an individual thinks an advertisement is creepy, worrying, and disturbing (De Keyzer, Van Noort, et al., 2022). Factor loading of each item was 0.897, 0.940, and 0.929, with Cronbach's α of 0.911. The third construct is related to an individual's urge to resist, dismiss, and avoid a particular advertisement, i.e., ad avoidance (De Keyzer, Van Noort, et al., 2022). Factor loading of each item was 0.904, 0.918, and 0.928, with Cronbach's α of 0.905.

Table 4. *Factor loading and Cronbach's alpha.*

Constructs and items	Factor loadings	Mean	Standard Deviation	Cronbach's alpha (α)
Perceived Relevance				
Relevance 1	0.821	0.607	0.956	
Relevance 2	0.727	0.595	1.070	0.688
Relevance 3	0.814	0.611	0.909	
Perceived Creepiness				
Creepiness 1	0.897	4.66	1.609	
Creepiness 2	0.940	4.82	1.858	0.911
Creepiness 3	0.929	4.92	1.808	
Ad Avoidance				
Avoidance 1	0.904	5.01	1.591	
Avoidance 2	0.918	4.97	1.665	0.905
Avoidance 3	0.928	5.10	1.621	

4.3.3 Conceptual model testing on SmartPLS

The theoretical concept was then tested using the SmartPLS structural mediation model. This strategy was used because it is a good approach for predicting correlations between latent variables, and furthermore, it determines how well the model describes the constructs of interest (Hair, 2010). The SmartPLS 4.1.1.3 software was used to do the analysis. Three steps are suggested for testing the conceptual model: First, to make sure that every construct was measured correctly, validity and reliability assessments were performed. Second, to confirm discriminant validity across all constructs, correlation analysis was performed. Third, the suggested hypotheses were tested using bootstrapping and structural path analysis to assess significance.

First, reliability and validity evaluations were used to evaluate the quality of the data. Convergent factor validity of the conceptual framework was tested for reliability using confirmatory factor analysis (CFA) on the entire collection of constructs. By determining whether the average variances extracted (AVE) values were more than 0.50, the convergent validity of the conceptions was evaluated (Hair, 2010). In terms of validity, each construct's reliability was examined by looking at its composite reliability (CR) values, which need to be higher than the 0.70 threshold (Hair Jr et al., 2014). Cronbach's alpha (α), which must be greater than 0.70, was used to evaluate the constructs' internal

consistency and dependability (Hair, 2010). Each condition's data was examined independently. **Table *5*** represents the reliability, validity and internal consistency results.

The majority of the Cronbach's α values for the different constructs (see Table 5) were higher than the minimum value of 0.70 (Ad Avoidance = 0.905; Perceived Creepiness = 0.912). Perceived Relevance (α = 0.694) was the only construct that marginally failed to satisfy the 0.70 criteria due to its low Cronbach's α. But for several reasons, the contents were kept. Some believe that 0.50 is a suitable threshold when constructs have fewer than ten items on the scale, even if this construct is marginally below the loading of 0.70 that Hair Jr et al. (2014) recommend (Pallant, 2010). This claim is supported by Hinton (2004), who remark that an alpha score of 0.50 to 0.70 is widely recognised as indicating moderate dependability.

All variables (Ad Avoidance = 0.940; Perceived Creepiness = 0.945, and Perceived Relevance = 0.831) are above the 0.50 criterion for composite reliability results. Lastly, the average variance extracted (AVE) scores for all variables (Ad Avoidance = 0.840, Perceived Creepiness = 0.851, and Perceived Relevance = 0.621) were higher than the suggested value of 0.50. Except for the perceived relevance measure, which has a Cronbach's α value slightly below 0.70, the results show sufficient reliability and convergent validity for the constructs employed overall.

Table 5. *Reliability, validity, and internal consistency*

Factors	Cronbach's alpha (α)	Composite reliability (CR)	Average variance extracted (AVE)
Ad Avoidance	0.905	0.940	0.840
Perceived Creepiness	0.912	0.945	0.851
Perceived Relevance	0.694	0.831	0.621

Second, the model was tested using correlation analysis to confirm discriminant validity among all the constructs in the conceptual framework, following an examination of the findings of the validity and reliability analyses in the previous section. The square root of the constructs' AVE must be greater than the correlation values to demonstrate discriminant validity. The correlation matrix for the different constructs is displayed in **Table *6***.

To make sure that each concept in the model was sufficiently different from the others, discriminant validity was evaluated using the Fornell–Larcker criterion. This criterion states that each construct's square root of the average variance extracted (√AVE) must be greater than its highest correlation with any other construct (Fornell & Larcker, 1981). Cronbach's alpha, composite reliability (CR), and AVE thresholds were used in the previous section to demonstrate appropriate reliability and convergent validity before this test was carried out.

Every construct exhibited satisfactory discriminant validity, as seen in **Table *6***. Perceived creepiness, for example, showed the highest association (r = 0.811); nevertheless, this value was still below the √AVE values (√AVE_Creepiness = 0.922). Other construct pairs that stayed below the √AVE values of the related constructs were Perceived Personalisation and Like (r = 0.366), Relevance and Click (r = 0.576), and Like and Comment (r = 0.435). These findings support discriminant validity across the measurement model by confirming that no construct shares more variation with another construct than it does with its own indicators. This gives assurance that the model's constructs are conceptually unique and suitably quantified.

Table 6. *Measurement Model Correlation Matrix*

	AI	Ad Avoidance	Business Experience	Click	Comment	Like	Perceived Creepiness	Perceived Personalisation	Perceived Relevance	Share	Business Experience x AI
AI	1.0										
Ad Avoidance	0.212	1.0									
Business Experience	-0.119	0.074	1.0								
Click	-0.072	0.037	0.009	1.0							
Comment	0.024	0.217	-0.032	0.381	1.0						
Like	-0.007	0.170	0.018	0.353	0.435	1.0					
Perceived Creepiness	0.181	0.811	0.061	-0.003	0.205	0.200	1.0				
Perceived Personalisation	-0.052	0.192	0.016	0.360	0.435	0.366	0.239	1.0			
Perceived Relevance	-0.131	-0.043	0.022	0.576	0.444	0.364	-0.059	0.456	1.0		
Share	-0.024	0.297	0.176	0.461	0.494	0.481	0.323	0.418	0.441	1.0	
Business Experience x AI	0.515	0.139	0.635	0.044	0.052	0.075	0.112	-0.024	-0.017	0.150	1.0

Thirdly, structural mediation modelling was used to assess the study hypotheses following validation of the overall model fit. The structural impacts derived from the SmartPLS model are shown in **Table** ***7***.

According to the results shown in **Table** ***7***, AI-generated advertising had a negative but marginally significant impact on perceived relevance (β = -0.226, t = 1.665, p = 0.096). In contrast, AI-generated ads significantly increased perceived creepiness (β = 0.408, t = 2.343, p = 0.019). However, AI advertising did not significantly influence perceived personalisation (β = -0.085, t = 0.341, p = 0.733), resulting in the rejection of H1a. Still, perceived personalisation strongly and significantly influenced both perceived creepiness (β = 0.249, t = 3.228, p = 0.001) and perceived relevance (β = 0.450, t = 4.913, p = 0.000), supporting H1b-H1c.

Business experience had no significant effect on perceived personalisation (β = 0.046, t = 0.174, p = 0.862), nor did the interaction between business experience and AI advertising (β = -0.038, t = 0.115, p = 0.909), resulting in the rejection of H4 (and its interaction term).

For H2a and H2b, perceived relevance positively and significantly predicted all engagement outcomes: click (β = 0.578, t = 8.430, p = 0.000), comment (β = 0.457, t = 5.574, p = 0.000), like (β = 0.377, t = 4.614, p = 0.000), and share (β = 0.461, t = 4.882, p = 0.000), supporting H2a. However, perceived relevance had no significant effect on ad avoidance (β = 0.005, t = 0.136, p = 0.892), leading to rejection of H2b.

In the context of H3a and H3b, interestingly, contrary to expectations, creepiness did not reduce engagement; instead, it was positively associated with comment (β = 0.232, t = 3.047, p = 0.002), like (β = 0.222, t = 3.139, p = 0.002), and share behaviour (β = 0.351, t = 6.377, p = 0.000). Its influence on click behaviour was not significant (β = 0.032, t = 0.517, p = 0.605), leading to a partial rejection of H3a. However, perceived creepiness had a strong and significant effect on ad avoidance (β = 0.812, t = 18.363, p = 0.000), confirming H3b.

In summary, the structural model results reveal a nuanced picture of AI-generated advertising effects. AI-generated ads did not significantly increase perceptions of personalisation (H1a not supported) or relevance but did significantly elevate feelings of

creepiness (H1c supported). Perceived personalisation emerged as a pivotal mediator, strongly increasing both relevance and creepiness, consistent with the personalisation paradox (de Groot, 2022). Among the outcome variables, perceived relevance was the most consistent predictor of positive engagement behaviours, click, comment, like, and share, while showing no significant impact on ad avoidance (H2a supported; H2b rejected). Conversely, perceived creepiness had a dual role: it strongly increased ad avoidance (H3b supported) but unexpectedly enhanced some engagement behaviours, including comments, likes, and shares, while having no significant effect on clicks (partial rejection of H3a). Business experience and its interaction with AI ad type did not significantly affect personalisation perceptions (H4 rejected), suggesting that experience levels did not moderate consumer evaluations of AI-generated content. Overall, the findings emphasise the importance of balancing relevance and emotional resonance in AI-driven campaigns, while also acknowledging the unintended influence of creepiness on user engagement and avoidance.

Table 7. *Structural Model Results*

Path	All (n=150)
AI-Generated Ad -> Perceived Relevance	β = -0.226 (*t* = 1.665, *p* = 0.096)
AI-Generated Ad -> Perceived Creepiness	β = 0.408 (*t* = 2.343, *p* = 0.019)
H1a: AI-Generated Ad -> Perceived Personalisation	β = -0.085 (*t* = 0.341, *p* = 0.733)
H1b: Perceived Personalisation -> Perceived Relevance	β = 0.450 (*t* = 4.913, *p* = 0.000)
H1c: Perceived Personalisation -> Perceived Creepiness	β = 0.249 (*t* = 3.228, *p* = 0.001)
Business Experience -> Perceived Personalisation	β = 0.046 (*t* = 0.174, *p* = 0.862)
H4: Business Experience x AI-Generated ad -> Perceived Personalisation	β = -0.038 (*t* = 0.115, *p* = 0.909)
H2a: Perceived Relevance -> Click	β = 0.578 (*t* = 8.430, *p* = 0.000)
H2a: Perceived Relevance -> Comment	β = 0.457 (*t* = 5.574, *p* = 0.000)
H2a: Perceived Relevance -> Like	β = 0.377 (*t* = 4.614, *p* = 0.000)
H2a: Perceived Relevance -> Share	β = 0.461 (*t* = 4.882, *p* = 0.000)
H2b: Perceived Relevance -> Ad Avoidance	β = 0.005 (*t* = 0.136, *p* = 0.892)
H3a: Perceived Creepiness -> Click	β = 0.032 (*t* = 0.517, *p* = 0.605)
H3a: Perceived Creepiness -> Comment	β = 0.232 (*t* = 3.047, *p* = 0.002)
H3a: Perceived Creepiness -> Like	β = 0.222 (*t* = 3.139, *p* = 0.002)
H3a: Perceived Creepiness -> Share	β = 0.351 (*t* = 6.377, *p* = 0.000)
H3b: Perceived Creepiness -> Ad Avoidance	β = 0.812 (*t* = 18.363, *p* = 0.000)

NOTE:

H1: (a) Due to the mediating effect of perceived personalisation, AI-generated ads, compared to human-created ads, will lead to (b) higher perceived relevance and (c) greater perceived creepiness.

