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Personalization in Marketing Communication: Exploring the Impact of AI Transparency on Advertising Effectiveness

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Generative AI tools were used in a supportive and supplementary capacity during the preparation of this thesis. Their use was limited to linguistic improvements, such as suggesting alternative phrasings, enhancing clarity, and refining stylistic coherence, as well as for the creation of experimental stimuli. All conceptual work, including the development of research ideas, literature review, study designs, data analysis, and interpretation of results, was carried out independently by the author. Suggestions provided by AI tools were critically reviewed, adapted, or substantially revised prior to integration. The author takes full responsibility for the academic content and the conclusions presented in this thesis.

Abstract

As artificial intelligence (AI) increasingly enables highly personalized advertising, regulatory developments like the EU AI Act are mandating greater transparency through explicit AI disclosure. This thesis investigates the impact of such disclosures on consumer responses and how they interact with the well-established effects of personalization.

Using a 2x2 between-subjects experimental design (n=172), the study manipulated personalization (personalized vs. non-personalized) and AI disclosure (disclosed vs. not disclosed) to measure their effects on attitude toward the ad, purchase intention, and privacy concerns. The findings demonstrate that while personalization significantly improves attitudes toward the ad, it also triggers higher privacy concerns. In contrast, AI disclosure negatively affects advertising evaluations without significantly increasing privacy concerns. Interestingly, no significant interaction effects were found, and neither variable significantly impacted purchase intention.

The results suggest that the negative reaction to AI disclosure in content creation is likely driven by peripheral cues, such as perceived authenticity or effort, rather than data-related concerns. Furthermore, the study indicates a habituation effect, which suggests that consumers have grown accustomed to personalization while remaining sceptical of the relatively novel cue of AI disclosure. For practitioners, the research suggests that personalization remains a powerful tool, the use of AI in marketing communication, however, should be handled with caution.

Abstract (Deutsch)

Mit der zunehmenden Nutzung künstlicher Intelligenz (KI) zur Ermöglichung hochgradig personalisierter Werbung gewinnen Transparenzanforderungen, auch durch regulatorische Entwicklungen wie den EU AI Act, an Bedeutung. Diese Masterarbeit untersucht, wie sich die explizite Offenlegung des KI-Einsatzes auf Konsumentenreaktionen auswirkt und wie sie mit den etablierten Effekten von Personalisierung interagiert.

In einem 2×2 Between-Subjects-Experiment ($n = 172$) wurden Personalisierung (personalisiert vs. nicht personalisiert) und die Offenlegung des KI-Einsatzes (offengelegt vs. nicht offengelegt) experimentell manipuliert. Als abhängige Variablen dienten die Einstellung zur Werbung, die Kaufintention sowie Datenschutzbedenken. Die Ergebnisse zeigen, dass Personalisierung die Einstellung zur Werbung signifikant verbessert, gleichzeitig jedoch höhere Datenschutzbedenken auslöst. Der Einsatz von KI wirkt sich negativ auf die Werbewirkung aus, ohne die Datenschutzbedenken signifikant zu erhöhen. Es konnten keine signifikanten Interaktionseffekte festgestellt werden; zudem zeigte sich für keine der beiden unabhängigen Variablen ein signifikanter Effekt auf die Kaufintention.

Die Ergebnisse legen nahe, dass die negative Reaktion auf die KI-Kennzeichnung bei der Erstellung von Werbeinhalten eher auf periphere Reize wie wahrgenommene Authentizität oder menschlichen Aufwand zurückzuführen ist als auf datenbezogene Bedenken. Darüber hinaus deuten die Ergebnisse auf einen Habituationseffekt hin: Während sich Konsumenten offenbar an personalisierte Werbung gewöhnt haben, reagieren sie auf das vergleichsweise neue Phänomen einer KI-Kennzeichnung weiterhin skeptisch. Für die Praxis impliziert dies, dass Personalisierung ein wirksames Instrument in der Marketingkommunikation bleibt, der Einsatz von KI in Werbungen jedoch nur sorgfältig genutzt und kommuniziert werden sollte.

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List of Abbreviations

Aad	Attitude toward the ad
AI	Artificial intelligence
ANOVA	Analysis of variance
APA	American Psychological Association
DV	Dependent variable
ELM	Elaboration Likelihood Model
EU	European Union
F	F statistic
GDPR	General Data Protection Regulation
IV	Independent variable
M	Mean
N	Total sample size
nPAI	Condition 1 - No personalization + AI dislosure
nPnAI	Condition 3 - No personalization + no AI dislosure
p	p value
PAI	Condition 2 - Personalization + AI dislosure
PC	Privacy concerns
PI	Purchase intention
PnAI	Condition 4 - Personalization + no AI dislosure
SD	Standard deviation

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1 Introduction

The rapid growth of artificial intelligence in recent years has significantly changed marketing communication. Companies increasingly rely on AI to automate advertising activities such as content creation, targeting, and personalization at an unprecedented scale. While these developments promise efficiency gains, they also raise fundamental questions about how consumers perceive, trust, and accept AI-driven advertising.

1.1 Background and Motivation

Headlines such as "Coca-Cola causes controversy with AI-made ad" (Horvath, 2024) or "Coca-Cola's AI-Generated Ad Controversy, Explained" (Di Placido, 2024) illustrate the public response to an advertisement released in November 2024 by The Coca-Cola Company. The ad was criticized not only for replacing human creative work with AI, but also for being perceived as inauthentic, soulless, and even creepy (Mouriquand, 2025). These reactions highlight that the use of AI in advertising is currently met with considerable consumer scepticism, and yet it is considered to hold substantial potential value in marketing and sales (Chui et al., 2018). However, regulations increasingly require the disclosure of AI-generated content (Cillo & Rubera, 2024), which raises the question of how consumers respond to AI disclosure in advertising and how these responses may evolve over time.

A comparable pattern emerged when personalization and the disclosure of data collection were first introduced into marketing communication. Although personalization was intended to increase relevance and advertising effectiveness (Bleier & Eisenbeiss, 2015), it initially triggered strong privacy concerns and perceptions of intrusiveness, particularly once consumers became aware of the extent of data collection (Salonen & Karjaluoto, 2016). After a while, however, consumers began to recognize the benefits of personalization, and privacy-related scepticism became less salient. Aguirre et al. (2015), for example, showed that consumer reactions to mandatory cookie disclosures under the Dutch Cookie Law improved over time, suggesting increasing habituation and appreciation of transparent communication.

Scepticism toward AI-generated advertising may therefore similarly be explained by the novelty of the technology and the absence of well-established regulatory frameworks. In contrast to personalized advertising, which is now governed by familiar data protection standards and disclosure practices (e.g., GDPR, cookie banners) (European Parliament and Council, 2016), AI-based advertising remains characterized by legal uncertainty and low consumer habituation. Prior research indicates that such uncertainty amplifies perceived risk and privacy concerns, particularly when consumers lack experience with a technology (Wu et al., 2025).

1.2 Research Gap

Both personalization as well as AI have been topic of conversation in research, however, recent studies highlight that consumer responses to AI disclosure in advertising remain underexplored. Concerning the use of AI, Cillo & Rubera (2024) claim that "research is warranted to explore the implications of such requirements for both consumers and firms" (p. 693). Wu et al. (2025) also explain that there is currently no sufficient consensus on consumer response to AI disclosure, and its study is according to Rhee & Lee (2024) gaining even more importance with regulatory advances and mandatory disclosure coming closer.

Additionally, existing research has largely examined personalization and AI disclosure in isolation, although Aksoy et al. (2021) mention that with respect to personalization the "ongoing developments in information technology and AI have more recently moved this phenomenon to a much more critical level" (p. 1091). AI has the potential to directly influence and transform how personalization will be used in the future (Gupta et al., 2024), however, little is known about how AI disclosure affects personalized advertising and whether the positive effects of personalization persist when AI involvement is explicitly disclosed. Research has shown that while consumer scepticism and, in this regard, especially privacy concerns toward personalization have decreased over time (due to habituation and established disclosure practices), AI disclosure represents a comparatively novel and less familiar transparency cue. It therefore remains unclear, whether negative consumer responses to AI disclosure are caused by its novelty and corresponding scepticism and whether it will follow a similar habituation pattern to personalization.

1.3 Research Objectives and Questions

The objective of this thesis is to examine how AI disclosure in advertising affects consumer responses and advertising effectiveness, with a particular focus on its interaction with personalized advertising. Building on prior research on personalization, privacy concerns, and AI in marketing communication, this study investigates whether the positive effects of personalization persist when AI involvement is explicitly disclosed.

Furthermore, the thesis examines privacy concerns as a central mechanism underlying negative consumer responses to both personalization and AI disclosure. It addresses whether privacy concerns are more pronounced in AI-disclosed advertising than in personalized advertising, based on the assumption that consumers are more familiar and habituated to personalization practices than to AI-disclosed advertising. Accordingly, this study provides insights into whether negative responses to AI being used in advertising are primarily driven by the novelty of the technology. This would suggest that scepticism may decrease over time in a manner similar to the development of consumer responses to personalized advertising. Based on the research gap and objectives outlined above, this thesis addresses the following research question:

"How do consumers respond differently to personalized ads when AI is disclosed and why?

1.4 Structure and Formatting of the Thesis

This thesis is structured as follows: Chapter 2 reviews the relevant literature on personalization, AI in marketing communication, consumer response mechanisms, and regulatory frameworks, after which it outlines the hypotheses. Chapter 3 describes the research methodology, including the experimental design, stimuli, measures, and method of data collection. Chapter 4 presents the results of the study. Chapter 5 discusses the findings in light of existing research, outlines theoretical and managerial implications, and addresses limitations and directions for future research. In terms of formatting, citation, and referencing, this thesis follows the APA Style guidelines of the American Psychological Association (American Psychological Association) (2020).

2 Literature Review

The literature review focuses on the topics of personalization and AI disclosure. In order to gain a substantial understanding of different perspectives and theories regarding the areas of interest, this paper focuses on scientific literature published in academic journals, the primary utilized databases being EBSCO and Google Scholar.

The following section defines personalization in marketing communication, outlines its underlying mechanisms and theoretical foundations, and discusses the role of privacy concerns in the context of personalization.

2.1 Personalization in Marketing Communication

Personalization in marketing communication is a process in which products and services are presented and tailored in a way that matches the consumers individual preferences. Although personalization is frequently used interchangeably with matching, customization, or tailoring, most authors define it as the delivery of individualized messages that treat each user as an audience of one (Kalyanaraman & Sundar, 2006). Some authors, conversely, differentiate between the terms customization and personalization based on where the action was initiated. In this case personalization is rather instigated by the company itself, whereas customization refers to customer-initiated concepts (Aksoy et al., 2021; Salonen & Karjaluoto, 2016). Other authors claim that the term customization can be seen as a subfield to personalization (Aksoy et al., 2021). This thesis focuses primarily on *company-initiated ads* that are created based on the consumer data collected by the company, thereby referring to personalization as firm-initiated adaptation of advertising content instead of customer-driven concepts.

Regardless of the terminology used, personalization in marketing communication aims to “individualise customer experience and enhance marketing effectiveness” (Aksoy et al., 2021, p. 1091). The overarching goal of personalization is to provide “the right content in the right format to the right person at the right time” (Tam & Ho, 2006, p. 867). To achieve this, customer preferences are collected and learned over time and subsequently synthesized into customized offers and recommendations delivered through advertisements (Salonen & Karjaluoto, 2016). A meta-analytic review of 53 studies by Yeo and Chu (2025) demonstrates that personalized advertising is more persuasive and, consequently, more effective than non-personalized, generic advertising regarding consumer attitudes and subsequent behavioural intentions. In an increasingly knowledge-driven environment, personalization therefore represents a crucial mechanism for achieving a competitive advantage (Aksoy et al., 2021).

From a managerial perspective personalization can be described as a *customer centric strategy* that is being employed when targeting customers via personalized advertising. By doing so, brands are able to create contextualized advertising in alliance with the user's preferences as well as their demographics. This consumer-centric approach guarantees relevance, interest, and a better overall assessment of the presented topic (Haq et al., 2025). It allows marketers to focus on "psychographics, behaviors, and the benefits of the product or service offering to the individual" (Dennis & Kizer, 2024, p. 3). Personalized ads enable consumers to no longer passively watch ads which they are likely to ignore or swipe away but create an interesting and relevant customer experience. This process can be described as "engaged customization" (Dennis & Kizer, 2024).