H2: Perceived relevance will (a) increase brand engagement by increasing click intention, like intention, comment intention, and share intention, but (b) reduce ad avoidance.

H3: Perceived creepiness will (a) reduce brand engagement by decreasing click intention, like intention, comment intention, and share intention, but (b) increase ad avoidance.

H4: Business experience moderates the indirect effect of ad type on consumer outcomes (engagement and ad avoidance) via perceived personalisation, such that the indirect effect is stronger among individuals with higher business experience.

4.4 Chapter Conclusion

This chapter reports the statistical analyses used to test the hypotheses concerning consumer responses to AI-generated social media advertising. SPSS Version 30 and SmartPLS 4.1.1.4 were used to assess the measurement and structural models based on a sample of 150 respondents, split between those interested in starting a business (n = 67) and those currently running one (n = 83).

The measurement model demonstrated acceptable reliability and convergent validity for most constructs, with Cronbach's alpha, composite reliability (CR), and average variance extracted (AVE) values meeting recommended thresholds. Perceived relevance showed slightly lower internal consistency ($\alpha = 0.694$) but was retained due to its theoretical importance and acceptable AVE (0.621). All other constructs exceeded the $\alpha > 0.70$ benchmark. Discriminant validity was confirmed using the Fornell–Larcker criterion, as each construct's AVE square root was greater than its correlations with other constructs.

The structural model provided detailed information about the behavioural and psychological effects of AI-generated advertising. Although AI-generated advertisements increased feelings of unease, they did not significantly improve perceived relevance or personalisation, suggesting that algorithmic material may cause unease without always providing value to the user. The "personalisation paradox" refers to the two-edged nature of tailored material, with perceived personalisation emerging as a significant influencer that enhances both relevance and creepiness.

Perceived relevance proved to be the strongest predictor of consumer engagement across behaviours such as clicking, commenting, liking, and sharing, reinforcing its central role in driving meaningful interaction. However, relevance did not significantly influence ad avoidance, suggesting that even relevant ads are not immune to user fatigue or resistance.

Interestingly, perceived creepiness did not discourage participation; on the contrary, it was linked to more social interaction in the form of shares, likes, and comments. Although it was still a strong predictor of ad avoidance, this research casts doubt on the notion that discomfort inevitably leads to disengagement and supports its function as a psychological trigger for resistance.

Lastly, responses to AI-generated advertising were neither moderated by business experience, nor did it significantly affect perceptions of personalization. This suggests that regardless of prior exposure to entrepreneurship, consumer responses to AI-driven content were generally similar.

In conclusion, although AI-generated advertising was associated with increased creepiness, it failed to enhance perceived personalisation or relevance directly. These findings challenge assumptions about AI's ability to personalise effectively and highlight the psychological trade-offs of automated targeting. The results underscore the central importance of relevance in driving meaningful consumer engagement, while also pointing to creepiness as a double-edged sword, amplifying ad avoidance yet potentially increasing superficial engagement like shares and likes. Business experience had no significant moderating effect, indicating that these patterns are consistent across entrepreneurial backgrounds. These results form the basis for Chapter 5, which interprets and discusses the findings in the context of existing literature and theoretical frameworks. By integrating the results with prior studies, Chapter 5 critically evaluates the implications of AI-generated advertising for consumer behaviour, marketing strategy, and future research. This discussion also highlights the managerial and ethical considerations emerging from the findings, paving the way for the final conclusions and recommendations.

Chapter 5: Discussion

5.1 Introduction

With an emphasis on perceived personalisation, relevance, and creepiness as psychological factors that influence engagement and ad avoidance, this thesis aimed to evaluate how consumers react to AI-generated advertising compared to that produced by humans. In order to better understand the affective and cognitive processes that influence consumer attitudes and behaviours in response to algorithmically tailored content, the research used the SNS-Post Processing Framework (Wagner et al., 2017) and concepts like the personalisation paradox (de Groot, 2022). The necessity to critically analyse how AI-enabled advertising affects authenticity, trust, and striking a balance between targeted relevance and customer discomfort is reflected in this aim.

To achieve this, the thesis aimed to address the main research question: "*How do consumers respond behaviourally to AI-generated versus non-AI-generated advertisements?*"

By answering these sub-questions:

(1) *How do AI-generated advertisements, compared to human-created advertisements, influence consumer responses through perceived personalisation?*
(2) *How does business experience influence consumers' perceptions of AI-generated advertisements in terms of personalisation?*

These research questions were operationalised through four hypotheses (H1–H4), which looked at the moderating effect of business experience as well as the interactions between ad type, personalisation, relevance, creepiness, engagement (click, like, remark, share), and ad avoidance. In-depth findings on these associations were obtained from the empirical analysis in Chapter 4, which also included information on the personalisation paradox, the mediating function of perceived personalisation, and the behavioural effects of perceived creepiness.

When evaluating the results, it is important to take the gender disparity in the sample into account. However, the research verified that gender had no discernible impact on the focus relationships because it was expressly considered in the structural model.

our implies that perceptions of personalization, relevance, and creepiness, as well as reactions to AI-generated versus human-created advertising, were similar across gender groups in our dataset. Therefore, the imbalance is unlikely to restrict the generalizability of the main findings; however, a greater gender-balanced sample may be beneficial for future studies to confirm the durability of these effects across demographic segments.

This chapter highlights the research's theoretical and practical contributions while discussing the main findings in the context of the body of current literature. It assesses the degree to which the findings support, expand upon, or contradict preexisting frameworks, including the SNS-Post Processing Framework and earlier research on algorithmic advertising. This chapter further provides a comprehensive interpretation of the study's findings and illustrates how they advance both academic research and the real-world use of AI in digital advertising by considering the findings, contributions, implications, limitations, and future research directions. By providing a summary of the research findings and talking about the theoretical and practical implications, research limitations, and future research directions, this chapter concludes the thesis.

5.2. Discussion

5.2.1 RQ1: How do AI-generated advertisements, compared to human-created advertisements, influence consumer responses through perceived personalisation?

The relationship between AI-generated advertising and perceived personalisation appears more complex than hypothesised. While H1 predicted that AI-generated ads would increase perceived personalisation, thereby enhancing relevance and increasing creepiness, the data did not support this direct effect. Specifically, AI-generated ads did not significantly enhance perceived personalisation ($\beta = -0.085$, $p = 0.733$), suggesting that consumers may not automatically view algorithmically delivered content as tailored to their needs. This finding contrasts with prior research suggesting that algorithmic targeting improves personalisation perceptions (De Keyzer et al., 2024). It implies that the effectiveness of personalisation relies more on consumers' subjective interpretations than on technological sophistication.

Nonetheless, perceived personalisation emerged as a strong predictor of both perceived relevance (β = 0.450, p = 0.000) and perceived creepiness (β = 0.249, p = 0.001), supporting H1b and H1c. This dual effect exemplifies the personalisation paradox: while customised content enhances perceived relevance, it may also increase discomfort if it feels intrusive or manipulative (de Groot, 2022). These results align with earlier work highlighting the tension between data-driven targeting and privacy concerns (Maslowska et al., 2016). Moreover, while perceived personalisation enhanced relevance (a driver of engagement), it also indirectly contributed to ad avoidance through heightened creepiness. This shows the partial mediation role of personalisation and highlights that AI-generated content alone may not be sufficient to generate favourable responses; consumers must perceive the content as genuinely tailored to their interests.

These findings align with the SNS-Post Processing Framework (Wagner et al., 2017), which highlights the importance of both cognitive and emotional evaluations in shaping user engagement. As previous studies suggest (Gu et al., 2024; Wu et al., 2022), AI systems may enable scalable personalisation but may also compromise perceived authenticity if the content lacks emotional depth. This suggests that advertisers must combine algorithmic precision with creative, emotionally resonant content to avoid over-reliance on automation.

Beyond these mediation effects, the results also provide insight into the behavioural outcomes associated with relevance and creepiness (H2 and H3). Supporting H2a, perceived relevance significantly increased all forms of engagement, clicks (β = 0.578, p = 0.000), likes (β = 0.377, p = 0.000), comments (β = 0.457, p = 0.000), and shares (β = 0.461, p = 0.000), highlighting its crucial role in driving consumer interaction. However, H2b was not supported: relevance had no significant effect on ad avoidance (β = 0.005, p = 0.892), suggesting that even highly relevant content does not necessarily reduce avoidance behaviour.

Interestingly, the findings for H3 revealed a more complex pattern. Contrary to expectations, perceived creepiness was positively associated with several engagement behaviours: comment (β = 0.232, p = 0.002), like (β = 0.222, p = 0.002), and share (β = 0.351, p = 0.000), though not with click intention (β = 0.032, p = 0.605). While H3a anticipated that creepiness would reduce engagement, these results suggest that moderate creepiness may, in some cases, spark curiosity or surprise, leading to interaction. This nuance echoes previous findings where unsettling or novel content can trigger reactive

engagement (Wu et al., 2022). However, as predicted by H3b, creepiness strongly predicted ad avoidance (β = 0.812, p = 0.000), reinforcing the idea that even engaging ads may ultimately trigger rejection if perceived as emotionally intrusive or ethically questionable.

Taken together, these results reinforce the importance of finding a balance between relevance and emotional tone. AI-generated content must not only align with user interests but also avoid crossing psychological boundaries that provoke defensive reactions.

5.2.2 RQ2: How does business experience influence consumers' perceptions of AI-generated advertisements in terms of personalisation?

Hypothesis H4 proposed that business experience would positively influence consumers' perceptions of personalisation in AI-generated ads. This assumption was grounded in the idea that individuals with marketing or entrepreneurial backgrounds are more familiar with data-driven targeting and may better recognise or appreciate algorithmic customisation (Barbosa et al., 2024; Wu et al., 2025). However, the statistical analysis did not support this hypothesis. Neither the interaction between business experience and ad type (β = -0.038, p = 0.909) nor the direct effect of business experience on perceived personalisation (β = 0.046, p = 0.862) was significant. Consequently, H4 is rejected. Contrary to expectations, business experience did not enhance participants' recognition or appreciation of personalised content in AI-generated advertising.

One possible explanation is that the level of personalisation presented in the ad stimuli was too subtle or generic to be detected, even by experienced individuals. Another explanation may relate to entrepreneurial scepticism: individuals familiar with marketing automation may approach AI-generated content more critically, potentially viewing it as lacking emotional authenticity or human nuance (El-Shihy & Hassan, 2025; Hardcastle et al., 2025). Although prior literature highlights entrepreneurs' appreciation of AI's strategic efficiency (Coffin, 2022), this study suggests that perceived ad quality and emotional resonance may matter more than digital expertise when evaluating personalisation.

These findings reinforce arguments from the personalisation paradox literature, which suggests that trust and emotional alignment are just as critical as technical accuracy

in driving perceived personalisation (De Keyzer et al., 2024; Maslowska et al., 2016). In sum, business experience does not appear to strengthen consumers' perceptions of AI-driven personalisation, highlighting the need for emotionally intelligent ad design rather than relying solely on algorithmic sophistication.

5.3 Theoretical Implications

The results of this study advance knowledge of how perceived personalisation, relevance, and creepiness interact to influence customer responses, thereby contributing to theoretical conversations on AI-generated advertising. First, the rejection of H1 challenges prior assumptions, as discussed by De Keyzer et al. (2024) and Wu et al. (2022), that AI-generated advertising automatically enhances perceptions of personalisation. This finding suggests that consumers' views of personalised content are not shaped by AI alone, but are instead mediated by the "human touch," user scepticism, and subjective interpretation. As such, theoretical models of personalisation must account for these psychological and emotional filters.

Second, while personalisation greatly increases perceived relevance, it also increases perceived creepiness, as the results empirically support the personalisation paradox (de Groot, 2022). The idea that personalisation is not always positive but rather functions on a continuum where too exact or excessive targeting can erode trust and lead to ad avoidance is further supported by this contradiction. Through the association of perceived creepiness (H3) with behavioural consequences like decreased engagement and greater ad avoidance, this study enhances the theoretical framework for comprehending negative affective reactions to algorithmic advertising.

Third, this study extends the SNS-Post Processing Framework (Wagner et al., 2017) by integrating AI-specific dimensions into its stages of cognitive and affective processing. Relevance and creepiness emerge as key variables influencing antecedents, processing styles, and outcome responses, with personalisation acting as a partial, rather than full, mediator of behavioural intent. This underscores the need to include algorithmic cues, perceived authenticity, and privacy concerns as critical antecedents in future theoretical adaptations of the framework.

Finally, the rejection of H4 demonstrates that business experience, contrary to expectations derived from research on digital literacy and entrepreneurship, does not moderate perceptions of personalisation (Barbosa et al., 2024). This calls for a reassessment of assumptions about expertise as a boundary condition in advertising research. Rather than enhancing recognition of personalisation, expertise may foster a more critical or sceptical stance, particularly toward AI-generated content that lacks emotional nuance or human creativity.

One explanation is that participants' processing of the AI-generated and human-created advertisements did not significantly differ based on variations in business experience. Many advertising responses, according to the SNS-Post Processing theory, are driven more by affective and intuitive emotions than by analytical assessment. Therefore, rather than relying on their understanding of marketing or digital platforms, even seasoned business leaders may react to AI-generated material based on emotional cues like relevancy, familiarity, or discomfort. Furthermore, it is possible that there was not enough variation in the sample's business experience to generate statistically significant processing patterns. It is possible that using a single self-categorization item to measure business experience hindered the capacity to capture more subtle variations in knowledge. When taken as a whole, these elements could contribute to the explanation of why the moderating effect was not validated.

Together, these insights emphasise that affective responses, trust, and perceived authenticity are central to advertising effectiveness. They also confirm that technological sophistication alone is insufficient to explain consumer receptivity to AI-driven advertising, reaffirming the need for human-centred design in algorithmic content strategies.

5.4 Managerial Implications

The findings of this research offer several practical suggestions for advertising professionals and marketers navigating the transition to AI-generated content. First, while personalisation significantly increases perceived relevance (H1b), it also increases perceived creepiness (H1c), which can negatively impact engagement and encourage ad avoidance (H3). Therefore, marketers should avoid overly aggressive or intrusive targeting. Transparency, user control, and opt-in procedures should be prioritised in

dynamic personalisation strategies to ensure that relevance does not come at the expense of consumer discomfort. For example, clear communication about how AI-driven recommendations is generated can preserve the benefits of customisation while building trust.

Second, the results suggest that consumers still value innovation and the "human touch" in advertising, as AI alone did not enhance perceptions of personalisation (H1a). Practitioners should consider blending AI with human creative input, allowing AI to optimise testing and targeting while human creators focus on emotional resonance, tone, and storytelling. This hybrid approach may help prevent AI campaigns from being perceived as manipulative or generic.

Third, given that perceived relevance (H2) is a strong predictor of behavioural engagement (e.g., clicks, likes, shares, comments), AI tools should be optimised to deliver contextually relevant content that aligns with user interests. Real-time A/B testing should include sentiment analysis to detect when personalisation becomes uncomfortable. Tactics such as frequency caps, creative rotation, and content format diversification can help reduce perceived intrusiveness and message fatigue.

Fourth, contrary to expectations, business experience did not increase perceptions of personalisation (H4). This suggests that digitally literate or entrepreneurial audiences may be more discerning, valuing authenticity over algorithmic accuracy. For these segments, marketers should focus on transparent, value-driven messaging. Positioning AI content as a tool that delivers insightful solutions or relevant utility, rather than merely personalised promotions, may be more effective.

Finally, the personalisation paradox shows that when targeting feels intrusive, consumer trust can quickly erode. To mitigate this, managers should embed privacy-by-design principles and ensure compliance with data protection regulations such as GDPR. Educating users about privacy protections, such as explaining the purpose of data collection and offering clear opt-out options, can build long-term trust and loyalty.

In conclusion, AI advertising should be viewed as an augmentative tool, one that enhances efficiency and targeting, but not a replacement for human creativity and ethical communication. By carefully balancing personalisation with emotional resonance, transparency, and ethical responsibility, managers can maximise the benefits of AI while minimising the risks of consumer resistance.

5.5 Limitations and Future Research

Although this study offers insightful information about how consumers react to AI-generated advertising, it should be noted that it has several limitations, which open new research avenues. Firstly, a controlled experimental design comprising three ad conditions, AI-generated personalised advertisements versus human-created non-personalised ads, was the foundation of the study. The stimuli might not have adequately conveyed the emotional nuance and creative diversity typical of actual advertising campaigns, even though this method allowed for strong comparisons. Future studies could build on this by comparing outcomes across various product categories and introducing multi-format or cross-platform stimuli (such as static versus video advertisements) (Yang & Zhao, 2021). Furthermore, testing AI-generated content on a range of social media channels and ad formats, such as interactive experiences, video, and AR/VR-based advertisements, may shed light on how platform affordances and content richness impact avoidance and engagement (Gu et al., 2024; Heo & Lee, 2025; Mishra et al., 2021). Additionally, future studies should look at the long-term effects of repeated exposure to AI-generated advertising on consumer-brand relationships, loyalty, and trust (Aljarah et al., 2025). It would be possible to ascertain through longitudinal research whether the initial scepticism or perceived creepiness (as noted in H3) lessens with familiarity or if it compounds with time.

Improving the way business experience is measured could help future studies better reflect the breadth and depth of participants' skills. The detection of moderating effects may be more sensitive when using multi-dimensional measurements, such as years of experience, familiarity with digital advertising tools, or prior exposure to AI-driven marketing. Additionally, it would be useful to divide people into groups based on behavioural metrics rather than self-reported categories, or to investigate if revealing AI authorship alters how experience influences perceptions of personalization. Additionally, employing a wider range of advertising stimuli, such as dynamic or graphically personalized information, may aid in determining whether experience plays a moderating effect in situations where the ad's AI-driven components are more prominent. When combined, these methods could shed light on whether the study's non-significant results were the result of restricted sample variation, measurement limitations, or more general psychological processes that hold for all experience levels.

The study’s results show participants' responses to message phrasing rather than visual or dynamic personalization because the advertising stimuli used in this study were only text-based. AI-driven personalization frequently encompasses graphics, layout, and dynamic creative optimization in modern digital advertising practice, where visuals and message components adjust in real time to user attributes. Therefore, future studies could investigate whether perceptions of personalization, relevance, or creepiness are enhanced or diminished by dynamic visual elements or personalized images, and whether these richer formats result in distinct behavioural results. Such components would improve ecological validity and provide a more thorough understanding of the performance of AI-generated advertising in a variety of creative styles.

Secondly, despite being adequate for statistical analysis, the sample's size and demographic variety were constrained. The representation of participants who are entrepreneurs might not accurately represent the wider range of digital literacy and business experience levels present in the general population. Larger and more varied sample sizes, as well as cross-cultural comparisons, should be considered in future research to see if opinions on personalisation and creepiness differ in markets with various privacy laws or cultural perspectives on artificial intelligence. Future research could look into additional moderating factors like cultural perceptions of AI, privacy sensitivity, and digital literacy (Ibrahim et al., 2024). Cross-cultural research could show whether the relationship between personalisation, relevance, and creepiness is changed by cultural variations in privacy norms and trust. Furthermore, if ad evaluation is affected differently by acquaintance with AI technology when stimuli include highly dynamic or interactive personalisation cues, this might be investigated in future studies with entrepreneurial audiences.

Another limitation is common with self-reported measures. The self-reported Likert scales used to measure all the major constructs, such as perceived personalisation, relevance, and creepiness, are prone to social desirability bias and common method variance. Future studies could include behavioural indicators (such as actual click-through rates, dwell duration, or conversion statistics) to triangulate findings with real engagement behaviour, even though steps like validity and reliability checks were carried out. Furthermore, future research could incorporate neuro-physiological indicators (like eye tracking, galvanic skin response) to capture subconscious reactions (Wetzels et al., 2024), even though this study relied on self-reported constructs like perceived relevance and creepiness. This multi-method approach would confirm the affective-cognitive

mechanisms suggested in frameworks like the SNS-Post Processing Framework (Wagner et al., 2017) and give a more accurate representation of how consumers interact with AI-generated advertising.

Fourthly, the primary objective of the study was to evaluate the immediate emotive and cognitive reactions to commercials. Long-term effects, including brand loyalty, the growth of trust, and changing purchasing patterns, were not taken into consideration. Future research might use field experiments or longitudinal designs to examine the effects of frequent exposure to AI-generated advertising on customer lifetime value, loyalty, and trust (Beyari, 2025).

Another limitation of the study is the fact that this study only looked at one type of AI-generated advertising may not accurately represent the vast array of AI-driven strategies that are now on the market (such as conversational AI, interactive advertisements, or deep learning-based creative development) (Faruk et al., 2025). To determine how different AI capabilities (such as speech synthesis and hyper-targeted suggestions) affect perceived authenticity and creepiness, future research should examine various forms and degrees of AI personalisation.

Lastly, despite referring to the personalisation paradox, this study did not experimentally alter privacy or transparency controls to evaluate their impact on consumer perceptions. Future studies could examine how user control mechanisms, algorithm explainability, and privacy disclosures affect engagement and ad avoidance (Oh et al., 2025). Furthermore, future studies should examine the effects of privacy disclosures, explainable AI, and ethical-by-design techniques in advertising, since consumer trust is a crucial factor in engagement (Paliwal et al., 2025). Experiments using transparency (such as explaining to customers how personalisation works) may shed light on how these tactics impact the perception of creepiness and authenticity. Furthermore, there is still a large research gap in advertising about how algorithmic fairness and prejudice influence consumers' opinions of a brand's credibility (Shin, 2022).

5.6 Chapter Conclusion

Considering the research questions, hypotheses, and theoretical frameworks presented previously in the thesis, this chapter examines the study's findings. The findings confirm

that personalisation is a strong motivator for engagement (H2) but can also cause discomfort when viewed as creepy (H3). They also shed important light on the intricate relationships between AI-generated advertising, perceived personalisation, relevance, and creepiness. AI-generated ads did not, as anticipated, significantly boost perceptions of personalisation (H1), indicating that increased technological complexity by itself does not ensure better customer responses. Furthermore, it was discovered that opinions of AI-driven personalisation were unaffected by business experience (H4), suggesting that proficiency may not always equate to a better understanding or appreciation of algorithmic targeting.

The chapter discussed the theoretical implications, such as the personalisation paradox and contributions to the SNS-Post Processing Framework, as well as the management insights, including the necessity of striking a balance between algorithmic accuracy and ethical protections, transparency, and emotional resonance. To provide a more comprehensive understanding of consumer responses, it also outlined the study's limitations and suggested future research directions, emphasising cross-cultural comparisons, longitudinal studies, and the integration of behavioural and neurophysiological measures.

Overall, by showing that the effectiveness of AI-generated advertising depends not only on sophisticated targeting capabilities but also on how users perceive and engage emotionally with the content, this thesis adds to the expanding body of research on AI in marketing. These findings provide a solid basis for further research into the ethical and efficient use of AI technology while preserving customer confidence and brand integrity. By separating the effects of AI-generated creative material from the algorithmic targeting systems that have long defined digital advertising, this study adds to the growing body of research on generative AI in advertising.