From a technical perspective, Aksoy et al. (2021) cluster the methods of personalization into three categories: the self-reference, the anthropomorphism, and the system characteristics method. The first method describes a prioritization of the consumer through individualized communication, indicating that the system knows the person. Anthropomorphism refers to a humanoid system that communicates personalized content by imitating similar characteristics (e.g. through chatbots). System characteristics encompass personalization methods that are performed automatically by the system and where the system decides on behalf of the user. Examples include showing standard automated recommendations like the sentence "Customers who bought these also bought..." (Aksoy et al., 2021, p. 1011), or generating personalized information based on big data analyses and complex processing methods. The present thesis concentrates on *system characteristic personalization*, where personalized content is generated automatically by the system based on data-driven decision processes.

The success of personalized advertisement is also dependent on the *method of data collection* that is used to generate the ads. Aguirre et al. (2015) divide the process into two mechanisms: *overt* and *covert* information collection. Overt data collection implies that consumers know that their data is being collected because the firm made a conscious effort to inform them (e.g., through cookies), whereas covert methods conceal the fact that data is being collected and do so without the consumers' awareness.

2.1.1 Mechanisms of Personalization

A key reason why personalized advertising tends to be more effective and persuasive is that audiences perceive the message as more relevant and personally meaningful. By tailoring content to individuals' preferences, such messages align more closely with recipients' needs and interests (Yeo & Chu, 2025). Yeo and Chu (2025) also found that relatable advertisements have a positive effect on attitudes toward the ad. Overall, perceived relevance can be considered the main driver and fully mediates the effects of personalization on persuasion. Shao et al. (2024) define this mechanism as perceived content personalization, describing the "perceived fit between ad content and individual needs, which is coherent with perceived relevance" (p. 60). The greater the perceived relevance, the greater the involvement, the greater the motivation to process the message (Kalyanaraman & Sundar, 2006).

In addition to perceived relevance, Haq et al. (2025) found that personalization can positively influence advertising value through the mediating effects of *perceived creativity* and *authenticity*. Creativity plays an important role, particularly in social media advertising, as consumers perceive creative ads as "unique, meaningful, and engaging," which in turn fosters positive behavioural responses (Haq et al., 2025, p. 6). Authenticity further contributes to advertising effectiveness, as messages perceived as genuine and truthful enhance trust and strengthen consumer-brand connections (Haq et al., 2025). Moreover, a high *perceived effort* of the advertising agent can positively influence behavioural advertising outcomes (Modig et al., 2014) as well as *brand reputation* and recommendation intentions (Shao et al., 2024).

2.1.2 Theoretical Foundation of Personalization

One theory that explains the effects of personalization in marketing communication is the *elaboration likelihood model* (ELM) developed by Cacioppo et al. (1986). The framework suggests two ways consumer can react to persuasive messages: the central route and the peripheral route. On the one hand, individuals who are highly motivated and able to process information tend to engage in central processing; on the other hand, low motivation or ability leads consumers to rely on peripheral processing. In this context, motivation can be explained by a personal interest and a high need for cognition, whereas ability describes the capability of a person to understand the content that is being presented (O'Keefe, 2018). Typically, central route processing occurs when the presented content is highly relevant to the user which can lead to appreciation of the message and attitudinal change. The peripheral route is taken if involvement in the product is low. In this case, peripheral, superficial cues such as aesthetic appeal and source or author credibility are more effective (Haq et al. 2025).

Increased perceived relevance is the primary factor through which personalization leads consumers to engage in central processing, which is followed by an enhanced motivation to elaborate on the topic. This enhances message recall and brand attitudes

(Dennis & Kizer, 2024). Tam & Ho (2005) explain this phenomenon through the concept of increased *preference matching*. The persuasiveness of the message is dependent on the quality and merits of the argument of the message. “The level of preference matching refers to the extent to which the web content generated by the personalization agent appeals to the user” (Tam & Ho, 2005, p. 276). In conclusion, if the content does match the users appeal, the user is more likely to process the content before making a decision.

Personalization also enhances the consumers ability to relate the information to themselves, which can be described as *self-referencing* (Yeo & Chu 2025). This basically means that users that are exposed to personalized context perceive a higher involvement as they detect a higher degree of personal references and associations, which Krugman (1965) describes as *bridging experiences* (Kalyanaraman & Sundar, 2006). In sum, personalization increases message relevance and self-referencing, thereby enhancing consumers’ motivation and ability to process information, ultimately leading them to engage in central route processing.

In addition to the positive effects of central routing, other authors have considered a *dual routing approach*. Haq at al. (2025) for instance claim that consumer centric personalization increases message relevance, therefore the central route, but at the same time, heuristic cues like perceived creativity and authenticity activate peripheral routing. Consequently, not only user cognition (central route) is activated but also user emotion which simultaneously, trigger affective responses. It therefore also "shapes the depth and type of psychological engagement" (Haq et al. 2025, p. 18). Authenticity, in particular, can be seen as a peripheral cue especially when consumers are not motivated to elaborate on an advertisement (low involvement), but instead rely on indicators such as the sincerity or credibility of the advertisement. Shao et al. (2024) explain reputation and social recommendation to be peripheral cues and of importance regarding consumer response. A high degree of trust in the brand can be accounted for by a good reputation and social recommendation which is a positive evaluation of an advertiser regarding its characteristics and quality. When the ad content is not personally relevant and consumers rely on peripheral processing, attitudes can still be positive if the brand has a strong reputation or is socially endorsed.

The mechanisms of central and peripheral routing are also influenced by the users’ *level of experience*. Consumers that have experience with the product or brand are inclined to scrutinize the content relying on the central route for their decision making. Users, therefore, have a high elaboration likelihood. The richer the experience, the more content is processed, and the more likely the consumer is to trust the advertiser. Users with less experience, may instead rely on peripheral cues (reputation and recommendation) when they are trying to shape their attitude (Shao et al., 2024).

2.1.3 Personalization and Privacy Concerns

"Personalized advertising is generally more effective than generic, non-personalized advertising." (Yeo & Chu, 2025, p. 1). Research, however, has also uncovered negative effects of personalization on consumer behaviour (Aguirre et al., 2015). Privacy is a highly discussed factor that consumers consider when experiencing personalization (Salonen & Karjaluoto, 2016). Privacy concerns and perceived risks oftentimes arise due to continuous collection and corresponding use of personal data. They play a negative role regarding consumer well-being and can lead to ad avoidance, feelings of intrusiveness and subsequently negatively influence advertising outcomes (Boerman & Smit, 2020).

The role of privacy concerns is strongly dependent on the firms' method for data collection. According to Aguirre et al. (2015), personalized advertising boosts click-through intentions only when consumers are aware that their data are being collected. Covert strategies can undermine the beneficial effects of increased relevance and advertising effectiveness, because consumer that become aware that their data have been collected without their consent (e.g. because they are being exposed to highly personalized ads), have feelings of vulnerability and distrust.

Enhanced relevance and ad effectiveness on the one hand, and increased sense of vulnerability and a lack of trust on the other hand, can be described as the *personalization-privacy-paradox*: "Personalization can be both an effective and an ineffective marketing strategy, depending on the context." (Aguirre et al., 2015, p. 35). The paradox reflects the consumers ambivalence toward personalized advertising, where privacy risks and concerns coincide with the positive effects of personalization (Boerman & Smit, 2020; Yeo & Chu, 2025).

The privacy calculus model is a frequently used theory to explain the effects of the personalization-privacy-paradox (Wu et al., 2023), as it helps to understand how consumers weigh the advantages and disadvantages of personalized marketing (Boerman & Smit, 2020). The model suggests a rather economical approach, claiming that individuals weigh the expected risks (costs) against the potential benefits (rewards). Wu et al. (2023) explain that privacy risks come from "organizational opportunistic behaviors, such as improper access, unauthorized secondary use, and unexpected data combination" (Wu et al., 2023, p. 3). The rewards of personalization can be described as the benefit of receiving more relevant content (Aguirre et al., 2015). Yeo and Chu (2025), however, suggest that increased perceived relevance and resulting persuasiveness effects outweigh the negative effects such as perceived intrusiveness. They found that perceived relevance fully mediates the effect of personalization in persuasion, whereas the effect of personalization on perceived intrusiveness did not show significant results.

Additionally, research by Wu et al. (2023) investigated how different types of accumulated experiences influence users' attitudes toward privacy disclosures. The authors divide these decisions into *habituation and vigilance effects*. Habituation effects describe the process of consumers getting accustomed to privacy disclosure with accumulating experience and claim that "experienced subjects perceived higher privacy benefits and lower privacy risks, thus leading to stronger information disclosure intentions compared with less experienced ones" (Wu et al., 2023, p. 7). They also found that users with a high degree of experience with privacy disclosure are more likely to directly consent to the requests of personal data. Consumers that have experienced a lot of privacy invasions (use of personal data was oftentimes not disclosed) become more vigilant. This shows in more pessimistic privacy assessments, as well as "perceived higher privacy risks and lower privacy benefits, which further deterred their information disclosure intentions" (Wu et al., 2023, p. 7).

2.2 Artificial Intelligence in Marketing Communication

In general terms, AI describes a set of mechanisms that achieve specific goals through the identification of patterns and creation of underlying rules (Sundar, 2020). The age of AI has initiated a transformative era in regard to marketing, customer service, and corresponding personalization. It has made its way into most industrial sectors like e-commerce and marketing (Gupta et al., 2024), resulting in the need for structural changes in the strategy and mindset of companies. In a highly knowledge-driven environment, information is one of the most important components when trying to achieve competitive advantage and will become an essential component of every existing company (Verma et al., 2025).

2.2.1 Role and Function of Artificial Intelligence

The implementation of AI has shifted marketing strategies from being primarily reactive to becoming more predictive. It can be seen as a useful tool on creating content and recommendation to match individual preferences, however, "it is too early to draw any firm conclusions” (Kumar et al., 2024, p. 2). Existing research showed that there is still a lack of depth in understanding how AI is being used in advertising and how it affects consumer responses. The following section therefore provides an overview on AI in marketing communication more broadly, not only in the context of personalization.

There are several areas of application of AI in advertising “including consumer insight mining, content creation, media planning and buying, and measurement and evaluation” (Wu et al., 2025, p. 21) with *ad placement* and *content creation* receiving most attention (Chen et al., 2019). In this context, ad placement, on the one side, means that AI analyses large amounts of data to decide where to show digital ads and to coordinate advertising purchases and sales in real time. (Wu et al., 2025). Content creation, on the other side, is generative AI creating advertising content in different formats such as text and images to enable marketing automation (Gupta et al., 2024), contextualization, scalability, and real-time creation (Chen et al., 2019). Additionally, AI chatbots or virtual assistants are used to improve customer interaction, by offering relevant and personalized real-time information. AI also improves predictive analysis to forecast market demands and trends and can detect fake reviews and counterfeit products protecting customers from fraud (Gupta et al., 2024).

In regard to personalization, AI is particularly influential with recommendation systems and real-time time personalization. For recommendation systems, AI uses sophisticated algorithms to analyse historical shopping behaviour, purchase trends, and demographic information to provide “personalized product recommendations that are remarkably accurate” (Gupta et al., 2024, p. 10). Verma et al. (2021) claim that AI enables the creation of personalized and customized messages based on individual customer profiles and preferences. By doing so consumers are presented with products that live up to their expectation and encouraged to make the purchase. Essentially, it enables a more accurate customer targeting and reduction in advertising spent (Hardcastle et al., 2025). Advanced algorithms and predictive analysis integrated by AI “automate tasks, and tailor messages to individual consumer profiles”, which “fosters a nuanced understanding of customer needs, leading to more efficient and impactful marketing efforts” (Kumar et al., 2024, p. 5).

Figure 1 depicts an overview of the functions of AI in marketing communication based on the information gathered above. The functions can roughly be divided into three categories: chatbots, predictive analysis, and advertising, although there are several commonalities, since e.g. predictive analysis also serves as a base for advertising.