References

Aarzoo, & Lal, R. (2024). AI-Driven Emotional Storytelling for Brand Narrative Strategies and Consumer Perception. *IUP Journal of Brand Management*, *21*(4), 30-50. https://research.ebsco.com/linkprocessor/plink?id=9d64f291-311b-3e7d-878c-18db8ff2c523

Abbas, Q. (2024). The impact of personalization strategies on consumer engagement and conversion rates in digital marketing. *International Journal of Advanced Multidisciplinary Research and Study*, *4*(1), 452-454. https://doi.org/10.62225/2583049X

Abhiseka, M. E., Riyandi, A. Y., Saputra, R. A., & Setiawan, A. (2024). AI for Digital Marketing. *Apollo: Journal of Tourism & Business*, *2*(2), 197-209. https://doi.org/10.58905/apollo.v2i2.298

AbouElgheit, E. (2024). The Role of Generative AI in Shaping Millennials and Gen Z's Orientation Toward Luxury Products. *Journal of Marketing Development & Competitiveness*, *18*(2), 11-29. https://doi.org/10.33423/jmdc.v18i2.7012

Akdim, K., & Casaló, L. V. (2023). Perceived value of AI-based recommendations service: the case of voice assistants. *Service Business*, *17*(1), 81-112. https://doi.org/10.1007/s11628-023-00527-x

Aljarah, A., Ibrahim, B., & López, M. (2025). In AI, we do not trust! The nexus between awareness of falsity in AI-generated CSR ads and online brand engagement. *Internet Research*, *35*(3), 1406-1426. https://doi.org/10.1108/INTR-12-2023-1156

Angus, D., Hayden, L., Obeid, A. K., Tan, X. Y., Carah, N., Burgess, J., Parker, C., Andrejevic, M., Fordyce, R., Cellard, L., & Bagnara, J. (2024). Computational Methods for Improving the Observability of Platform-Based Advertising. *Journal of Advertising*, *53*(5), 661-680. https://doi.org/10.1080/00913367.2024.2394156

Arango, L., Singaraju, S. P., & Niininen, O. (2023). Consumer Responses to AI-Generated Charitable Giving Ads. *Journal of Advertising*, *52*(4), 486-503. https://doi.org/10.1080/00913367.2023.2183285

Arbaiza, F., Arias, J., & Robledo-Dioses, K. (2024). AI-Driven Advertising Activity: Perspectives from Peruvian Advertisers. *Communication & Society*, *37*(4), 273-292. https://doi.org/10.15581/003.37.4.273-292

Bagozzi, R. P., & Yi, Y. (1988). On the evaluation of structural equation models. *Journal of the Academy of Marketing Science*, *16*(1), 74-94. https://doi.org/10.1007/BF02723327

Barbosa, B., Saura, J. R., & Bennett, D. (2024). How do entrepreneurs perform digital marketing across the customer journey? A review and discussion of the main uses. *The Journal of Technology Transfer*, *49*(1), 69-103. https://doi.org/10.1007/s10961-022-09978-2

Benlian, A., Klumpe, J., & Hinz, O. (2020). Mitigating the intrusive effects of smart home assistants by using anthropomorphic design features: A multimethod investigation. *Information Systems Journal*, *30*(6), 1010-1042.

Beyari, H. (2025). Assessing artificial intelligence's impact on e-customer loyalty in the Saudi Arabian market. *Frontiers in Artificial Intelligence*, 1-16. https://doi.org/10.3389/frai.2025.1541678

Bleier, A., & Eisenbeiss, M. (2015). The importance of trust for personalized online advertising. *Journal of retailing*, *91*(3), 390-409.

Buvár, Á., & Gáti, M. (2023). Digital marketing adoption of microenterprises in a technology acceptance approach. *Management & Marketing*, *18*(2), 127-144. https://doi.org/10.2478/mmcks-2023-0008

Buzeta, C., De Keyzer, F., Dens, N., & De Pelsmacker, P. (2024). Branded content and motivations for social media use as drivers of brand outcomes on social media: a cross-cultural study. *International Journal of Advertising*, *43*(4), 637-671. https://doi.org/10.1080/02650487.2023.2215079

Campbell, C., Plangger, K., Sands, S., & Kietzmann, J. (2022). Preparing for an Era of Deepfakes and AI-Generated Ads: A Framework for Understanding Responses to Manipulated Advertising. *Journal of Advertising*, *51*(1), 22-38. https://doi.org/10.1080/00913367.2021.1909515

Carvalho Proença, J. J. (2024). Business innovation self-assessment with artificial intelligence support for small and medium-sized enterprises. *Business Management / Biznes Upravlenie*(4), 5-17. https://doi.org/10.58861/tae.bm.2024.4.01

Chang, Y., Gao, Y., Zhu, D., & Safeer, A. A. (2023). Social robots: Partner or intruder in the home? The roles of self-construal, social support, and relationship intrusion in consumer preference. *Technological Forecasting and Social Change*, *197*, 122914. https://doi.org/10.1016/j.techfore.2023.122914

Chen, W.-K., Ling, C.-J., & Chen, C.-W. (2023). What affects users to click social media ads and purchase intention? The roles of advertising value, emotional appeal and credibility. *Asia Pacific journal of marketing and logistics*, *35*(8), 1900-1916. https://doi.org/10.1108/APJML-01-2022-0084

Chiguvi, D. (2022). Effectiveness of traditional and digital advertising platforms for the marketing of tourism. *International Journal of Research in Business & Social Science*, *11*, 1-12. https://doi.org/10.20525/ijrbs.v11i10.2141

Chin, W. W. (1998). The partial least squares approach to structural equation modeling. In *Modern methods for business research* (pp. 295-336). Psychology Press.

Choi, D., & Kim, J. (2022). The impacts of ad skip option and ad time display on viewer response to in-stream video ads: the role of perceived control and reactance. In *Internet Research* (Vol. 32, pp. 790-813): Emerald Publishing Limited. https://doi.org/10.1108/INTR-09-2020-0514

Chung, Y. C., Chang, H.-H., & Kitamura, Y. (2021). Digital and traditional media advertising and business performance of agribusiness firms-Empirical evidence in Japan. *Agricultural Economics/Zemědělská ekonomika*, *67*(2), 51-59. https://doi.org/10.17221/393/2020-AGRICECON

Coffin, J. (2022). Asking Questions of AI Advertising: A Maieutic Approach. *Journal of Advertising*, *51*(5), 608-623. https://doi.org/10.1080/00913367.2022.2111728

Corstjens, M., & Umblijs, A. (2012). The Power of Evil: The Damage of Negative Social Media Strongly Outweigh Positive Contributions. *Journal of Advertising Research*, *52*(4), 433-450. https://doi.org/10.2501/JAR-52-4-433-449

Creswell, J. W., &, & Creswell, J. D. (2017). *Research design: Qualitative, quantitative, and mixed methods approaches* (4th ed). Sage publications.

Creswell, J. W., & Creswell, J. D. (2018). *Research design: qualitative, quantitative, and mixed methods approaches* (5th ed.). SAGE.

Dae Hee, K., Yu Kyoum, K., & Zimmerman, M. H. (2010). User-Versus Mainstream-Media-Generated Content: Media Source, Message Valence, and Team Identification and Sport Consumers' Response. *International Journal of Sport Communication*, *3*(4), 402-421. https://research.ebsco.com/linkprocessor/plink?id=3caa57bd-e64d-3ee2-b8f6-77535d786536

Daly, T. M., & Nataraajan, R. (2015). Swapping bricks for clicks: Crowdsourcing longitudinal data on Amazon Turk. *Journal of Business Research*, *68*(12), 2603-2609.

Datareportal. (2025). *Digital 2025: Global advertising trends*. Datareportal. Retrieved 14 April 2025 from https://datareportal.com/reports/digital-2025-sub-section-global-advertising-trends#:~:text=Changing%20channels,offline%E2%80%9D%20channels%20every%20year%20since.&text=Absolute%20levels%20of%20digital%20spend,spend%20between%202020%20and%202021.

Davvetas, V., Ulqinaku, A., & Abi, G. S. (2022). Local impact of global crises, institutional trust, and consumer well-being: Evidence from the COVID-19 pandemic. *Journal of international marketing*, *30*(2), 73-101. https://doi.org/10.1177/1069031X211022688

de Groot, J. I. M. (2022). The Personalization Paradox in Facebook Advertising: The Mediating Effect of Relevance on the Personalization–Brand Attitude Relationship and the Moderating Effect of Intrusiveness. *Journal of Interactive Advertising*, *22*(1), 57-74. https://doi.org/10.1080/15252019.2022.2032492

De Keyzer, F., Buzeta, C., & Lopes, A. I. (2024). The role of well-being in consumer's responses to personalized advertising on social media. *Psychology & Marketing*, *41*(6), 1206-1222.

De Keyzer, F., Dens, N., & De Pelsmacker, P. (2022). How and When Personalized Advertising Leads to Brand Attitude, Click, and WOM Intention. *Journal of Advertising*, *51*(1), 39-56. https://doi.org/10.1080/00913367.2021.1888339

De Keyzer, F., Van Noort, G., & Kruikemeier, S. (2022). Going too far? How consumers respond to personalized advertising from different sources. *Journal of Electronic Commerce Research*, *23*(3), 138-159. http://www.jecr.org/node/664

Deng, S., Tan, C.-W., Wang, W., & Pan, Y. (2019). Smart Generation System of Personalized Advertising Copy and Its Application to Advertising Practice and Research. *Journal of Advertising*, *48*(4), 356-365. https://doi.org/10.1080/00913367.2019.1652121

Dong, B., Zhuang, M., Fang, E., & Huang, M. (2024). Tales of Two Channels: Digital Advertising Performance Between AI Recommendation and User Subscription Channels. *Journal of Marketing*, *88*(2), 141-162. https://doi.org/10.1177/00222429231190021

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J., Eirug, A., Galanos, V., Ilavarasan, P. V., Janssen, M., Jones, P., Kar, A. K., Kizgin, H., Kronemann, B., Lal, B., Lucini, B.,….. Williams, M. D. (2021). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management*, *57*, 101994. https://doi.org/https://doi.org/10.1016/j.ijinfomgt.2019.08.002

Edmonds, W. A., & Kennedy, T. D. (2013). *An applied reference guide to research designs: quantitative, qualitative, and mixed methods*. SAGE Publication.

El-Shihy, D., & Hassan, N. (2025). Classification of start-ups' digital marketing adoption experiences: an investigation of characteristics and interactions. *Future Business Journal*, *11*(1), 1-10. https://doi.org/10.1186/s43093-025-00467-0

Ezzahra, Y. F., Houssame, N., Lahiala, M. A., & Hamid, H. (2024). Unveiling the Influence of AI-Social Fusion: Enhancing Consumer Community Engagement and Advertising Dynamics. 2024 Mediterranean Smart Cities Conference (MSCC), Martil - Tetuan, Morocco.

Faruk, L. I. D., Pal, D., Funilkul, S., Perumal, T., & Mongkolnam, P. (2025). Introducing CASUX: A Standardized Scale for Measuring the User Experience of Artificial Intelligence Based Conversational Agents. *International Journal of Human-Computer Interaction*, *41*(9), 5274-5298. https://doi.org/10.1080/10447318.2024.2359206

Field, A. P. (2018). *Discovering statistics using IBM SPSS statistics* (5th ed.). Sage Publications.

Fisher, N. S. (2024). But First, A Word from Our Sponsor: Engagement with Podcasts and their Advertising. *Southwestern Mass Communication Journal*, *40*(1), 1-16. https://research.ebsco.com/linkprocessor/plink?id=2d6d10a2-198d-3a0c-9296-0c76f566b497

Florenthal, B. (2019). Young consumers' motivational drivers of brand engagement behavior on social media sites: A synthesized U&G and TAM framework. *Journal of Research in Interactive Marketing*, *13*(3), 351-391. https://doi.org/https://doi.org/10.1108/JRIM-05-2018-0064

Ford, J., Jain, V., Wadhwani, K., & Gupta, D. G. (2023). AI advertising: An overview and guidelines. *Journal of Business Research*, *166*, 114124. https://doi.org/https://doi.org/10.1016/j.jbusres.2023.114124

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, *18*(1), 39-50.

Gao, B., Wang, Y., Xie, H., Hu, Y., & Hu, Y. (2023). Artificial intelligence in advertising: advancements, challenges, and ethical considerations in targeting, personalization, content creation, and ad optimization. *Sage Open*, *13*(4), 21582440231210759.

Gavin, H. (2008). *Understanding Research Methods and Statistics in Psychology*. SAGE Publications Ltd. https://doi.org/10.4135/9781446214565

Ghanbarpour, T., Sahabeh, E., & Gustafsson, A. (2022). Consumer response to online behavioral advertising in a social media context: The role of perceived ad

complicity. *Psychology & Marketing*, *39*(10), 1853-1870. https://doi.org/https://doi.org/10.1002/mar.21703

Ghufran, A., & Ahmad, W. (2025). The Impact of AI-Enhanced Digital Marketing Strategies on Consumers' Purchase Intention for Lifestyle Products. *Cihan University-Erbil Journal of Humanities and Social Sciences*, *9*(1), 77-85. https://doi.org/10.24086/cuejhss.v9n1y2025.pp77-85

Goktas, P., & Grzybowski, A. (2025). Shaping the Future of Healthcare: Ethical Clinical Challenges and Pathways to Trustworthy AI. *Journal of Clinical Medicine*, *14*(5), 1605. https://www.mdpi.com/2077-0383/14/5/1605

Gray, D. E. (2018). *Theoretical perspectives and research methodologies. In doing research in the real world* (4th ed.). SAGE Publication.

Gu, C., Jia, S., Lai, J., Chen, R., & Chang, X. (2024). Exploring Consumer Acceptance of AI-Generated Advertisements: From the Perspectives of Perceived Eeriness and Perceived Intelligence. *Journal of Theoretical & Applied Electronic Commerce Research*, *19*(3), 2218-2238. https://doi.org/10.3390/jtaer19030108

Guo, B., & Jiang, Z.-b. (2025). Influence of personalised advertising copy on consumer engagement: a field experiment approach. *Electronic Commerce Research*, *25*(2), 1281-1310. https://doi.org/10.1007/s10660-023-09721-5

Gutierrez, A., O'Leary, S., Rana, N. P., Dwivedi, Y. K., & Calle, T. (2019). Using privacy calculus theory to explore entrepreneurial directions in mobile location-based advertising: Identifying intrusiveness as the critical risk factor. *Computers in human behavior*, *95*, 295-306. https://doi.org/https://doi.org/10.1016/j.chb.2018.09.015

Gutuleac, R., Baima, G., Rizzo, C., & Bresciani, S. (2024). Will virtual influencers overcome the uncanny valley? The moderating role of social cues. *Psychology & Marketing*, *41*(7), 1419-1431. https://doi.org/10.1002/mar.21989

Haenlein, M., & Kaplan, A. M. (2004). *A beginner's guide to partial least squares analysis*. *Understanding statistics*, *3*(4), 283-297.

Häglund, E., & Björklund, J. (2024). AI-Driven Contextual Advertising: Toward Relevant Messaging Without Personal Data. *Journal of Current Issues & Research in*

Advertising (Routledge), *45*(3), 301-319. https://doi.org/10.1080/10641734.2024.2334939

Hair, J. F., Ortinau, D. J., & Harrison, D. E. . (2010). *Essentials of Marketing Research* (2 ed.). McGraw-Hill Education.

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed a silver bullet. *Journal of Marketing theory and Practice*, *19*(2), 139-152.

Hair Jr, J. F., Sarstedt, M., Hopkins, L., & Kuppelwieser, V. G. (2014). Partial least squares structural equation modeling (PLS-SEM) : An emerging tool in business research. In *European Business Review* (Vol. 26, pp. 106-121): Emerald Group Publishing Limited.

Hallam, C., & Zanella, G. (2017). Online self-disclosure: The privacy paradox explained as a temporally discounted balance between concerns and rewards. *Computers in human behavior*, *68*, 217-227.

Hancock, G., & Mueller, R. (2001). Factor analysis and latent structure: Confirmatory factor analysis. *International encyclopedia of the social and behavioral sciences*, 5239-5244.

Hardcastle, K., Vorster, L., & Brown, D. M. (2025). Understanding Customer Responses to AI-Driven Personalized Journeys: Impacts on the Customer Experience. *Journal of Advertising*, 1-20. https://doi.org/10.1080/00913367.2025.2460985

Harmata, J., & Kondak, A. (2024). The application of aritficial intelligence based tools in marketing activities. *Scientific Papers of Silesian University of Technology. Organization & Management/Zeszyty Naukowe Politechniki Slaskiej. Seria Organizacji i Zarzadzanie*(211).

Hassan, H. E. (2024). Social Media Advertising Features that Enhance Consumers' Positive Responses to Ads. *Journal of Promotion Management*, *30*(5), 874-900. https://doi.org/10.1080/10496491.2024.2318668

Hassan, N., Abdelraouf, M., & El-Shihy, D. (2025). The moderating role of personalized recommendations in the trust–satisfaction–loyalty relationship: an empirical study of AI-driven e-commerce. *Future Business Journal*, *11*(1), 1-15. https://doi.org/10.1186/s43093-025-00476-z

Hassan, N., Salem, M., & Abdelraouf, M. (2024). The impact of social media (method of advertising) on customer loyalty. *International Journal of Accounting & Management Sciences (IJAMS)*, *3*(4), 762-732. https://doi.org/10.56830/IJAMS10202408

Hayes, J. L., Brinson, N. H., Bott, G. J., & Moeller, C. M. (2021). The influence of consumer–brand relationship on the personalized advertising privacy calculus in social media. *Journal of Interactive Marketing*, *55*(1), 16-30.

Henkens, B., Verleye, K., & Larivière, B. (2021). The smarter, the better?! Customer well-being, engagement, and perceptions in smart service systems. *International Journal of Research in Marketing*, *38*(2), 425-447. https://doi.org/10.1016/j.ijresmar.2020.09.006

Hensman, S., Jayasinghe, S., & Fernando, I. (2024). Antecedents Of Driving Customer Purchase Intention Via AI Based Customer Engagement Strategies In The Post Pandemic Era. 2024 International Research Conference on Smart Computing and Systems Engineering (SCSE),

Heo, H., & Lee, S. (2025). Consumer Information-Seeking and Cross-Media Campaigns: An Interactive Marketing Perspective on Multi-Platform Strategies and Attitudes Toward Innovative Products. *Journal of Theoretical & Applied Electronic Commerce Research*, *20*(2), 68-89. https://doi.org/10.3390/jtaer20020068

Hillqvist, O., & Johnsson Östergren, A. (2020). *The personalization–privacy paradox: Personalized ads on social media in relation to perceived usefulness, privacy, and trust [Bachelor's thesis, Jönköping University]. DiVA Portal.* https://www.diva-portal.org/smash/get/diva2:1438026/FULLTEXT02.pdf

Hinton, P. R., McMurray, I., & Brownlow, C. (2004). *SPSS Explained*. Routledge.

Hoyle, R. H. (1995). *Structural equation modeling: Concepts, issues, and applications*. Sage.

Hu, X., & Wise, K. (2024). Disentangling Control and Personalization: Exploring the Effects of Ad Choice and Ad Personalization in Digital Advertising Effectiveness. *Journal of Interactive Advertising*, *24*(3), 265-288. https://doi.org/10.1080/15252019.2024.2375970

Huh, J., Nelson, M. R., & Russell, C. A. (2023). ChatGPT, AI Advertising, and Advertising Research and Education. *Journal of Advertising*, *52*(4), 477-482. https://doi.org/10.1080/00913367.2023.2227013

Ibrahim, A., Idris, A. H., & Haruna, S. S. (2024). Artificial Intelligence in Digital Literacy: Ethical Concerns of Cultural Sensitivity in Katsina State, Nigeria. International Conference on recent advances in science, Engineering and management, Pune, India.

IoniȚĂ, C.-G., Leovaridis, C., & Popescu, G. (2025). Use of Artificial Intelligence in Advertising Agencies: Opportunities and Challenges. *Management Dynamics in the Knowledge Economy*, *13*(1), 38-51. https://doi.org/10.2478/mdke-2025-0003

Jin-Myong, L., & Jong-Youn, R. (2017). Ambivalence toward personalized technology and intention to use location-based mobile commerce: The moderating role of gender. *International Journal of Electronic Commerce Studies*, *8*(2), 158-179. https://doi.org/10.7903/ijecs.1526

Kankam, P. K. (2019). The use of paradigms in information research. *Library & Information Science Research*, *41*(2), 85-92.

Keith, M. G., Tay, L., & Harms, P. D. (2017). Systems Perspective of Amazon Mechanical Turk for Organizational Research: Review and Recommendations. *Frontiers in Psychology*, *8*. https://doi.org/10.3389/fpsyg.2017.01359

Kelly, L., Gayle, K., & Drennan, J. (2020). Triggers of engagement and avoidance: Applying approach-avoid theory. *Journal of Marketing Communications*, *26*(5), 488-508. https://doi.org/10.1080/13527266.2018.1531053

Khamitov, M., Rajavi, K., Huang, D.-W., & Hong, Y. (2024). Consumer Trust: Meta-Analysis of 50 Years of Empirical Research. *Journal of Consumer Research*, *51*(1), 7-18. https://doi.org/10.1093/jcr/ucad065

Kim, J., & Jeong, H. J. (2023). 'It's my virtual space': the effect of personalized advertising within social media. *International Journal of Advertising*, *42*(8), 1267-1294. https://doi.org/10.1080/02650487.2023.2274243

Kim, T., Barasz, K., & John, L. K. (2019). Why Am I Seeing This Ad? The Effect of Ad Transparency on Ad Effectiveness. *Journal of Consumer Research*, *45*(5), 906-932. https://doi.org/10.1093/jcr/ucy039

Koch, T. K., Frischlich, L., & Lermer, E. (2023). Effects of fact-checking warning labels and social endorsement cues on climate change fake news credibility and engagement on social media. *Journal of Applied Social Psychology*, *53*(6), 495-507. https://doi.org/10.1111/jasp.12959

Kunekar, P., Usman, M., Veena, C., Singla, A., Anute, N., & Polke, N. (2024). Enhancing Advertising Initiatives: Using Machine Learning Algorithms to Engage Targeted Customer. 2024 International Conference on Communication, Computer Sciences and Engineering (IC3SE), Gautam Buddha Nagar, India.

Lavuri, R., Jaiswal, D., & Thaichon, P. (2022). Extrinsic and intrinsic motives: panic buying and impulsive buying during a pandemic. *International Journal of Retail & Distribution Management*, *51*(2), 190-204.

Lee, C. H., & Cranage, D. A. (2011). Personalisation–privacy paradox: The effects of personalisation and privacy assurance on customer responses to travel Web sites. *Tourism Management*, *32*(5), 987-994. https://doi.org/10.1016/j.tourman.2010.08.011

Lee, J., Kim, C., & Lee, K. C. (2022). Exploring the personalization-intrusiveness-intention framework to evaluate the effects of personalization in social media. *International Journal of Information Management*, *66*, 102532.

Lee, S., Moon, W.-K., & Song, Y. G. (2024). Is It Transparent or Surveillant? The Effects of Personalized Advertising and Privacy Policy on Advertising Effectiveness. *Journal of Interactive Advertising*, 1-21. https://doi.org/10.1080/15252019.2024.2417422

Levers, M.-J. D. (2013). Philosophical paradigms, grounded theory, and perspectives on emergence. *Sage Open*, *3*(4), 2158244013517243.