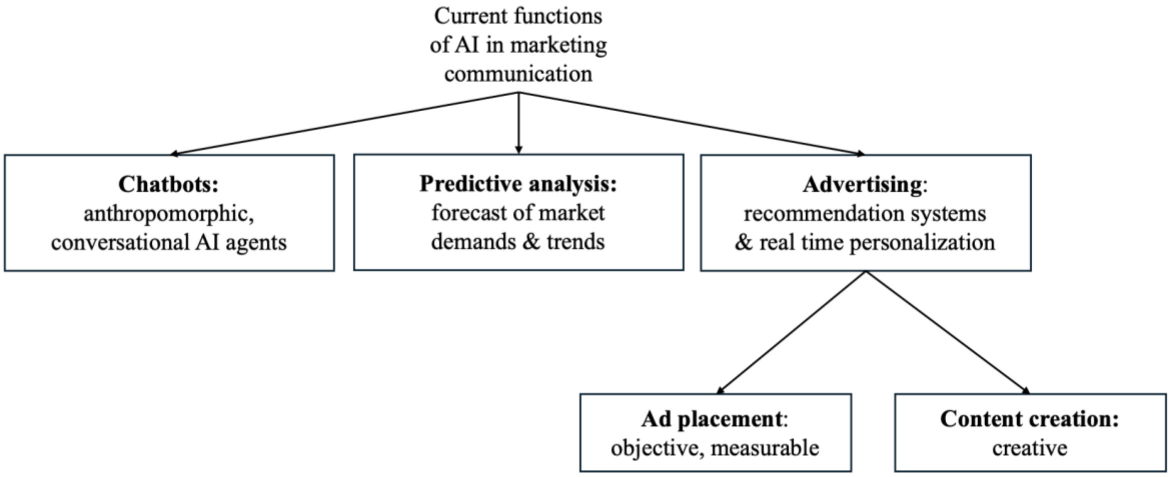


Figure 1: Current Functions of AI in Marketing Communication

2.2.2 Consumer Response to Artificial Intelligence

The main rationale for using AI in advertising is the assumption that it drastically improves business results and operational efficiency (Gupta et al., 2024). The enablement of highly personalized and targeted ads optimizes the use of resources and raises the return on investment (Verma et al., 2025).

According to Sundar (2020), consumer response to identification of AI being used is dependent on a variety of heuristics that can be explained by stereotypes about the technology. Machines for example are often associated with accuracy and objectivity, which is called the machine heuristic. Due to these attributes AI is, therefore, mostly seen as suitable for quantitative tasks (e.g. financial services), and rather unsuitable for qualitative work (e.g. subjective recommendations). On the one hand, consumers tend to view tasks involving systematic analyses of big data, like ad placement and targeting, as objective, quantifiable, and measurable. On the other hand, content creation is typically perceived as less objective or more subjective, as creativity is long regarded as a unique human characteristic (Wu et al., 2025). This phenomenon is also confirmed by Cillo & Rubera (2024, p. 694) who claim that "consumers are more inclined to trust algorithms for tasks perceived as objective".

Gupta et al. (2024) describe one common consumer response as the dark side of AI implementation, which is privacy concerns. As described above, AI algorithms generate individualized recommendations by using consumer data, which raises questions regarding data security and privacy. Coffin (2022) describes a tension between the desire for personalized advertising, and the awareness of surveillance practices, creating a need to balance technological innovation with the protection of privacy (Hardcastle et al., 2025). Especially the lack of transparency regarding where the data are being stored and who has access to it makes evaluation for consumers challenging (Gupta et al., 2024). Negative consumer responses take particularly place when advertisings are hyper personalized, with consumers thinking it is too predictive and manipulative leading to a feeling of surveillance. If recommendations are overly intrusive and without adequate benefit, consumers feel that their privacy is being compromised. This may be the case if customers are retargeted "for already bought single-purchase products, thereby diminishing relevance and frustrating the customer" (Hardcastle et al., 2025, p. 180). Recommendation algorithms also risk the perceived autonomy of customers by creating filter bubbles leading to limited options solely based on past behaviour, resulting in frustration and the feeling of diminished control (Hyman, et al., 2023).

Additionally to privacy concerns, consumers are also confronted with moral dilemmas and ethical mandate. Kim et al. (2024) describe the concern of anthropomorphising of AI chatbots (chatbots become human-like) as the uncanny valley of mind. Consumers worry that AI agents develop autonomous intentions and misuse personal data and are more alert of the persuasion intent leading to the sense of being manipulated and exploited. A study by Qiu et al. (2025) revealed that ads that are disclosed as generated by AI reduces the purchase intention in cause-related marketing (marketing that is linked to social causes to increase profit) (Howie et al., 2018), which the authors explain as a conflict between the instrumental rationality of AI and the ethical aspects of cause-related marketing. This divergence leads to increased consumer scepticism toward the ad, which consecutively worsens advertisement attitudes and decreases purchase intentions. This effect is particularly strong in individuals that experience a high degree of AI aversion. Other concerns among consumers arise, due to a fear of being misled by for example deep fakes, that spread false information by creating content of products and people that do not exist (Wu et al., 2025).

The use of AI can also lead to lower perceived effort and negative brand attitude. Rhee and Lee (2024) conducted a study that showed that AI disclosure negatively affects perceived effort which mediates a negative effect on brand attitude and curiosity. Wu et al. (2025) also concluded that AI disclosure for ad creation leads to negative brand attitudes in comparison to when no disclosure is provided.

Contradictory to the mostly negative effects of AI disclosure on consumers attitude toward the brand, Kim et al. (2024) found that providing algorithmic disclosure by transparently informing consumers about how data are being handled and explaining criteria for personalization, privacy concerns can be mitigated. The authors suggest that "if consumers understand how AI algorithms work, they may feel assured about how their data is used and safeguarded, balancing the perceived risks with the benefits of personalized ads." (Kim et al., 2024, p. 3).

2.3 Regulatory Frameworks

The regulatory frameworks for the disclosure of personalization and AI in advertising differ significantly in their maturity and practical application. The core legal framework for personalization disclosure in Europe is the General Data Protection Regulation (Regulation (EU) 2016/679) short GDPR, which has been in force since 2018. One of the core principals of the GDPR is transparency in regard to how personal data is collected, processed, used, and consulted. Concerning this thesis, it regulates profiling, which encompasses the automated processing of personal data to analyse and predict a person's preferences. The subject must be informed with meaningful information about the involved logic, has the right to object to the processing, and must also be informed about said right (European Parliament and Council, 2016). To comply with the GDPR's regulation of online tracking enforced by the regulation, most European websites adopted cookie banners (also known as consent mechanisms) to seek user permission for the use of cookies, which are online identifiers often employed by third parties to construct user profiles for behavioural targeting (Lefrère et al., 2025). In addition to the GDPR, the framework regulating cookies is the EU ePrivacy Directive (Naithani, 2025).

Although the GDPR and the ePrivacy Directive do require companies to disclose the use of personalisation and personal data, the specific implementation is not fully regulated leading to widely varying cookie banners and use of dark patterns. Dark patterns include design practices that nudge users toward accepting cookies. This can happen either through positive nudging, for example by showing only partial or overly positive information about consenting, or through negative nudging, such as exploiting users' loss aversion. Common examples include pre-selected options that users do not actively change, the absence of a "reject all cookies" option, and cookie walls that restrict access when cookies are refused (Naithani, 2025). The inconsistent use of cookies requires users to spend additional time and cognitive effort in order to understand what is being requested, leading users to "swiftly accept cookies to expedite entries into websites, foregoing in-depth scrutiny of terms and condition, and highlighting customers' prioritization of speed, convenience and simplicity" (Hardcastle et al., 2025, p. 188). Wein (2022) explains this phenomenon as *consent fatigue*, which is the consumers acceptance of data privacy disclosures without gaining an understanding of what that actually means.

Regulations for the use of AI in marketing have been formulated in the Artificial Intelligence Act (Regulation (EU) 2024/1689) short AI Act. The act was adopted in June of 2024, entered into force in February 2025, however, it will only become fully applicable in August 2026. The regulation demands that consumers must be informed when they are interacting with an AI system, “unless this is obvious from the point of view of a natural person who is reasonably well-informed, observant and circumspect” (European Parliament and Council, 2024, p. 82). According to the Austrian Federal Chamber of Labour the rather lose definition for AI system and their level of autonomy opens up a somewhat broad scope for interpretation leading to a lack of precision and legal certainty regarding the extent to which practices are permitted and which applications are affected by the measures suggested in the AI act (Austrian Federal Chamber of Labour, 2025). Wu et al. (2025, p. 20) even claim that although AI is a widespread application in advertising “there is no consensus on whether consumers should be informed of AI’s involvement in ad placement and ad creation”.

2.4 Outcome Variables

Research so far has examined benefits and challenges of personalization as well as AI in regard to the effectiveness of the ad from several different perspectives. To build hypotheses and research effects on ad effectiveness, three outcome variables will be examined more closely.

In accordance with Choi et al. (2001), two key factors that determine the effectiveness of the ad are *Attitude toward the Ad* (Aad) and *Purchase Intention* (PI). The attitude toward the ad is the first communication effect consumers have after being exposed to advertising content and can lead to advertising processing responses when it comes to the overall evaluation of the ad (Rossiter & Bellman, 1999). Aad is considered a critical metric as it mediates the impact of advertising on brand attitudes, which in turn influences behavioural intentions like purchase intention (Brown & Stayman, 1992). Purchase intention is a key outcome measure which is used to determine if an advertisement successfully moves a consumer toward the likelihood of buying the product (Choi et al., 2001) and assesses the chance that a consumer will acquire the advertised product, brand, or service in the future (Chen et al., 2024).

The reviewed literature uncovered the privacy-personalization paradox: consumers both experience benefits of personalization as well as privacy concerns. *Privacy concerns* (PC) are defined as the unease or perceived risk individuals feel about how their personal data are collected, used, and potentially misused by organizations, companies, or other actors (Malhotra et al., 2004). As privacy concerns not only influence the outcomes of personalization efforts but also reflect how AI disclosure is perceived, they are examined as the third outcome variable in this thesis.

2.5 Hypotheses

The reviewed literature showed: personalized ads are generally more effective than generic ads. This can mainly be attributed to the fact that they increase perceived relevance and self-referencing (Yeo & Chu, 2025; Shao et al., 2024; Kalyanaraman & Sundar, 2006). A theoretical foundation for this effect is the Elaboration-Likelihood-Model (ELM), claiming that an increase in perceived relevance activates central-routing processing (Cacioppo et al., 1986; Kalyanaraman & Sundar, 2006). In addition to central cues, peripheral cues such as perceived creativity and authenticity can also increase ad effectiveness (Haq et al., 2025).

Personalization not only comes with positive effects, but privacy concerns among consumers are also a common disadvantage of personalization practices. These concerns particularly arise when the collection of data feels intrusive or unexpected, which is mostly the case when data are being collected covertly. This ambivalence of positive and negative outcomes of personalization is described as the personalization-privacy paradox (Aguirre et al., 2015; Boerman & Smit, 2020). Due to longstanding regulation to disclose data collection, mostly in the form of cookies, data collection is largely overt. This leads to habituation, meaning that repeated exposure to and experience with data collection and personalization reduce perceived risks and increase acceptance of disclosure. (Wu et al., 2023). According to Yeo and Chu's (2025) meta-analysis, personalization's persuasive benefits, which are mostly driven by higher perceived relevance, clearly outweigh concerns about intrusiveness, which did not show significant effects. This can be theoretically explained by the privacy calculus model (Wu et al., 2023). Taken together, these findings provide the basis for the following hypotheses:

H1a: Personalized (vs. non-personalized) ads increase attitude toward the ad

H1b: Personalized (vs. non-personalized) ads increase purchase intention

The age of AI has been changing and will be continuing to change the marketing landscape significantly. The introduction of AI has transformed promotion tactics in several areas including ad placement, content creation, recommender systems, predictive analysis, conversational assistant chatbots, and predictive analysis (Gupta et al., 2024; Hardcastle et al., 2025; Verma et al. 2021/2025). Existing research shows that AI in marketing is applied, on the one hand, in customer service through AI-driven, anthropomorphic chatbots or virtual assistants designed to handle customer inquiries and perform support-related tasks (Gupta et al., 2024; Kim et al., 2024). On the other hand, it is used in advertising in the areas of ad placement and content creation.

In both ad placement and AI-generated content (such as images or text), marketers rely on predictive analytics to predict market trends or demand and to deliver real-time personalized recommendations (Wu et al., 2025; Chen et al., 2019; Rhee & Lee, 2024; Qiu et al., 2025; Verma et al., 2021; Hardcastle et al., 2025; Kumar et al., 2024).

Consumer perception of AI being used in advertising depends on its function and what role they play in marketing communication. Consumers connect AI with attributes of machines, which Sundar (2020) describes with the term machine heuristic. Consumers tend to accept analytical tasks that need accuracy or objectivity more than creative ones that are subjective. In regard to the functions of recommender systems, this means, that ad placement is seen as less critical than content creation (Sundar, 2020; Wu et al., 2025). Despite its benefits, consumers often evaluate AI-generated creative content more sceptically, as creativity is seen as a fundamentally human ability. Thus, when AI use is disclosed, this can lower perceived effort, brand attitudes, and curiosity (Rhee & Lee, 2024). Especially in sensitive topics (cause-related marketing) AI-generated ads can reduce purchase intention due to concerns about authenticity and ethical appropriateness (Qiu et al., 2025). Concerns about deepfakes and misinformation further undermine trust in AI-generated content (Wu et al., 2025).