Li, C. (2016). When does web-based personalization really work? The distinction between actual personalization and perceived personalization. *Computers in human behavior*, *54*, 25-33. https://doi.org/10.1016/j.chb.2015.07.049

Li, H. (2019). Special Section Introduction: Artificial Intelligence and Advertising. *Journal of Advertising*, *48*(4), 333-337. https://doi.org/10.1080/00913367.2019.1654947

Li, Z., Ziting, Z., & Kang, C. (2024). Navigating the Intrusiveness Paradox: A Comprehensive Literature Review on AI Marketing and Consumer Perception. *Advances in Consumer Research*, *1*(1), 1-19. https://research.ebsco.com/linkprocessor/plink?id=de6d03b4-5265-3155-89b0-52c989728a4e

Ma, Y. M., Dai, X., & Deng, Z. (2023). Using machine learning to investigate consumers' emotions: the spillover effect of AI defeating people on consumers' attitudes toward AI companies. *Internet Research*, *34*(5), 1679-1713.

MacRury, I., & Manika, D. (2025). *Digital Advertising Evolution*. Taylor & Francis Group. http://ebookcentral.proquest.com/lib/aut/detail.action?docID=31607577

Malheiros, M., Jennett, C., Patel, S., Brostoff, S., & Sasse, M. A. (2012). *Too close for comfort: a study of the effectiveness and acceptability of rich-media personalized advertising Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, Austin, Texas, USA. https://doi.org/10.1145/2207676.2207758

Mangold, W. G., & Faulds, D. J. (2009). Social media: The new hybrid element of the promotion mix [Article]. *Business Horizons*, *52*(4), 357-365. https://doi.org/10.1016/j.bushor.2009.03.002

Martin, K. D., & Murphy, P. E. (2017). The role of data privacy in marketing. *Journal of the Academy of Marketing Science*, *45*(2), 135-155. https://doi.org/10.1007/s11747-016-0495-4

Maslowska, E., Smit, E. G., & van den Putte, B. (2016). It Is All in the Name: A Study of Consumers' Responses to Personalized Communication. *Journal of Interactive Advertising*, *16*(1), 74-85. https://doi.org/10.1080/15252019.2016.1161568

McAndrew, F. T., & Koehnke, S. S. (2016). On the nature of creepiness. *New Ideas in Psychology*, *43*, 10-15. https://doi.org/https://doi.org/10.1016/j.newideapsych.2016.03.003

McKee, K. M., Dahl, A. J., & Peltier, J. W. (2024). Gen Z's personalization paradoxes: A privacy calculus examination of digital personalization and brand behaviors. *Journal of Consumer Behaviour*, *23*(2), 405-422. https://doi.org/10.1002/cb.2199

Menon, A. M., Deshpande, A. D., Zinkhan, G. M., & Perri Iii, M. (2004). A model assessing the effectiveness of direct-to-consumer advertising: integration of concepts and measures from marketing and healthcare. *International Journal of Advertising*, *23*(1), 91-118. https://doi.org/10.1080/02650487.2004.11072874

Mertler, C. A., & Charles, C. M. (2005). *Introduction to educational research* (Fifth edition ed.). Pearson A & B.

Ming, F. A. N., Kumar, S., & Whinston, A. B. (2007). Selling or Advertising: Strategies for Providing Digital Media Online. *Journal of Management Information Systems*, *24*(3), 143-166. https://doi.org/10.2753/MIS0742-1222240305

Mirek-Rogowska, A., Kucza, W., & Gajdka, K. (2024). AI in communication: Theoretical perspectives, ethical implications, and emerging competencies. *Communication Today*, *15*(2), 16-29. https://doi.org/10.34135/communicationtoday.2024.Vol.15.No.2.2

Mishra, A., Shukla, A., Rana, N. P., & Dwivedi, Y. K. (2021). From "touch" to a "multisensory" experience: The impact of technology interface and product type on consumer responses. *Psychology & Marketing*, *38*(3), 385-396. https://doi.org/10.1002/mar.21436

Moro Visconti, R. (2024). Artificial Intelligence-Driven FinTech Valuation: A Scalable Multilayer Network Approach. *FinTech*, *3*(3), 479-495. https://doi.org/10.3390/fintech3030026

Munsch, A. (2021). Millennial and generation Z digital marketing communication and advertising effectiveness: A qualitative exploration. *Journal of Global Scholars of Marketing Science*, *31*(1), 10-29. https://doi.org/10.1080/21639159.2020.1808812

MurÁR, P., Kubovics, M., & JuriŠOvÁ, V. (2024). The impact of brandvoice integration and artificial intelligence on social media marketing. *Communication Today*, *15*(1), 50-63. https://doi.org/10.34135/communicationtoday.2024.Vol.15.No.1.4

Nayak, S., Pereira, V., Kazmi, B. A., & Budhwar, P. (2024). To Buy or Not to Buy? Exploring Ethical Consumerism in an Emerging Market—India. *Journal of Business Ethics*, *191*(4), 811-835. https://doi.org/10.1007/s10551-024-05670-7

Niu, X., Wang, X., & Liu, Z. (2021). When I feel invaded, I will avoid it: The effect of advertising invasiveness on consumers' avoidance of social media advertising. *Journal of Retailing and Consumer Services*, *58*, 102320. https://doi.org/10.1016/j.jretconser.2020.102320

Oh, J., Nah, S., & Yang, Z. D. (2025). How Autonomy of Artificial Intelligence Technology and User Agency Influence AI Perceptions and Attitudes: Applying the Theory of Psychological Reactance. *Journal of Broadcasting & Electronic Media*, *69*(3), 161-182. https://doi.org/10.1080/08838151.2025.2485319

Olney, T. J., Holbrook, M. B., & Batra, R. (1991). Consumer Responses to Advertising: The Effects of Ad Content, Emotions, and Attitude toward the Ad on Viewing Time. *Journal of Consumer Research*, *17*(4), 440-453. https://research.ebsco.com/linkprocessor/plink?id=e8916e75-6ce2-3641-8efd-a170b2e9e914

Paliwal, G., Kumar, A., Sharma, K. P., Bhargava, D., & Shrimal, V. M. (2025). Transformative impact of explainable artificial intelligence: bridging complexity and trust. *Discover Artificial Intelligence*, *5*(1), 1-21. https://doi.org/10.1007/s44163-025-00281-1

Pallant, J. (2010). *SPSS Survival Manual: A step by step guide to data analysis using SPSS*. Open University Press/McGraw-Hill.

Pfiffelmann, J., Dens, N., & Soulez, S. (2020). Personalized advertisements with integration of names and photographs: An eye-tracking experiment. *Journal of Business Research*, *111*, 196-207.

Qin, X., & Jiang, Z. (2019). The Impact of AI on the Advertising Process: The Chinese Experience. *Journal of Advertising*, *48*(4), 338-346. https://doi.org/10.1080/00913367.2019.1652122

Raji, M. A., Olodo, H. B., Oke, T. T., Addy, W. A., Ofodile, O. C., & Oyewole, A. T. (2024). E-commerce and consumer behavior: A review of AI-powered personalization and market trends. *GSC Advanced Research and Reviews*, *18*(3), 066-077.

Rhee, C. E., & Choi, J. (2020). Effects of personalization and social role in voice shopping: An experimental study on product recommendation by a conversational voice agent. *Computers in human behavior*, *109*, 106359. https://doi.org/https://doi.org/10.1016/j.chb.2020.106359

Rita, P., Omran, W., Ramos, R. F., & Costa, T. (2025). Exploring the Applications of Artificial Intelligence in Marketing: A Topic Modelling Analysis. *Tourism & Management Studies*, *21*(1), 39-55. https://doi.org/10.18089/tms.20250103

Rodgers, W., & Nguyen, T. (2022). Advertising Benefits from Ethical Artificial Intelligence Algorithmic Purchase Decision Pathways. *Journal of Business Ethics*, *178*(4), 1043-1061. https://doi.org/10.1007/s10551-022-05048-7

Roos, J. M., & Bauldry, S. (2022). *Confirmatory Factor Analysis*. SAGE Publications, Inc. https://doi.org/10.4135/9781071938959

Sargın, S. (2024). Antecedents and Consequences of Consumers' Attitudes Towards Artificial Intelligence in Social Media. *Business & Economics Research Journal*, *15*(3), 229-256. https://doi.org/10.20409/berj.2024.443

Segijn, C. M., & van Ooijen, I. (2022). Differences in consumer knowledge and perceptions of personalized advertising: Comparing online behavioural advertising and synced advertising. *Journal of Marketing Communications*, *28*(2), 207-226. https://doi.org/10.1080/13527266.2020.1857297

Shin, D. (2022). How do people judge the credibility of algorithmic sources? *AI & SOCIETY*, *37*(1), 81-96. https://doi.org/10.1007/s00146-021-01158-4

Shumanov, M., Cooper, H., & Ewing, M. (2022). Using AI predicted personality to enhance advertising effectiveness. In *European Journal of Marketing* (Vol. 56, pp. 1590-1609): Emerald Publishing Limited.

Srivastava, R. K., & Dorsch, M. J. (2020). Understanding the viability of three types of approach of advertising in emerging markets. *Journal of Marketing*

Communications, *26*(8), 799-812. https://doi.org/10.1080/13527266.2019.1586749

Statista. (2025). *Facebook - statistics & facts*. Retrieved 17 April from https://www.statista.com/topics/751/facebook/#topicOverview

Subeh, P. (2024). Advertising, Promotion and Marketing Communications: Evaluating the Impact of Personalization Techniques on Consumer Engagement in Digital Marketing: A Comprehensive Analysis. *AMA Summer Academic Conference Proceedings*, *35*, 14-34. https://research.ebsco.com/linkprocessor/plink?id=32239ca5-01a0-3f17-aeab-1e769a49716e

Surucu-Balci, E., & Balci, G. (2023). Building social capital in cruise travel via social network sites. *Current Issues in Tourism*, *26*(7), 1096-1111. https://doi.org/10.1080/13683500.2022.2047904

Tam, K. Y., & Ho, S. Y. (2006). Understanding the impact of web personalization on user information processing and decision outcomes. *MIS Quarterly*, *30*(4), 865-890. https://doi.org/10.2307/25148757

Tang, A. (2024). Design and Implementation of Real-Time Bidding Advertising System Based on Big Data Platform. 2024 6th International Conference on Frontier Technologies of Information and Computer (ICFTIC), Qingdao, China.

Terason, S., Pattanayanon, P., & Phawitpiriyakliti, C. (2025). From Interaction to Loyalty: The Role of Digital Engagement in Automobile Consumers. *Human Behavior and Emerging Technologies*, *2025*(1), 1-14. https://doi.org/https://doi.org/10.1155/hbe2/9912657

Toti, J.-F., & Steils, N. (2024). Showing or Hiding? The Impact of Visibility of General Conditions of Use on Retargeted Ad Intrusiveness and Perceived Ethicality of Mobile Apps. *Journal of Interactive Marketing*, *59*(3), 251-272. https://doi.org/10.1177/10949968231221472

Tran, M. T. (2024). *A systematic analysis of artificial intelligence's usage in online advertising: How artificial intelligence affects digital marketing initiatives*. IGI Global. https://doi.org/10.4018/979-8-3693-4453-8.ch002

Tran, T. P., van Solt, M., & Zemanek Jr, J. E. (2020). How does personalization affect brand relationship in social commerce? A mediation perspective. *Journal of Consumer Marketing*, *37*(5), 473-486.

Uribe, R., Labra, R., & Manzur, E. (2022). Modeling and evaluating the effectiveness of AR advertising and the moderating role of personality traits. *International Journal of Advertising*, *41*(4), 703-730. https://doi.org/10.1080/02650487.2021.1908784

Van den Broeck, E., Zarouali, B., & Poels, K. (2019). Chatbot advertising effectiveness: When does the message get through? *Computers in human behavior*, *98*, 150-157. https://doi.org/10.1016/j.chb.2019.04.009

van Doorn, J., & Hoekstra, J. C. (2013). Customization of online advertising: The role of intrusiveness. *Marketing Letters*, *24*(4), 339-351. https://doi.org/10.1007/s11002-012-9222-1

van Noort, G., Himelboim, I., Martin, J., & Collinger, T. (2020). Introducing a Model of Automated Brand-Generated Content in an Era of Computational Advertising. *Journal of Advertising*, *49*(4), 411-427. https://doi.org/10.1080/00913367.2020.1795954

Veloso, M., Ieva, M., & Gómez-Suárez, M. (2024). Social media content strategy in hospitality: the impact of experiential posts and response congruence on engagement, hotel image, and booking intention. *Journal of Hospitality Marketing & Management*, *33*(1), 57-77. https://doi.org/10.1080/19368623.2023.2241041

Wagner, T. F., Baccarella, C. V., & Voigt, K.-I. (2017). Framing social media communication: Investigating the effects of brand post appeals on user interaction. *European Management Journal*, *35*(5), 606-616. https://doi.org/10.1016/j.emj.2017.05.002

Wetzels, R., Wetzels, M., Lemmink, J. G. A. M., Grewal, D., & Kuppelwieser, V. (2024). Service experience lies in the eye of the beholder: contextualizing extant literature toward integrating eye-tracking in service research. *Journal of Services Marketing*, *38*(9), 1117-1131. https://doi.org/10.1108/jsm-06-2024-0299

Wilson, J. (2010). *Essentials of business research: a guide to doing your research project*. SAGE Publications.

Winter, S., Maslowska, E., & Vos, A. L. (2021). The effects of trait-based personalization in social media advertising. *Computers in human behavior*, *114*, 106525. https://doi.org/10.1016/j.chb.2020.106525

Wu, L., Dodoo, N. A., & Wen, T. J. (2025). Disclosing AI's Involvement in Advertising to Consumers: A Task-Dependent Perspective. *Journal of Advertising*, *54*(1), 20-38. https://doi.org/10.1080/00913367.2024.2309929

Wu, L., Dodoo, N. A., Wen, T. J., & Ke, L. (2022). Understanding Twitter conversations about artificial intelligence in advertising based on natural language processing. *International Journal of Advertising*, *41*(4), 685-702. https://doi.org/10.1080/02650487.2021.1920218

Wu, L., & Jing Wen, T. (2021). Understanding AI Advertising From the Consumer Perspective. *Journal of Advertising Research*, *61*(2), 133-146. https://doi.org/10.2501/JAR-2021-004

Yang, C., & Hu, J. (2022). When do consumers prefer AI-enabled customer service? The interaction effect of brand personality and service provision type on brand attitudes and purchase intentions. *Journal of Brand Management*, *29*(2), 167-189.

Yang, J., & Zhao, X. (2021). The Impact of Information Processing Styles and Persuasive Appeals on Consumers' Engagement Intention Toward Social Media Video Ads. *Journal of Promotion Management*, *27*(4), 524-546. https://doi.org/10.1080/10496491.2020.1851846

Yanping, S., Wenbing, W., Fangyuan, C., Lingyu, S., & Yue, Z. (2024). Influence mechanism of social support of social media on users' information-seeking behaviour. *Transformations in Business & Economics*, *23*(1), 443-469. https://research.ebsco.com/linkprocessor/plink?id=5eb6f8d5-2ce8-3cad-bb01-fdfaecc58264

Yoo, C., & MacInnis, D. (2005). The brand attitude formation process of emotional and informational ads. *Journal of Business Research*, *58*(10), 1397-1406.

Yousaf, A., Amin, I., Jaziri, D., & Mishra, A. (2021). Effect of message orientation/vividness on consumer engagement for travel brands on social networking sites. *Journal of Product & Brand Management*, *30*(1), 44-57.

Zahirović, M., Marić, E., & Husić-Mehmedović, M. (2024). The Role of Consumer Knowledge in the Privacy Paradox of Personalised Advertising. *South East European Journal of Economics & Business (1840118X)*, *19*(2), 46-59. https://doi.org/10.2478/jeb-2024-0015

Zhang, Y., & Zhang, S. Human-AI Alignment in Ad Targeting: Addressing Misestimation for Vulnerable Groups. *Journal of Advertising*, 1-17. https://doi.org/10.1080/00913367.2025.2465381

Zheng, L., Huang, B., Qiu, H., & Bai, H. (2024). The role of social media followers' agency in influencer marketing: a study based on the heuristic–systematic model of information processing. *International Journal of Advertising*, *43*(3), 554-579. https://doi.org/10.1080/02650487.2023.2229148

Zhu, Y.-Q., & Kanjanamekanant, K. (2021). No trespassing: Exploring privacy boundaries in personalized advertisement and its effects on ad attitude and purchase intentions on social media. *Information & Management*, *58*(2), 103314.

Appendices

Appendix A *AUTEC Approval*

Auckland University of Technology Ethics Committee (AUTEC)

14 April 2025

Pornchanoke Tipgomut
Faculty of Business Economics and Law

Dear Pornchanoke

Re Ethics Application: **25/37 The Effect of Automated vs. Non-Automated Advertising on Customer Response on Social Media Ads: The Moderating Role of Customer Segment**

Thank you for your responses to AUTEC's conditions.

Your ethics application has been approved for three years until 14 April 2028.

Non-Standard Conditions of Approval

1. In the 'Will I receive feedback' section of the Information Sheet, amend to provide a URL and possible date to access a summary of findings (as this will be more accessible for participants than reading a thesis).
2. In the questionnaire only the AUT Information Sheet is required as the first block. Please remove the non-logo Information Sheet.

Non-standard conditions do not need to be submitted to or reviewed by AUTEC unless requested but must be completed before commencing your study.

Standard Conditions of Approval

1. The research is to be undertaken in accordance with the {HYPERLINK "https://www.aut.ac.nz/__data/assets/pdf_file/0006/274371/AUT-CODE-OF-CONDUCT-FOR-RESEARCH-2019.pdf"} and as approved by AUTEC.
2. All public facing documents must have the AUTEC approval number and be of a high standard of spelling and grammar. Dates on the Information Sheet(s) and Consent Form(s) must be consistent.
3. Any amendments to the project must be approved by AUTEC prior to being implemented.
4. A progress report is due annually on the anniversary of the approval date.
5. A final report is due at the expiration of the approval period, or, upon completion of project.
6. Any serious or adverse events must be reported to AUTEC, this includes unforeseen issues that might affect continued ethical acceptability of the project.
7. AUTEC grants ethical approval only. You are responsible for obtaining management permission for access from any institution or organisation at which your research is being conducted and you need to meet all ethical, legal, public health, and locality obligations or requirements for the jurisdictions in which the research is being undertaken.

The application number and title need to be referenced on all correspondence related to this project.

All forms are available online {HYPERLINK "http://www.aut.ac.nz/research/researchethics"}

For any enquiries, please contact the Secretariat at {HYPERLINK "mailto:ethics@aut.ac.nz"}
(This is a computer-generated letter for which no signature is required)

The AUTEC Secretariat
Auckland University of Technology Ethics Committee

Cc: drvienings@gmail.com;wpy3741@autuni.ac.nz

Appendix B *Participant Sheet*

Participant Information Sheet

Date Information Sheet Produced:

4 April 2025

Project Title

The effect of online social media advertisements in promoting a business

An Invitation

My name is Daniel Vienings. I am a Master of Business student, specialising in Marketing, at Auckland University of Technology (AUT) in New Zealand. I am undertaking my Master's thesis project under the Marketing and International Business department at the Faculty of Business, Economics and Law. I would like to invite you to participate in my research on the effect of online social media advertisements in promoting a business. The purpose of this participant information sheet is to help you decide whether or not to participate in the study. This information sheet explains the rationale behind the research study, describes the involvement of each participant, outlines the potential risks and benefits, and explains how anonymity will be ensured.

What is the purpose of this research?

This study aims to understand how consumers react to online social media advertisements. The data collected in this study will be used primarily for the completion of Daniel Vienings' Master's thesis. There is also a possibility that the findings may be published in a journal or presented at an academic conference. But, this survey is anonymous. Your identity will not be collected or stored, and your responses cannot be linked back to you. As such, confidentiality is not applicable. Participation is voluntary, and by submitting the completed survey, you are giving your informed consent to take part in the study.

How was I identified and why am I being invited to participate in this research?

You have been invited to participate in this research because you are at least 18 years old and either interested in starting a business or currently running or managing your own business. Participants who do not meet these criteria will not be eligible to take part in this study.

How do I agree to participate in this research?

If you decide you would like to take part in this research, click on the link to the project advertised on the MTurk platform for workers to complete a task. This link will redirect you to the online survey hosted on Qualtrics, where you can start the survey.

To agree to participate, you must read the Participant Information Sheet carefully and ensure you understand the study's purpose, your role, and your rights. By clicking "Next" to proceed with the survey, you indicate your consent to participate in this research. Completion of the survey will confirm your consent. Please note that participation is entirely voluntary, and you can withdraw at any time by closing the browser window before completing the survey.

What will happen in this research?

Once you click the link to the project on MTurk, you will be directed to the Qualtrics survey, where you can read the study description. You will be able to complete the online questionnaire. This survey will take approximately 15 minutes to complete. Please note that consent is implied by completing the survey.

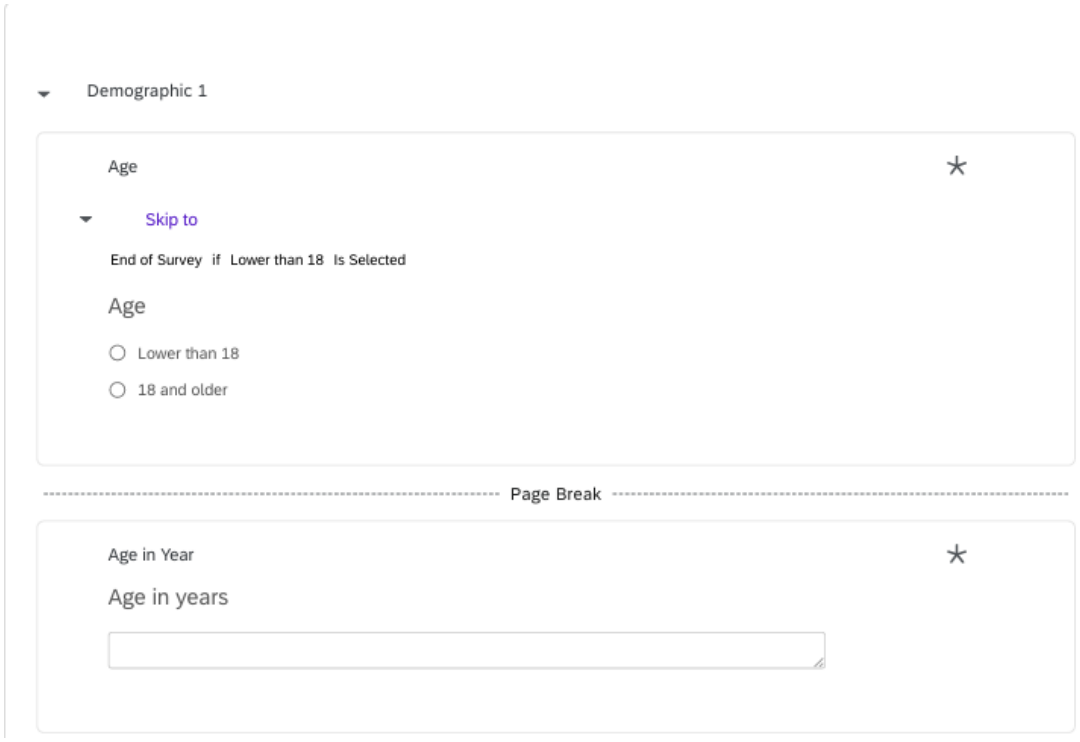
What are the discomforts and risks?