The literature largely suggests that the use of AI tends to have a negative impact on advertising effectiveness. This negative effect appears to be particularly pronounced when AI is employed for content creation, compared to other AI functions in marketing, making the study of consumer responses to AI disclosure of content creation even more relevant.

H2a: Content of ads disclosed as AI-generated (vs. not AI-generated) decrease attitude toward the ad

H2b: Content of ads disclosed as AI-generated (vs. not AI-generated) decrease purchase intention

H1 and H2 show rather positive effects of personalization and the negative effects of AI-disclosure. On the one hand, habituation effects of personalization can be attributed to long-standing regulatory frameworks that mandate overt data collection that needs to be disclosed and resulting consent fatigue (European Parliament & Council, 2016; Wein, 2022; Hardcastle et al., 2025). Through repeated exposure, consumers develop habituation, perceiving personalization as normal and less privacy threatening. As experience increases, perceived risks drop while perceived benefits rise (Wu et al., 2023). On the other hand, as the AI Act was only adopted recently, it is not yet fully applicable and leaves many areas legally unclear (European Parliament & Council, 2024; Austrian Federal Chamber of Labour, 2025). Consumers, therefore, have not yet had sufficient opportunity to gain experience with AI disclosure or to become habituated to it. The lack of transparency, inconsistent disclosure practices, and unclear consumer rights lead to higher uncertainty and perceived risk (Gupta et al., 2024; Wu et al., 2025). Because personalization has become familiar and largely habituated, its positive effects tend to dominate. In contrast, AI disclosure is still relatively novel, uncertain, and not sufficiently regulated, amplifying negative consumer reactions. Therefore, when personalization is explicitly linked to AI, its persuasive effect is weakened.

H3a: AI disclosure moderates the effect of personalization; the positive effect of personalization on attitude toward the ad is weaker under AI disclosure

H3b: AI disclosure moderates the effect of personalization; the positive effect of personalization on purchase intention is weaker under AI disclosure

The independent variable *personalization* has a positive influence on the dependent variables *ad effectiveness* and *purchase intention*, which literature mainly explains by an increased perceived relevance. *AI disclosure* moderates this effect in the sense that it weakens the positive relationship between personalization and ad effectiveness. This moderation can primarily be explained by a decrease in trust and an increase in scepticism. The literature review showed that, due to its novelty and the absence of habituation, privacy-related concerns are more salient in the context of AI disclosure and primarily reduce perceived trust (Gupta et al., 2024; Hardcastle et al., 2025). In contrast, when messages are personalized, perceived relevance tends to outweigh privacy concerns, even though such concerns may still arise (Yeo & Chu, 2025). For this reason, it is assumed that privacy concerns are higher when AI is disclosed than when ads are personalized, leading to H4:

H4a: Personalized ads increase privacy concerns

H4b: AI disclosure in ads increase privacy concerns

H4c: Privacy concerns are higher in AI-disclosed vs. personalized ads

Following this reasoning, privacy concerns are expected to be highest when both personalization and AI disclosure are present. Importantly, when only one cue is present, AI disclosure is assumed to elicit stronger privacy concerns than personalization, as it more directly signals data-driven processing. Consequently, privacy concerns are expected to be lowest when neither cue is present. The following image provides an overview of the hypotheses and illustrates how they are interrelated.

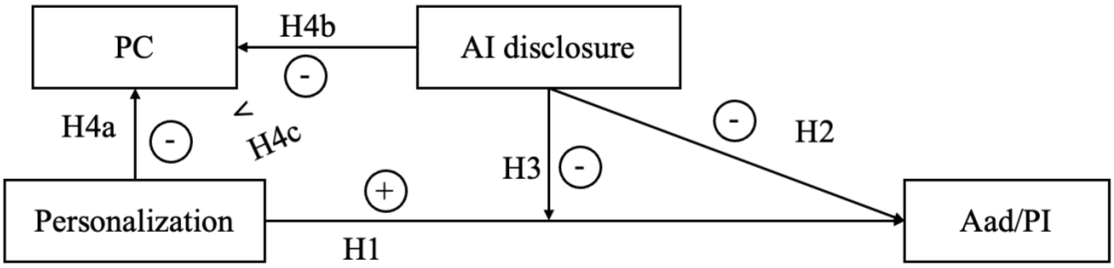


Figure 2: Visual Depiction of H1-H4

3 Methodology

The objective of this study is to examine the effects of personalized marketing communication and AI disclosure on ad effectiveness and privacy concerns. The following section lays out the methodological approach for this study.

3.1 Research Design

The chosen research design is a quantitative analysis with an experimental online study. The study employs a 2x2 between-subject factorial design in which each participant is shown only one of four experimental conditions. The effect of the two independent variables (IVs) personalization and AI disclosure on the dependent variables (DVs) attitude toward the ad (Aad), purchase intention (PI), and privacy concerns (PC) is tested. The study design implicates the four experimental conditions depicted in the table below:

1. No personalization + AI disclosure (nPAI)	2. Personalization + AI disclosure (PAI)
3. No personalization + no AI disclosure (nPnAI)	4. Personalization + no AI disclosure (PnAI)

Table 1: Four Experimental Conditions

This research design allows testing of the main effects of the IV’s personalization and AI disclosure on the DV’s as well as interaction effects between both factors (moderation). The literature review revealed *perceived relevance* to be the main explanation for personalization effects which is why the condition personalization is manipulated by showing a relevant vs. not relevant advertisement to the participant. AI disclosure is manipulated by a disclaimer explicitly disclosing that AI was used in the creation of this ad vs. that it was not used. Randomization procedures are implemented throughout the survey to minimize personal bias and enhance internal validity (Fowler & Fleming, 2023). This means that participants are randomly assigned with equal probability to one of the four experimental conditions, ensuring balanced distribution across groups. The design focuses on immediate attitudinal responses following a single exposure to marketing communication.

3.2 Sample and Data Collection

The target population for this experiment consisted of adults who are potential recipients of digital marketing communication. Participants were required to be at least 18 years old and to indicate that they were residing in a country within the European Union. Participants not meeting these criteria were excluded from the analysis. The study aimed to recruit approximately 30 participants per experimental condition, resulting in a minimum total sample size of at least 120 participants (Geuens & De Pelsmacker, 2017). Recruitment for this online survey was done through messenger services, social media platforms, as well as SurveyCircle (SurveyCircle, 2026). The sampling approach is, therefore, non-probability, convenience sampling.

The collection of data was conducted using an online questionnaire which was self-administered, completed remotely, and within the period 05.01.2026 - 19.01.2026. The survey was implemented using the online survey platform QuestionPro (QuestionPro, 2026) with the randomization of conditions occurring randomly within the survey environment. The collected data were analysed using the statistical software IBM SPSS Statistics (Version 31). The data were collected anonymously, and participants were informed that their participation is voluntary and could be withdrawn at any time without consequences.

The initial target of 120 participants was exceeded, and a total of 235 responses had been collected. To ensure data reliability, all incomplete responses were excluded from the dataset, resulting in a final sample of 172 participants and a completion rate of approximately 73%. In terms of gender, the majority identified as female with 98 responses making up 57%. 69 of respondents identified as male (40.1%), which signals a rather equal distribution between the male and female gender, with only 2.9% belonging to another category ("other" (3) or "I prefer not to say (2)). Moreover, the average age of the participants was 29.98 years, thus, it can be concluded that the sample size consisted predominantly of a rather younger demographic. For education, 24.4% have finished high school or an equivalent, 39.0% of participants had a bachelor's degree, 31.4% a master's degree and 2.9% a doctoral degree, indicating a high educational level of respondents. Through the equal randomization the participants were approximately evenly distributed across the four experimental conditions (nPAI = 53, PAI = 38, nPnAI = 39, PnAI = 42). Further information and statistics regarding the socio-demographic data of the sample group can be found in Appendix A.

3.3 Experimental Procedure

For the experimental procedure, a standardized and identical sequence across all conditions was followed and the differences only resulted from the experimental manipulations.

Prior research on personalized marketing communication showed that personalization is effective primarily due to the increased perceived relevance. To reflect this mechanism and to ensure a realistic decision context, at the beginning of the survey there was a short scenario participants had to imagine to be in, consistent with Aguirre et al. (2015), Bleier & Eisenbeiss (2015), Kim et al. (2024), or Qui et al. (2024). The scenario suggested that they had recently moved into a new apartment and had already spent time searching for furniture online to establish a situational need and to create expectations regarding relevant advertising content. Based on this scenario, personalization was operationalized through the relevance of the advertised product to the activated situation. In the personalization condition, participants were shown an ad for a floor lamp, a product directly related to the previously described furniture scenario. In contrast, the no-personalization condition, showed an advertisement for a suitcase, a product which is not related to the scenario and therefore low in perceived relevance. To ensure that observed effects could be attributed to perceived relevance rather than extraneous factors, both advertisements were matched closely in terms of price range, visual layout, and overall involvement level. The advertisements followed the same structural design, used similar neutral colours, and were presented against a white background, to ensure that distraction from the stimuli was minimized (Geuens & De Pelsmacker, 2017).

In all four conditions there was a banner below the advertisement indicating whether AI was used in the creation of the content of this ad or not. The banner was the same size, the text the same font, and only the message changed from "The content of this ad was generated using AI ." in the AI disclosure condition to "The content of this ad was generated without the use of AI ." in the no AI disclosure condition.

Immediately after viewing the advertisement, participants were asked to complete the questionnaire. First the DV attitude toward the ad was measured, then the DV purchase intention. In the next step participants had to indicate their level of privacy concerns after viewing the ad. After that the manipulation checks were conducted asking for personalization and AI disclosure. In the last step participants were asked for some sociodemographic data to gain a deeper understanding of the sample population. The complete survey items are fully listed in Appendix B.

3.4 Measures and Data Analysis

In order to test statistical validity, manipulation checks were conducted to assess perceived personalization and creator identification. Perceived personalization was measured using two items on a 7-point Likert scale (1 = strongly disagree, 7 = strongly agree): "*This ad is directed to me personally"; "This ad takes my personal situation into account"* adapted from Dijkstra (2005). The measures for creator identification, testing whether participants understood whether the ad was created by AI or not by AI, was assessed with a 7-point Likert-scale item (1 = strongly disagree, 7 = strongly agree) *"The advertisement stated* that it was created using artificial intelligence" following the operationalization in Song et al. (2024).

The hypothesis testing was conducted based on established multi-item scales from prior literature. All items were measured on 7-point scales with higher values indicating stronger agreement. The first DV Aad was measured using a 7-point semantic differential scale based on Choi et al. (2001) measure for Aad (*good / bad; like / dislike; favourable / unfavourable; enjoyable / unenjoyable; pleasant / unpleasant; appealing / unappealing; interesting / uninteresting*).

In order to understand the participants' purchase intention, a 7-point Likert scale (1 = strongly disagree; 7 = strongly agree) used by Chen et al. (2024) was adapted *("I might consider purchasing the product in this advertisement."; "If needed, I would choose to buy this product."; "I would select this* product again in future purchases.").

Privacy concerns were measured using a 7-point Likert scale asking for the level of agreeing (1 = strongly disagree; 7 = strongly agree). The scale that was used was adapted from Dolnicar and Jordaan (2007) in accordance with Wu et al. (2025) using three items asking for privacy concerns *(„I am concerned that my personal information could be misused by the advertiser.“*, *„I feel that my privacy is being invaded when my personal data is used in advertising.“,* and *„I am worried that the advertiser may share my personal information without my consent.“).*

4 Results

In order to gain insightful results and as a first step, a pre-test was conducted to see, whether the manipulation works and to receive feedback by participants. Based on the outcomes of the pre-test, feedback was implemented and adjustments were made for the final survey. The SPSS results from the pre-test can be found in Appendix C, all the results from the main analyses conducted based the survey data in are listed in Appendix D.

4.1 Pre-Test

The pre-test for the study was sent out on the 3rd of January 2026 and filled out 15 times before taken into consideration. Due to the small sample size, the randomization of conditions was not distributed equally, especially in the personalization condition (P = 3, nP = 12; AI = 8, nAI = 7), nonetheless, the independent samples t-test showed a significant difference of $p = 0.03$ within the personalization condition (M nP = 2.33, M P = 6). The manipulation check for the AI condition was not successful with $p = 0.10$ (M nAI = 3.43, M AI = 5.75). Based on feedback obtained from participants in the pre-test, the advertisement was revised by increasing the size of the AI disclosure and highlighting the phrases “using artificial intelligence” and “without the use of artificial intelligence” in bold to ensure a successful manipulation of the AI disclosure condition in the final survey. Additionally, other adjustments were made regarding some wording and comprehension issues of the questions before distribution.

4.2 Survey

The manipulations of the two IVs Personalization and AI disclosure were both successful. Participants assessed personalization significantly higher in the AI condition ($M = 5.79$; $SD = 1.98$) in comparison to the no AI condition ($M = 2.06$, $SD = 1.95$) with very strong effects ($p = <0.001$, $t(170) = -12.45$). The personalization effects were less strong, however still significant ($p = <0.001$, $t(170) = -6.87$) with the personalized condition achieving higher mean scores ($M = 4.48$, $SD = 1.99$) than the condition without personalization ($M = 2.60$, $SD = 1.58$). This suggests a qualified scenario construction that participants understood enabling further analyses.

Manipulation	**Condition**	**M**	**SD**	**Test Statistic**
AI Disclosure	AI	5.79	1.98	t(170) = -12.45, p < 0.001
	No AI	2.06	1.95	
Personalization	Personalized	4.48	1.99	t(170) = -6.87, p < 0.001
	Non-personalized	2.60	1.58	

Table 2: Overview Manipulation Checks

Reliability analysis showed strong internal consistencies among all scales of the DVs. The Cronbach's Alpha for Aad was 0.96, and none of the 8 items had to be removed as this value did not increase if any of the items were deleted. The reliability for PI was also very high with Cronbach's Alpha of 0.90, again none of the three items were deleted. PC had the lowest internal consistency with a Cronbach's Alpha of 0.89, however all three items were included into the analyses as the effect was still very strong, therefore no adaptions of the measures needed to be made.

In order to examine the hypotheses, analyses of variance (ANOVA) were conducted. To ensure, that ANOVA was a suitable testing method, normality assumptions were assessed visually by creating and evaluating histograms and normal Q–Q plots for all dependent variables (Aad, PC and PI). Across the three dependent variables, the distributions appeared approximately normal, with data points closely following the diagonal reference lines in the Q–Q plots and no indication of severe deviations. Given the sufficiently large sample size, the analysis of variance is considered robust to minor deviations from normality. Therefore, ANOVA was deemed an appropriate analytical approach.

4.2.1 Effects on Attitude toward the Ad (H1a, H2a, H3a)

Descriptive statistics indicated that attitudes toward the advertisement differed across the experimental conditions. Overall, participants exposed to personalized advertisements reported higher Aad scores than participants exposed to non-personalized advertisements. Specifically, across AI disclosure conditions, personalized ads resulted in a higher mean Aad (M = 4.02, SD = 1.46) compared to non-personalized ads (M = 3.53, SD = 1.19). Regarding AI disclosure, ads without AI disclosure elicited higher Aad (M = 4.00, SD = 1.28) than ads with AI disclosure (M = 3.54, SD = 1.36). At the cell level, the highest Aad was observed in the personalized, non-AI-disclosed condition (M = 4.29, SD = 1.43), whereas the lowest Aad occurred in the non-personalized, AI-disclosed condition (M = 3.41, SD = 1.29).

To test hypotheses H1a, H2a, and H3a, a 2x2 between-subjects ANOVA was conducted with personalization (present vs. absent) and AI disclosure (present vs. absent) as independent variables and Aad as the dependent variable. The overall ANOVA model was significant, $F(3, 168) = 3.585$, $p = .015$, $\eta p^2 = .060$ and revealed a significant main effect of personalization on Aad, $F(1, 168) = 5.12$, $p = .025$, $\eta^2_p = .030$, indicating that personalized advertisements led to more favourable attitudes toward the ad than non-personalized advertisements. In addition, a significant main effect of AI disclosure on Aad was found, $F(1, 168) = 4.38$, $p = .038$, $\eta^2_p = .025$. Advertisements including AI disclosure resulted in lower Aad compared to advertisements without AI disclosure. The interaction effect between personalization and AI disclosure was not significant, $F(1, 168) = 0.53$, $p = .467$, $\eta^2_p = .003$, which means that the effect of personalization on Aad did not differ depending on whether AI disclosure was present. Based on these results, H1a, predicting that personalized advertisements increase attitude toward the ad, was supported. H2a, predicting that AI disclosure decreases attitude toward the ad, was also supported. In contrast, H3a, proposing an interaction effect between personalization and AI disclosure on Aad, was not supported.

4.2.2 Effects on Purchase Intention (H1b, H2b, H3b)

Descriptive statistics showed relatively small differences in purchase intention across the experimental conditions. Overall, personalized advertisements resulted in, as expected slightly higher purchase intention (M = 3.34, SD = 1.64) compared to non-personalized advertisements (M = 3.16, SD = 1.42). With respect to AI disclosure, ads without AI disclosure yielded higher purchase intention (M = 3.49, SD = 1.46) than ads including AI disclosure (M = 3.03, SD = 1.55), which was again in accordance with expectations.

The overall ANOVA model was not significant, $F(3, 168) = 1.624$, $p = .186$, $\eta p^2 = .028$ and showed that there was neither a significant main effect of personalization, $F(1, 168) = 0.35$, $p = .553$, $\eta^2_p = .002$ nor of AI disclosure on purchase intention, $F(1, 168) = 3.82$, $p = .052$, $\eta^2_p = .022$. Furthermore, the interaction effect between personalization and AI disclosure on purchase intention was also not significant, $F(1, 168) = 0.66$, $p = .419$, $\eta^2_p = .004$. Therefore, H1b, predicting a positive effect of personalization on purchase intention, was not supported. Likewise, H2b, proposing a negative effect of AI disclosure on purchase intention, was also not supported, and finally, H3b, which predicted an interaction effect between personalization and AI disclosure on purchase intention, was not supported.

4.2.3 Effects on Privacy Concerns (H4a, H4b, H4c)

When looking at the descriptive statistics for the DV privacy concerns across experimental conditions, the means showed contrary to what was initially expected, that privacy concerns were descriptively slightly higher in the non-AI disclosure condition ($M = 3.62$, $SD = 1.77$) in comparison to the AI disclosure condition ($M = 3.56$, $SD = 1.64$). Although the difference was only small, it indicates that AI disclosure did not increase perceived privacy concerns at the descriptive level. In contrast, personalization showed a clear descriptive result. Participants exposed to the personalized advertisement condition showed substantially higher privacy concerns ($M = 4.06$, $SD = 1.81$) than those that saw the non-personalized advertisements ($M = 3.18$, $SD = 1.49$). This pattern was consistent across both AI disclosure conditions.

The overall model of the conducted 2x2 ANOVA was statistically significant, $F(3, 168) = 4.82$, $p = .003$, explaining approximately 7.9% of the variance in privacy concerns ($\eta^2 = .079$). The results revealed a significant main effect of personalization, $F(1, 168) = 12.55$, $p < .001$, $\eta^2 = .070$, which indicates that personalized advertisements led to higher privacy concerns than non-personalized advertisements. The main effect of AI disclosure was not significant, $F(1, 168) < 0.01$, $p = .984$, $\eta^2 < .001$. as well as the interaction effect between personalization and AI disclosure, $F(1, 168) = 2.29$, $p = .132$, $\eta^2 = .013$. Hypothesis H4a, predicting higher privacy concerns for personalized advertisements, was supported. In contrast, H4b and H4c, which expected higher privacy concerns under AI disclosure and higher privacy concerns for AI-disclosed compared to personalized advertisements, were not supported.

To further examine H4c, which suggested that privacy concerns would be highest for personalized ads with AI disclosure, followed by non-personalized ads with AI disclosure, personalized ads without AI disclosure, and non-personalized ads without AI disclosure, a one-way ANOVA was conducted with presented conditions as the independent variable and privacy concerns as the dependent variable. The analysis revealed a significant overall effect of the conditions on privacy concerns, $F(3, 168) = 4.82$, $p = .003$, $\eta^2 = .079$, indicating that privacy concerns differed across the four experimental conditions. Descriptive statistics showed the highest level of privacy concerns for personalized ads without AI disclosure ($M = 4.24$, $SD = 1.82$), followed by personalized ads with AI disclosure ($M = 3.86$, $SD = 1.80$), non-personalized ads with AI disclosure ($M = 3.35$, $SD = 1.50$), and non-personalized ads without AI disclosure ($M = 2.96$, $SD = 1.48$).

Post-hoc comparisons using Tukey's HSD indicated that privacy concerns were significantly higher for personalized ads without AI disclosure compared to non-personalized ads without AI disclosure ($p = .003$) as well as non-personalized ads with AI disclosure ($p = .047$). Additionally, personalized ads with AI disclosure elicited no significantly higher privacy concerns than non-personalized ads without AI disclosure ($p = .080$). No significant differences were found between the two personalized conditions ($p = .734$).

Overall, while the results confirm that personalization substantially increases privacy concerns, the expected ordered pattern proposed in H4c, explicitly the assumption that the PAI condition would raise highest privacy concerns, was not supported. Instead, privacy concerns were highest for personalized ads without AI disclosure. Consequently, H4c is rejected.

4.2.4 Overview of Results

All results of the hypothesis testing are presented in the table below. For the sake of clarity, the hypotheses are presented in a simplified wording.

#	Hypothesis	Test Statistic	Outcome
H1a	Personalized ads increase Aad	$F(1,168) = 5.12$, $p = .025$, $\eta^2p = .030$	Supported
H1b	Personalized ads increase PI	$F(1,168) = 0.35$, $p = .553$, $\eta^2p = .002$	Rejected
H2a	AI disclosure decrease Aad	$F(1,168) = 4.38$, $p = .038$, $\eta^2p = .025$	Supported
H2b	AI disclosure decreases PI	$F(1,168) = 3.82$, $p = .052$, $\eta^2p = .022$	Rejected
H3a	Interaction effect on Aad	$F(1,168) = 0.53$, $p = .467$, $\eta^2p = .003$	Rejected
H3b	Interaction effect on PI	$F(1,168) = 0.66$, $p = .419$, $\eta^2p = .004$	Rejected
H4a	Personalization increases PC	$F(1,168) = 12.55$, $p < .001$, $\eta^2p = .070$	Supported
H4b	AI disclosure increases PC	$F(1,168) \approx 0.00$, $p = .984$, $\eta^2p = .000$	Rejected
H4c	Privacy concerns are higher in AI-disclosed vs. personalized ads	$F(1,168) = 2.29$, $p = .132$, $\eta^2p = .013$ $M\_PnAI = 4.24$, $M\_PAI = 3.86$, $M\_nPAI = 3.35$, $M\_nPnAI = 2.96$	Rejected

Table 3: Overview of Hypotheses Outcomes

4.2.5 Exploratory Analysis

The main analyses indicated that personalization increases both privacy concerns and attitude toward the ad. Although higher privacy concerns would logically lead to the assumption to have a negative effect on advertising evaluation, Aad increased in the personalized conditions. Therefore, an additional analysis was conducted to statistically examine whether increased privacy concerns weaken the positive effect of personalization on Aad.

A multiple linear regression analysis was conducted with Aad as the dependent variable, personalization as the independent variable (0 = non-personalized, 1 = personalized), and privacy concerns as a control variable. The regression model was significant overall, $F(2, 169) = 4.09$, $p = .018$, and 4.6% of the variance in Aad was explained ($R^2 = .046$). The results showed that personalization remained a positive and marginally significant predictor of Aad ($\beta = .15$, $p = .050$), while privacy concerns were not significantly associated with Aad ($\beta = .12$, $p = .137$).

These findings suggest that although personalization increases privacy concerns, the concerns are not strong enough to reduce Aad or weaken the positive effect of personalization on advertising effectiveness. In other words, the benefits of personalized advertising seem to outweigh the negative effects of privacy concerns.

5 Discussion

This thesis investigated the effects of personalization and AI disclosure on ad effectiveness and explored the role of privacy concerns in shaping these effects. Some key findings can be drawn from the results that lead to theoretical and managerial implications.

5.1 Key Findings

The first thing worth highlighting is that personalization had a positive effect on attitude toward the ad, supporting H1a. This indicates that personalized advertising is evaluated more favourably than non-personalized advertising. H2a was also supported indicating that AI disclosure negatively affected Aad. This means that ads that explicitly disclosed the use of AI for content creation were evaluated worse than ads without such disclosure. Taken together, these findings confirm the two main effects of personalization and AI disclosure on advertising evaluations.