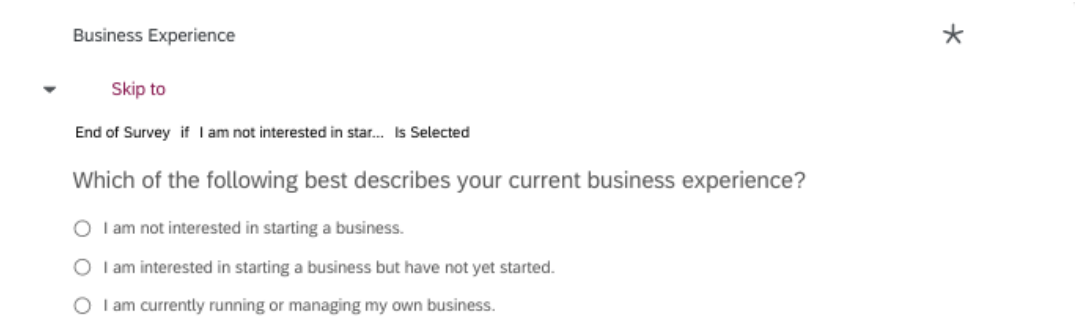
There are no anticipated risks or discomforts associated with participating in this study.

How will these discomforts and risks be alleviated?

Participation in this study is completely voluntary. If, for any reason, you feel uncomfortable, you may withdraw from the study at any time without consequences. You can do so by simply closing the browser window before completing the survey.

Appendix C *Sample Questionnaire*

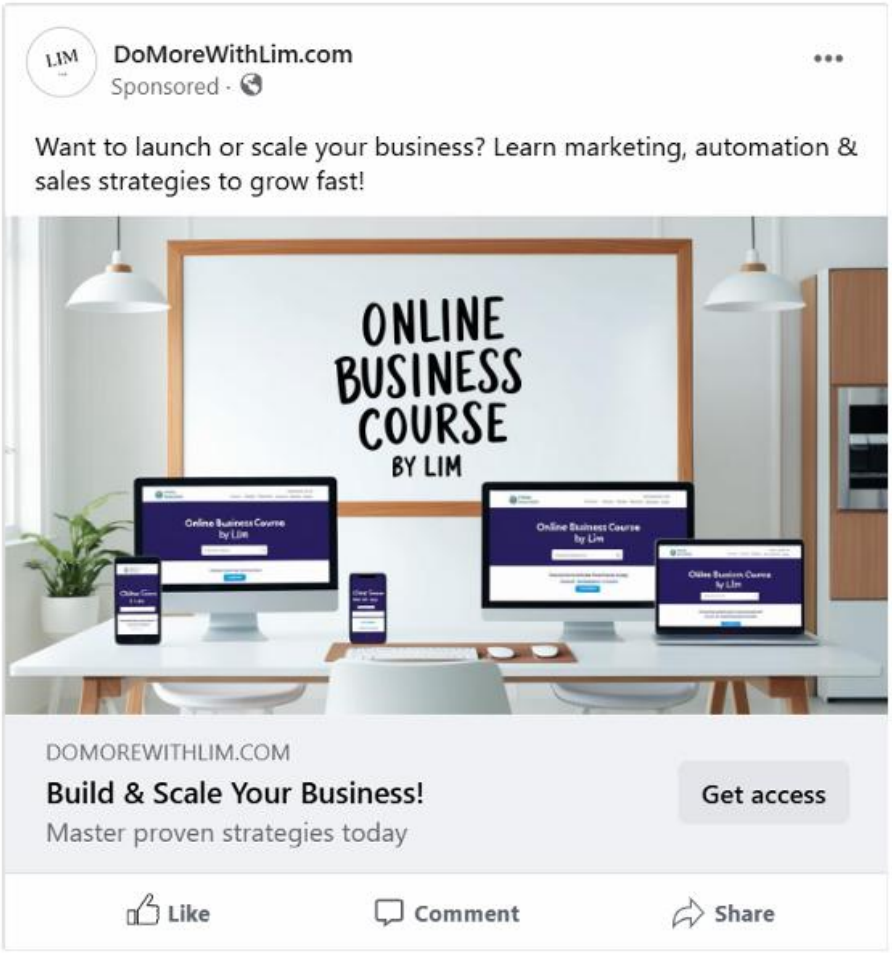




Ad - Overall

Please take a moment to carefully view and read the following Facebook-style advertisement.

You will see a simulated ad designed to look like a real Facebook post. Please review the ad as if you encountered it while browsing your own Facebook feed. There are no right or wrong answers — we are simply interested in your impressions and reactions. After viewing the ad, you will be asked a few questions about what you saw.



Con 1 - Personalised

Please select one answer for each following statement.

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
This ad is tailored to my situation.	○	○	○	○	○	○	○
I believe this ad is customised to my needs.	○	○	○	○	○	○	○
This ad was targeted at me as a unique individual.	○	○	○	○	○	○	○
I believe this ad is customised to my characteristics.	○	○	○	○	○	○	○
This ad was personalized according to my profile.	○	○	○	○	○	○	○

Con 1 - Relevance

For me, this Facebook advertisement by LIM is

Not important	○	○	○	○	○	○	○	Important
Not relevant	○	○	○	○	○	○	○	Relevant
Meaningless	○	○	○	○	○	○	○	Meaningful

Con 1 - Creepiness

To what extent do you think the advertisement by LIM was

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
Creepy	○	○	○	○	○	○	○
Disturbing	○	○	○	○	○	○	○
Worrying	○	○	○	○	○	○	○

Con 1 - Engagement

Please select one answer for each following statement.

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
I would click the advertisement to obtain more information.	○	○	○	○	○	○	○
I would click like this Facebook advertisement.	○	○	○	○	○	○	○
I would share this Facebook advertisement.	○	○	○	○	○	○	○
I would comment on this Facebook advertisement.	○	○	○	○	○	○	○

AI Ad

Do you think this advertisement was developed by AI?

○ No

○ Yes

AI/Human

To what extent do you think this advertisement was created by an automated system or AI rather than a human marketer?

Definitely created by a human ○ ○ ○ ○ ○ ○ ○ Definitely created by AI

Personalise

Skip to

Please select one answer for each fol... if No Is Selected

Do you think this advertisement uses your personal data to generate the ad?

○ No

○ Yes

Page Break

AI Level

If yes, how much do you think the personal data has been used to generate this ad?

○ None at all

○ A little

○ A moderate amount

○ A lot

○ A great deal

End of Survey

We thank you for your time spent taking this survey.

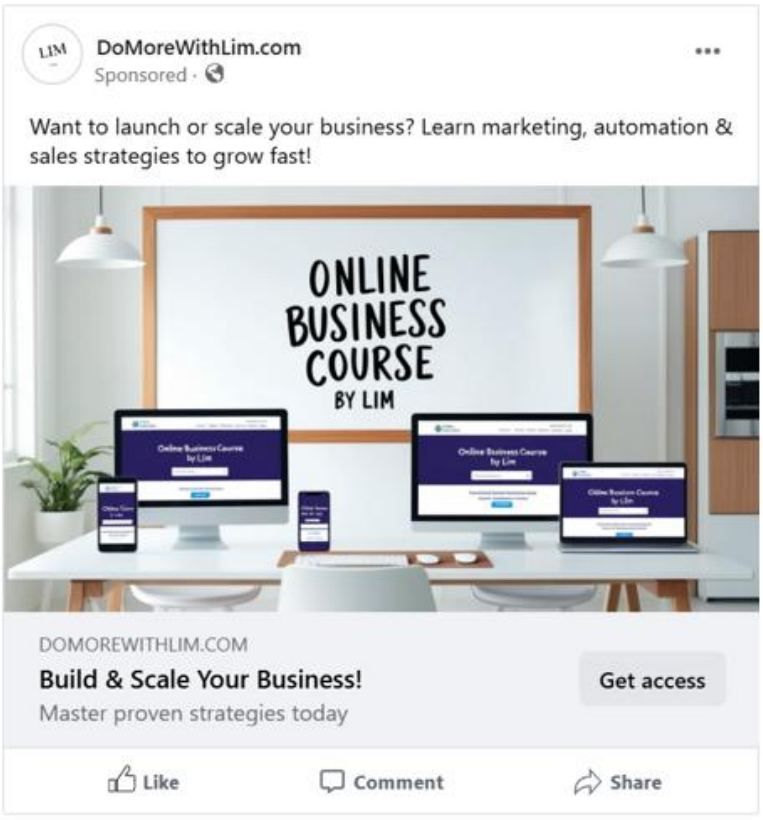
Your response has been recorded.

Appendix D *Experimental Design Copy and Graphics*

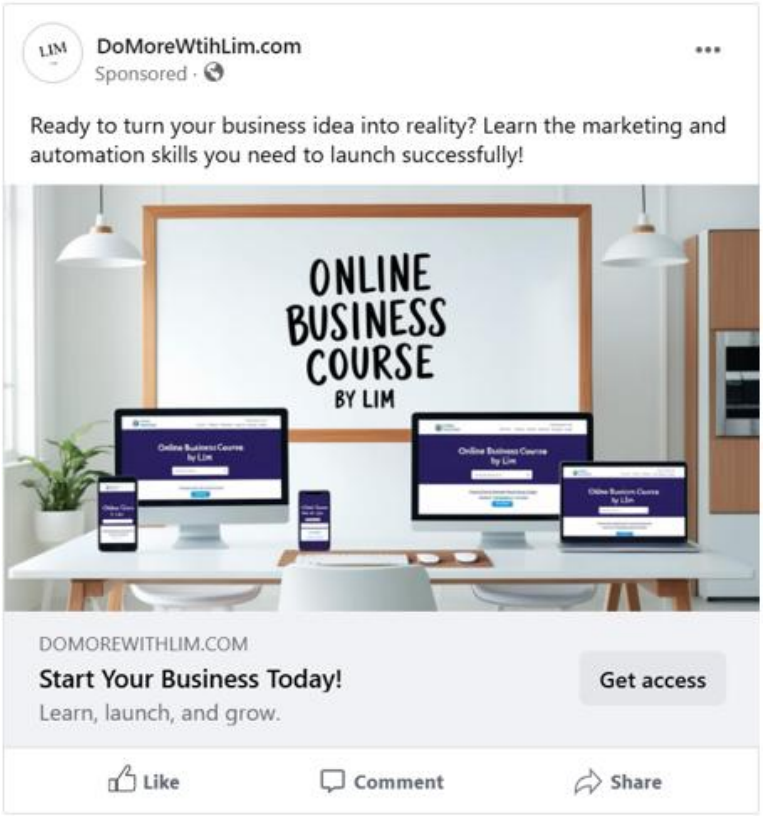
Experimental Design Copy and Graphics

Audience Segment	Primary Text (Max 125)	Headline (Max 40)	Description (Max 25)
Overall (Non-Automated Ad)	Want to launch or scale your business? Learn marketing, automation & sales strategies to grow fast!	Build & Scale Your Business!	Master proven strategies today
Aspiring Entrepreneurs	Ready to turn your business idea into reality? Learn the marketing and automation skills you need to launch successfully!	Start Your Business Today!	Learn, launch, and grow
Experienced Entrepreneurs	Ready to take your business to the next level? Automate your marketing and sales to grow faster with less effort!	Expand Your Business!	Boost sales, reach more

Non-Automated Ads



Aspiring Entrepreneurs



Experienced Entrepreneurs