It is also important to mention that neither personalization nor AI disclosure had a significant effect on the DV purchase intention (H1b, H2b). While both manipulations influenced Aad, these effects did not translate into differences in purchase intention in the present study. This suggests, that the two DVs measure different levels of ad effectiveness.

Next, there were no interaction effects between personalization and AI disclosure neither for Aad nor for purchase intention (H3a, H3b). This indicates that the effects of personalization and AI disclosure work independently rather than jointly.

Lastly, personalization significantly increased privacy concerns (H4a was supported). In contrast, AI disclosure did not increase privacy concerns, nor were privacy concerns higher in AI-disclosed compared to personalized ads (H4b, H4c). Moreover, privacy concerns did not meaningfully weaken the positive effect of personalization on Aad. These results suggest that privacy concerns and negative reactions to AI disclosure represent distinct mechanisms operating in the experiment.

5.2 Theoretical Implications

When examining the results there are several implications that can be drawn in light of the theoretical insights gained in the literature review.

At a conceptual level, the lack of significant effects on the outcome variable purchase intention indicate that the effects depend on the stage of the customer journey at which responses are measured. Aad reflects an immediate and affective response to an advertising stimulus, whereas purchase intention represents a more distal outcome that only becomes relevant later in the customer journey. Since the experiment measured consumer responses directly after ad exposure, the absence of significant effects on purchase intention might be explained by rather proximal attitudinal evaluations instead of downstream behavioural intentions.

Based on this distinction, the positive effect of personalization on Aad is consistent with the Elaboration Likelihood Model (ELM). By increasing perceived relevance within the experiment, personalization appears to activate central-route processing, leading to better advertising evaluations than when the advertisement is not personalized. At the same time, the findings also contribute to the personalization-privacy paradox and privacy calculus literature. Although personalization increased privacy concerns, Aad still improved, and privacy concerns did not meaningfully weaken this effect. This suggests that perceived relevance outweighs privacy-related costs which directly aligns with the privacy calculus model.

In contrast, the negative effects of AI disclosure on Aad cannot be explained by privacy concerns. AI disclosure neither increased privacy concerns nor were privacy concerns higher in comparison to when ads were personalized. This indicates that privacy-related concerns do not explain scepticism induced by AI disclosure, at least not in the context of AI-based content creation. It is possible, that alternative mechanisms that were also found in literature are responsible for negative evaluations, such as perceived authenticity, human effort, or creativity. From an ELM perspective, this would mean that AI disclosure of content creation operates primarily through those peripheral cues rather than through central processing.

The absence of interaction effects between personalization and AI disclosure also supports this interpretation. The lack of moderation indicates that personalization and AI disclosure are influenced by distinct mechanisms rather than a shared evaluative process.

Although privacy concerns were not identified as the main driver of negative responses to AI disclosure in the context of content creation, habituation may nevertheless provide a plausible explanation for the observed pattern of results. While personalization led to increased attitudes toward the ad, AI disclosure resulted in negative outcomes. This implies that there is consumer scepticism and a lack of trust about AI being used in advertisement, whereas this is less the case for personalization. This could be explained by the novelty of AI, which is lacking regulatory frameworks, and little consumer experiences with its disclosure. In contrast, the positive evaluation outcomes for personalization suggest that consumers have become habituated to it through repeated experiences and a certain familiarity.

5.3 Managerial Implications

The findings of this study also offer implications for managerial practices in advertising and marketing communication. First, personalization, particularly when implemented through system characteristics-based methods, should continue to be leveraged, as it enhances ad attitudes by increasing perceived relevance. However, managers should be mindful that personalization does simultaneously raise privacy concerns. This means that excessive or overly intrusive personalization could lead to avoidable risks, which suggests that personalization strategies should be implemented carefully to ensure that perceived benefits outweigh perceived privacy costs.

Second, the use of AI in advertising should only be approached cautiously, especially in the context of content creation. The results indicate that AI disclosure negatively affects attitudes toward ads and, consequently, ad effectiveness. These negative reactions are unlikely to be driven by privacy concerns but may instead be due to perceptions of reduced authenticity, effort, or creativity. When AI is used for content creation, firms should point out that it is only used as a supportive tool and the ad was created with human involvement, rather than a replacement for creativity in order to preserve authenticity and trust.

Finally, managers should consider the potentially dynamic nature of consumer responses to AI. As regulatory frameworks increasingly mandate AI disclosure, firms must comply transparently while keeping in mind that negative consumer reactions could improve over time. Only gradually integrating AI into advertising communication may enhance habituation and help reduce initial scepticism over time, particularly as AI becomes a more normalized part of marketing practice.

5.4 Limitations and Directions for Future Research

Despite its contributions, the study has several limitations that could provide directions for future research. The present study focused on attitude toward the ad and purchase intention as dependent variables. As mentioned, there were no significant effects of purchase intention, likely due to its more distal outcome. When researching similar topics, future research could therefore be enhanced by capturing affective and attitudinal responses to further verify the observed effects on Aad. Additionally, the scenario-based experimental design may have limited the strength of behavioural responses. Other experimental designs that rely less on hypothetical scenarios and more on realistic ad exposures could help improve the results by enhancing external validity.

Another limitation concerns the sample composition. The study relied predominantly on a relatively young sample. Given that younger consumers are generally more familiar with digital technologies and AI-based tools, their responses to AI disclosure may differ systematically from those of older consumer segments. Future research should therefore examine more age-diverse samples to investigate whether familiarity with AI moderates the responses to AI disclosure.

The findings also highlight the need for a clearer conceptual distinction between the different functions of AI in marketing communication. While both AI-based content creation and ad placement may trigger scepticism or distrust, the results suggested that the underlying mechanisms are different. Future research should explicitly differentiate between both functions and could e.g. examine whether privacy concerns are more pronounced in AI applications that are more data-driven such as ad placement, whereas peripheral cues such as perceived authenticity, human effort, or creativity drive the negative responses to disclosure of AI-generated content. To better understand these underlying mechanisms, qualitative approaches such as in-depth interviews could complement experimental designs and provide richer insights into how consumers interpret AI disclosure and which mediating processes shape their evaluations.

Due to its research design, this study could not directly test habituation effects. Habituation to AI disclosure is likely to increase over time as consumers experience repeated exposure. Future research could therefore employ longitudinal research designs to examine how consumer responses to AI disclosure evolve over time. Since regulatory frameworks, that will make AI disclosure mandatory, are currently emerging it would be particularly relevant to compare consumer reactions at the point of initial implementation to the responses in the weeks and months to follow. Such research could help determine whether scepticism toward AI disclosure decreases as consumers become more familiar with AI disclosure suggesting the presence of habituation effects.

6 Conclusion

The public backlash in response to The Coca-Cola Company's AI-generated advertisement in late 2024 can be seen as an example of the tensions in regard to the use of the use of AI in marketing communication. The headlines criticized the ad as inauthentic and soulless implying that consumer reactions to AI-generated advertising are often characterized by scepticism and resistance. At the same time, AI is seen as one of the most promising technologies for improving marketing and sales effectiveness (e.g. in the area of personalization) and regulatory frameworks increasingly mandate transparency regarding AI use. This thesis examined consumer responses to AI disclosure in advertising and compared these responses to reactions toward personalization. This comparison is particularly relevant, as personalization is an advertising practice that has undergone a similar pathway of initial scepticism followed by widespread adoption.

The findings showed that personalization continues to enhance advertising effectiveness despite increasing privacy concerns, whereas AI disclosure can trigger negative advertising outcomes. The results also suggested that consumer resistance to AI in advertising is a nuanced construct that depends on how, and in which function AI is made visible to consumers. Beyond their implications for marketing practice, the findings can also be interpreted in light of societal and ethical considerations, especially because of the growing role of personal data and AI in advertising. Consumers appear to be increasingly willing to share personal data in exchange for more relevant and convenient advertising experiences. At the same time, the rising use of AI in personalisation practices makes debates about data protection, privacy, and transparency, more critical. They are not only influenced by regulatory environments, but also by broader geopolitical developments that raise questions of data ownership, control, and accountability. Additionally, the increasing automation of creative tasks raises ethical questions about the role and value of human effort in advertising and whether the efficiency that is gained through AI might compromise authenticity and creativity. Consumer scepticism toward AI-disclosed advertising, therefore, might indicate deeper uncertainties about how far AI should be integrated into marketing communication and life in general.

Reference List

Aguirre, E., Mahr, D., Grewal, D., de Ruyter, K., & Wetzels, M. (2015). *Unraveling the personalization paradox: The effect of information collection and trust-building strategies on online advertisement effectiveness*. *Journal of Retailing, 91*(1), 34–49. https://doi.org/10.1016/j.jretai.2014.09.005

Aksoy, N. C., Kabadayi, E. T., Yilmaz, C., & Kocak Alan, A. (2021). *A typology of personalisation practices in marketing in the digital age*. *Journal of Marketing Management, 37*(11–12), 1091–1122. https://doi.org/10.1080/0267257X.2020.1866647

American Psychological Association (APA). (2020). *Publication Manual of the American Psychological Association* (7th ed.). American Psychological Association.

Austrian Federal Chamber of Labour. (2025, February). Regulation (EU) 2024/1689 on artificial intelligence (AI Act): Guidelines on the definition of an AI system and on prohibited AI practices. https://www.akeuropa.eu/sites/default/files/2025-03/KI%20Verordnung%20-%20ENG.pdf

Bleier, A., & Eisenbeiss, M. (2015). *Personalized online advertising effectiveness: The interplay of what, when, and where*. *Marketing Science, 34*(5), 669–688. https://doi.org/10.1287/mksc.2015.0930

Boerman, S. C., & Smit, E. G. (2022). *Advertising and privacy: An overview of past research and a research agenda*. *International Journal of Advertising, 41*(8), 1231–1255. https://doi.org/10.1080/02650487.2022.2122251

Brown, S. P., & Stayman, D. M. (1992). Antecedents and Consequences of Attitude Toward the Ad: A Meta-Analysis. *Journal of Consumer Research*, *19*(1), 34–51. http://www.jstor.org/stable/2489186

Cacioppo, J. T., Petty, R. E., Kao, C. F., & Rodriguez, R. (1986). *Central and peripheral routes to persuasion: An individual difference perspective*. *Journal of Personality and Social Psychology, 51*(5), 1032–1043. https://doi.org/10.1037/0022-3514.51.5.1032

Chen, G., Xie, P., Dong, J., & Wang, T. (2019). *Understanding programmatic creative: The role of AI*. *Journal of Advertising, 48*(4), 347–355. https://doi.org/10.1080/00913367.2019.1654421

Chen, Y., Wang, H., Hill, S. R., & Li, B. (2024). *Consumer attitudes toward AI-generated ads: Appeal types, self-efficacy, and AI's social role*. *Journal of Business Research, 185*, 114867. https://doi.org/10.1016/j.jbusres.2024.114867

Choi, Y. K., Miracle, G. E., & Biocca, F. (2001). T*he Effects of Anthropomorphic Agents on Advertising Effectiveness and the Mediating Role of Presence. Journal of Interactive Advertising, 2*(1), 19–32. https://doi.org/10.1080/15252019.2001.10722055

Chui, M., Manyika, J., Miremadi, M., Henke, N., Chung, R., Nel, P., & Malhotra, S. (2018, April 17). *Notes from the AI frontier: Applications and value of deep learning*. McKinsey &

Company. https://www.mckinsey.com/featured-insights/artificial-intelligence/notes-from-the-ai-frontier-applications-and-value-of-deep-learning

Cillo, P., & Rubera, G. (2024). *Generative AI in innovation and marketing processes: A roadmap of research opportunities*. *Journal of the Academy of Marketing Science, 53*(4), 684–701. https://doi.org/10.1007/s11747-024-01044-7

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

Dennis, M., & Kizer, T. H. (2025). *Lights, camera, engagement! The role of personalized video as a marketing strategy in capturing consumer attention*. *Journal of Marketing Communications*. Advance online publication. https://doi.org/10.1080/13527266.2025.2478571

Di Placido, D. (2024, November 16). *Coca-Cola's AI-generated ad controversy, explained.* Forbes. https://www.forbes.com/sites/danidiplacido/2024/11/16/coca-colas-ai-generated-ad-controversy-explained/

Dijkstra, A. (2005). *Working mechanisms of computer-tailored health education: Evidence from smoking cessation*. *Health Education Research, 20*(5), 527–539. https://doi.org/10.1093/her/cyh014

Dolnicar, S., & Jordaan, Y. (2007). *A market-oriented approach to responsibly managing information privacy concerns in direct marketing*. *Journal of Advertising, 36*(2), 123–149. https://doi.org/10.2753/JOA0091-3367360209

European Parliament and Council. (2016). *Regulation (EU) 2016/679 of 27 April 2016 on the protection of natural persons with regard to the processing of personal data and on the free movement of such data, and repealing Directive 95/46/EC (General Data Protection Regulation)*. *Official Journal of the European Union, L 119*, 1–88. https://eur-lex.europa.eu/eli/reg/2016/679/oj

European Parliament and Council. (2024). *Regulation (EU) 2024/1689 of 13 June 2024 laying down harmonised rules on artificial intelligence and amending Regulations (EC) No 300/2008, (EU) No 167/2013, (EU) No 168/2013, (EU) 2018/858, (EU) 2018/1139 and (EU) 2019/2144 and Directives 2014/90/EU, (EU) 2016/797 and (EU) 2020/1828 (Artificial Intelligence Act)*. *Official Journal of the European Union*. https://eur-lex.europa.eu/eli/reg/2024/1689/oj

Fowler, K. L., & Fleming, M. D. (2023). *Principles and methods of randomization in research* (Chap. 58). In *Translational surgery: Handbook for designing and conducting clinical and translational research* (pp. 353–358). Academic Press. https://doi.org/10.1016/B978-0-323-90300-4.00038-0

Geuens, M., & De Pelsmacker, P. (2017). Planning and Conducting Experimental Advertising Research and Questionnaire Design. *Journal of Advertising*, *46*(1), 83–100. https://doi.org/10.1080/00913367.2016.1225233

Gupta, C. P., Kumar, V. V. R., & Khurana, A. (2024). *Artificial intelligence application in e-commerce: Transforming customer service, personalization, and marketing*. In *Proceedings of the 11th International Conference on Computing for Sustainable Global Development (INDIACom 2024)* (pp. 10–16). IEEE. https://doi.org/10.23919/INDIACom61295.2024.10498474

Hardcastle, K., Vorster, L., & Brown, D. M. (2025). *Understanding customer responses to AI-driven personalized journeys: Impacts on the customer experience*. *Journal of Advertising, 54*(2), 176–195. https://doi.org/10.1080/00913367.2025.2460985

Haq, I., Mazhar, B., Maqsood, F., Nawaz, M., & Shahzadi, A. (2025). *How consumer-centric personalization enhances advertising value: An empirical study on Instagram ad effectiveness*. *Journal of Internet Commerce, 24*(3), 260–286. https://doi.org/10.1080/15332861.2025.2544857

Horvath, B. (2024, November 18). *Coca-Cola causes controversy with AI-made ad.* NBC News. https://www.nbcnews.com/tech/innovation/coca-cola-causes-controversy-ai-made-ad-rcna180665

Howie, K. M., Yang, L., Vitell, S. J., Bush, V., & Vorhies, D. (2018). *Consumer participation in cause-related marketing: An examination of effort demands and defensive denial*. *Journal of Business Ethics, 147*, 679–692. https://doi.org/10.1007/s10551-015-2961-1

Hyman, M. R., Kostyk, A., & Trafimow, D. (2023). *True consumer autonomy: A formalization and implications*. *Journal of Business Ethics, 183*(3), 841–863. https://doi.org/10.1007/s10551-022-05114-0

Kalyanaraman, S., & Sundar, S. S. (2006). *The psychological appeal of personalized content in web portals: Does customization affect attitudes and behavior? Journal of Communication, 56*(1), 110–132. https://doi.org/10.1111/j.1460-2466.2006.00006.x

Kim, W., Ryoo, Y., & Choi, Y. K. (2024). *That uncanny valley of mind: When anthropomorphic AI agents disrupt personalized advertising*. *International Journal of Advertising*. Advance online publication. https://doi.org/10.1080/02650487.2024.2411669

Krugman, H. E. (1965). *The impact of television advertising: Learning without involvement*. *Public Opinion Quarterly, 29*(3), 349–356. https://doi.org/10.1086/267335

Kumar, V., Ashraf, A. R., & Nadeem, W. (2024). *AI-powered marketing: What, where, and how? International Journal of Information Management, 77*, 102783. https://doi.org/10.1016/j.ijinfomgt.2024.102783

Lefrère, V., Warberg, L., Cheyre, C., Marotta, V., & Acquisti, A. (2025). *Does privacy regulation harm content providers? A longitudinal analysis of the impact of the GDPR.* Management Science. https://doi.org/10.1287/mnsc.2022.03186

Malhotra, N. K., Kim, S. S., & Agarwal, J. (2004). *Internet users' information privacy concerns (IUIPC): The construct, the scale, and a causal model*. *Information Systems Research, 15*(4), 336–355. https://doi.org/10.1287/isre.1040.0032

Modig, E., Dahlén, M., & Colliander, J. (2014). *Consumer-perceived signals of "creative" versus "efficient" advertising: Investigating the roles of expense and effort*. *International Journal of Advertising, 33*(1), 137–154. https://doi.org/10.2501/IJA-33-1-137-154

Mouriquand, D. (2025, November 5). *'Real magic'? Coca-Cola's AI-generated Christmas ad sparks widespread backlash (again).* Euronews. https://www.euronews.com/culture/2025/11/05/real-magic-coca-colas-ai-generated-christmas-ad-sparks-widespread-backlash-again

Naithani, P. (2025). *Standardised cookie banner: A solution to the cookie consent problem*. *International Review of Law, Computers & Technology, 39*(2), 213–230. https://doi.org/10.1080/13600869.2024.2364995

O'Keefe, D. J. (2018). *Message pretesting using assessments of expected or perceived persuasiveness: Evidence about diagnosticity of relative actual persuasiveness*. *Journal of Communication, 68*(1), 120–142. https://doi.org/10.1093/joc/jqx009

Qiu, X., Wang, Y., Zeng, Y., & Cong, R. (2025). *Artificial intelligence disclosure in cause-related marketing: A persuasion knowledge perspective. Journal of Theoretical and Applied Electronic Commerce Research, 20*(3), 193. https://doi.org/10.3390/jtaer20030193

QuestionPro. (2026). *Online-Umfragetools und Marktforschungslösungen*. https://www.questionpro.com/

Rhee, H., & Lee, K.-H. (2024). *Generative AI disclosure in fashion marketing: A tectonic shift in the advertising landscape*. In *Proceedings of the Bridging the Divide Conference*. https://doi.org/10.31274/itaa.17359

Rossiter, J. R., & Bellman, S. (1999). *A proposed model for explaining and measuring web ad effectiveness*. *Journal of Current Issues & Research in Advertising*, 21(1), 13–31. https://doi.org/10.1080/10641734.1999.10505086

Salonen, V., & Karjaluoto, H. (2016). *Web personalization: The state of the art and future avenues for research and practice*. *Telematics and Informatics*, 33(4), 1088–1104. https://doi.org/10.1016/j.tele.2016.03.004

Shao, Z., Zhang, L., Pan, Z., & Benitez, J. (2023). *Uncovering the dual influence processes for click-through intention in the mobile social platform: An elaboration likelihood model perspective*. *Information & Management, 60*, 103799. https://doi.org/10.1016/j.im.2023.103799

Song, M., Chen, H., Wang, Y., & Duan, Y. (2024). *Can AI fully replace human designers? Matching effects between declared creator types and advertising appeals on tourists' visit intentions*. *Journal of Destination Marketing & Management*, 32, 100892. https://doi.org/10.1016/j.jdmm.2024.100892

Sundar, S. S. (2020). *Rise of machine agency: A framework for studying the psychology of human–AI interaction (HAII). Journal of Computer-Mediated Communication*, 25(1), 74–88. https://doi.org/10.1093/jcmc/zmz026

SurveyCircle (2026*). Forschungswebseite SurveyCircle*. https://www.surveycircle.com

Tam, K. Y., & Ho, S. Y. (2005). *Web personalization as a persuasion strategy: An Elaboration Likelihood Model perspective. Information Systems Research, 16*(3), 271–291. https://doi.org/10.1287/isre.1050.0058

Verma, S., Sharma, R., Deb, S., & Maitra, D. (2021). *Artificial intelligence in marketing: A systematic review and future research directions. International Journal of Information Management Data Insights*, 1(1), 100002. https://doi.org/10.1016/j.jjimei.2020.100002

Verma, C., Vijayalakshmi, P., Chaturvedi, N., Rai, A., (2025). *Artificial intelligence in marketing management: Enhancing customer engagement and personalization*. *Proceedings of the 2025 International Conference on Pervasive Computational Technologies (ICPCT),* 397–401. IEEE. https://doi.org/10.1109/ICPCT64145.2025.10940626

Wein, T. (2022). *Data protection, cookie consent, and prices*. *Economies*, 10(12), 307. https://doi.org/10.3390/economies10120307

Wu, D., Min, C., Li, Z., & Wang, Y. (2023). *Vigilance and habituation: Polymorphic experience effects in internet users' privacy disclosure decisions*. *Decision Support Systems, 170*, 113961. https://doi.org/10.1016/j.dss.2023.113961

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

Yeo, T. E. D., & Chu, T. H. (2025). *How persuasive is personalized advertising? A meta-analytic review of experimental evidence of the effects of personalization on ad effectiveness. Journal of Advertising Research, 65*(2), 616–631. https://doi.org/10.1080/00218499.2025.2467763

Appendix

Appendix A: Demographic Statistics

Descriptives Age

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
What is your age?	172	18	70	29.98	11.870
Valid N (listwise)	172				

Frequencies Gender

Statistics

What is your gender?

N	Valid	172
	Missing	0

What is your gender?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Female	98	57.0	57.0	57.0
	Male	69	40.1	40.1	97.1
	Other	3	1.7	1.7	98.8
	Prefer not to say	2	1.2	1.2	100.0
	Total	172	100.0	100.0	

Frequencies Education

Statistics

What is your highest level of education?

N	Valid	172
	Missing	0

What is your highest level of education?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	High school or equivalent	42	24.4	24.4	24.4
	Bachelor’s degree	67	39.0	39.0	63.4
	Master’s degree	54	31.4	31.4	94.8
	Doctoral degree	5	2.9	2.9	97.7
	Other	4	2.3	2.3	100.0
	Total	172	100.0	100.0	

Appendix B: Survey Items

Introduction

“You are invited to participate in a short academic study on online advertising.

In this study, you will be asked to view an advertisement and answer a few questions about your perceptions and reactions. There are no right or wrong answers; we are interested in your personal opinion.

Your participation is voluntary. All responses are anonymous and will be used for research purposes only. You may stop the survey at any time.

The survey takes approximately 3-5 minutes to complete.

By clicking "Next" you agree to participate in this study.

Exclusion Criteria

Please confirm that you are at least 18 years old

- Yes
- No

Do you currently live in a country that is part of the European Union (EU)?

- Yes
- No

Scenario Introduction

Please **imagine the following situation**:

You have recently moved into a **new apartment**. Over the past few weeks, you have been browsing online and **searching** for various **pieces of furniture**.

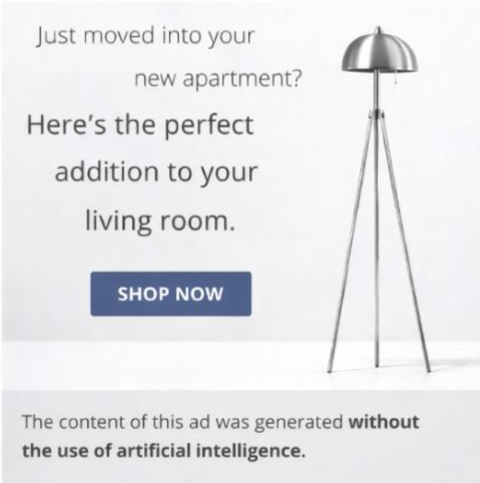
While scrolling through social media, you come across the following advertisement.

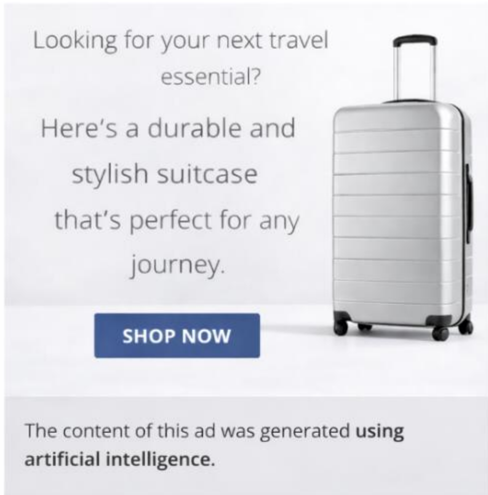
Please look at the advertisement carefully, as you will be asked questions about it afterward.

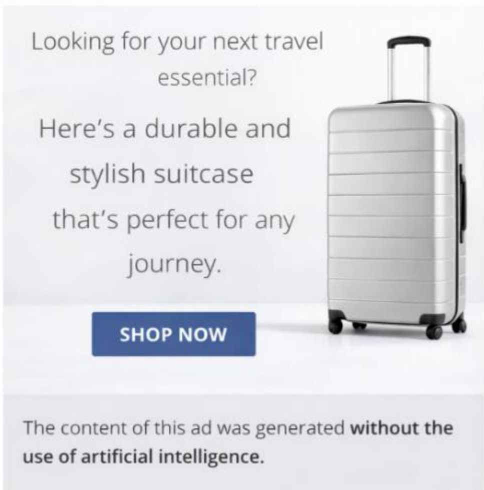
Stimuli Presentation

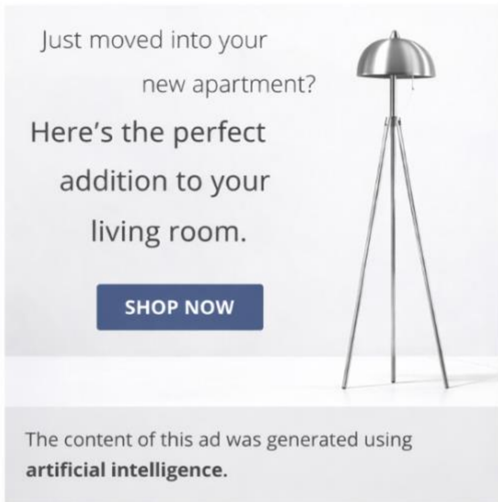
Participants were presented one of the following four ads

Please closely examine following advertisement:









Question 1

7-point semantic differential scale

How would you evaluate the advertisement?

- good / bad
- like / dislike
- favourable / unfavourable
- enjoyable / unenjoyable
- pleasant / unpleasant
- appealing / unappealing
- interesting / uninteresting
- nice / awful

Question 2

7-point Likert scale (1 = strongly disagree; 7 = strongly agree)

To what extent do you agree with the following statements? (1 = Strongly Disagree; 7 = Strongly Agree)

- “I might consider purchasing the product in this advertisement.”
- “If needed, I would choose to buy this product.”
- “I would select this product again in future purchases.”

Question 3

7-point Likert scale (1 = strongly disagree; 7 = strongly agree)

To what extent do you agree with the following statements? (1 = Strongly Disagree; 7 = Strongly Agree)

- „I am concerned that my personal information could be misused by the advertiser.“
- „I feel that my privacy is being invaded when my personal data is used in advertising.“
- „I am worried that the advertiser may share my personal information without my consent.“

Question 4

7-point Likert scale (1 = strongly disagree; 7 = strongly agree)

To what extent do you agree with the following statement? (1 = Strongly Disagree; 7 = Strongly Agree)

- „The advertisement stated that it was created using artificial intelligence.“

Question 5

7-point Likert scale (1 = strongly disagree; 7 = strongly agree)

To what extent do you agree with the following statements? (1 = Strongly Disagree; 7 = Strongly Agree)

- “This ad is directed to me personally.”
- “This ad takes my personal situation into account.”

Demographics

How old are you?

- *Open question*

What is your gender?

- Female
- Male
- Other
- Prefer not to say

What is your highest level of education?

- High school or equivalent
- Bachelor's degree
- Doctoral degree
- Other

Thank-You Note and Research Purpose

Thank you for participating in this study.

The purpose of this research is to examine how different types of online advertisements are perceived. Your responses will be used for academic research only and remain anonymous.

SurveyCircle code:

TP6D-4KT4-44MF-4QK3

If you have any questions about this study, please contact the researcher at a12330240@unet.univie.ac.at

Appendix C: Results Pre-Test

Pre-Test Manipulation Check Personalization

T-Test

Group Statistics

	P_dummy	N	Mean	Std. Deviation	Std. Error Mean
Personalization	0	12	2.3333	1.69670	.48979
	1	3	6.0000	.00000	.00000

Independent Samples Test

		t-test for Equality of Means				
				Significance		
		t	df	One-Sided p	Two-Sided p	Mean Difference
Personalization	Equal variances assumed	-3.640	13	.001	.003	-3.66667
	Equal variances not assumed	-7.486	11.000	<.001	<.001	-3.66667

Independent Samples Test

		t-test for Equality of Means		
			95% Confidence Interval of the Difference	
		Std. Error Difference	Lower	Upper
Personalization	Equal variances assumed	1.00745	-5.84313	-1.49020
	Equal variances not assumed	.48979	-4.74470	-2.58864

Independent Samples Effect Sizes

				95% Confidence Interval	
		Standardizer[a]	Point Estimate	Lower	Upper
Personalization	Cohen's d	1.56074	-2.349	-3.868	-.770
	Hedges' correction	1.65862	-2.211	-3.640	-.725
	Glass's delta	.	.	.	.

a. The denominator used in estimating the effect sizes.
Cohen's d uses the pooled standard deviation.
Hedges' correction uses the pooled standard deviation, plus a correction factor.
Glass's delta uses the sample standard deviation of the control (i.e., the second) group.

Pre-Test Manipulation Check AI Dislosure

Group Statistics

	AI_dummy	N	Mean	Std. Deviation	Std. Error Mean
AI	0	7	3.43	2.699	1.020
	1	8	5.75	2.375	.840

Independent Samples Test

		t-test for Equality of Means					
				Significance			
		t	df	One-Sided p	Two-Sided p	Mean Difference	Std. Error Difference
AI	Equal variances assumed	-1.773	13	.050	.100	-2.321	1.309
	Equal variances not assumed	-1.757	12.118	.052	.104	-2.321	1.321

Independent Samples Test

		t-test for Equality of Means 95% Confidence Interval of the Difference	
		Lower	Upper
AI	Equal variances assumed	-5.150	.507
	Equal variances not assumed	-5.197	.555

Independent Samples Effect Sizes

		Standardizer[a]	Point Estimate	95% Confidence Interval Lower	Upper
AI	Cohen's d	2.530	-.918	-1.975	.171
	Hedges' correction	2.689	-.863	-1.858	.161
	Glass's delta	2.375	-.977	-2.082	.182

a. The denominator used in estimating the effect sizes.
Cohen's d uses the pooled standard deviation.
Hedges' correction uses the pooled standard deviation, plus a correction factor.
Glass's delta uses the sample standard deviation of the control (i.e., the second) group.

Appendix D: Results Final Survey

Manipulation Check AI Disclosure

T-Test

Group Statistics

	AI Disclosure (0 = no, 1 = yes)	N	Mean	Std. Deviation	Std. Error Mean
The advertisement stated that it was created using artificial intelligence.	0	81	2.06	1.945	.216
	1	91	5.79	1.975	.207

Independent Samples Test

		t-test for Equality of Means				
				Significance		
		t	df	One-Sided p	Two-Sided p	Mean Difference
The advertisement stated that it was created using artificial intelligence.	Equal variances assumed	-12.450	170	<.001	<.001	-3.729
	Equal variances not assumed	-12.461	168.250	<.001	<.001	-3.729

Independent Samples Test

		t-test for Equality of Means		
			95% Confidence Interval of the Difference	
		Std. Error Difference	Lower	Upper
The advertisement stated that it was created using artificial intelligence.	Equal variances assumed	.300	-4.321	-3.138
	Equal variances not assumed	.299	-4.320	-3.139

Independent Samples Effect Sizes

				95% Confidence Interval	
		Standardizer[a]	Point Estimate	Lower	Upper
The advertisement stated that it was created using artificial intelligence.	Cohen's d	1.961	-1.902	-2.261	-1.539
	Hedges' correction	1.970	-1.893	-2.251	-1.532
	Glass's delta	1.975	-1.888	-2.292	-1.479

a. The denominator used in estimating the effect sizes.
Cohen's d uses the pooled standard deviation.
Hedges' correction uses the pooled standard deviation, plus a correction factor.
Glass's delta uses the sample standard deviation of the control (i.e., the second) group.

Manipulation Check Personalization
T-Test

Group Statistics

	Personalization (0 = no, 1 = yes)	N	Mean	Std. Deviation	Std. Error Mean
P_mean	0	92	2.60	1.580	.165
	1	80	4.48	1.990	.223

Independent Samples Test

		t-test for Equality of Means					
				Significance			
		t	df	One-Sided p	Two-Sided p	Mean Difference	Std. Error Difference
P_mean	Equal variances assumed	-6.868	170	<.001	<.001	-1.872	.273
	Equal variances not assumed	-6.760	150.178	<.001	<.001	-1.872	.277

Independent Samples Test

		t-test for Equality of Means 95% Confidence Interval of the Difference	
		Lower	Upper
P_mean	Equal variances assumed	-2.410	-1.334
	Equal variances not assumed	-2.419	-1.325

Independent Samples Effect Sizes

		Standardizer[a]	Point Estimate	95% Confidence Interval	
				Lower	Upper
P_mean	Cohen's d	1.783	-1.050	-1.368	-.729
	Hedges' correction	1.791	-1.045	-1.362	-.726
	Glass's delta	1.990	-.940	-1.271	-.605

a. The denominator used in estimating the effect sizes.
Cohen's d uses the pooled standard deviation.
Hedges' correction uses the pooled standard deviation, plus a correction factor.
Glass's delta uses the sample standard deviation of the control (i.e., the second) group.

Reliability Test

Reliability Aad

Case Processing Summary

		N	%
Cases	Valid	172	100.0
	Excluded[a]	0	.0
	Total	172	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.960	8

Item Statistics

	Mean	Std. Deviation	N
How would you evaluate the advertisement?: Bad[Good]	3.94	1.547	172
How would you evaluate the advertisement?: Dislike[Like]	3.84	1.531	172
How would you evaluate the advertisement?: Unfavourable[Favourable]	3.78	1.486	172
How would you evaluate the advertisement?: Unenjoyable[Enjoyable]	3.61	1.383	172
How would you evaluate the advertisement?: Unpleasant[Pleasant]	3.79	1.503	172
How would you evaluate the advertisement?: Unappealing[Appealing]	3.58	1.585	172
How would you evaluate the advertisement?: Uninteresting[Interesting]	3.45	1.561	172
How would you evaluate the advertisement?: Awful[Nice]	4.02	1.522	172

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted

How would you evaluate the advertisement?: Bad[Good]	26.08	87.561	.861	.954
How would you evaluate the advertisement?: Dislike[Like]	26.18	87.388	.879	.953
How would you evaluate the advertisement?: Unfavourable[Favourable]	26.24	88.338	.871	.953
How would you evaluate the advertisement?: Unenjoyable[Enjoyable]	26.41	91.215	.824	.956
How would you evaluate the advertisement?: Unpleasant[Pleasant]	26.23	88.542	.851	.954
How would you evaluate the advertisement?: Unappealing[Appealing]	26.44	87.195	.850	.954
How would you evaluate the advertisement?: Uninteresting[Interesting]	26.57	88.562	.813	.957
How would you evaluate the advertisement?: Awful[Nice]	26.00	88.912	.825	.956

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
30.02	114.888	10.719	8

Reliability PI

Case Processing Summary

		N	%
Cases	Valid	172	100.0
	Excluded[a]	0	.0
	Total	172	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.902	3

Item Statistics

	Mean	Std. Deviation	N

	Mean	Std. Deviation	N
I might consider purchasing the product in this advertisement.	3.14	1.718	172
If needed, I would choose to buy this product.	3.58	1.626	172
I would select this product again in future purchases.	3.02	1.642	172

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
I might consider purchasing the product in this advertisement.	6.59	9.506	.787	.877
If needed, I would choose to buy this product.	6.16	9.981	.795	.869
I would select this product again in future purchases.	6.72	9.597	.836	.834

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
9.73	20.794	4.560	3

Reliability PC

Case Processing Summary

		N	%
Cases	Valid	172	100.0
	Excluded[a]	0	.0
	Total	172	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.891	3

Item Statistics

	Mean	Std. Deviation	N
I am concerned that my personal information could be misused by the advertiser.	3.30	1.823	172

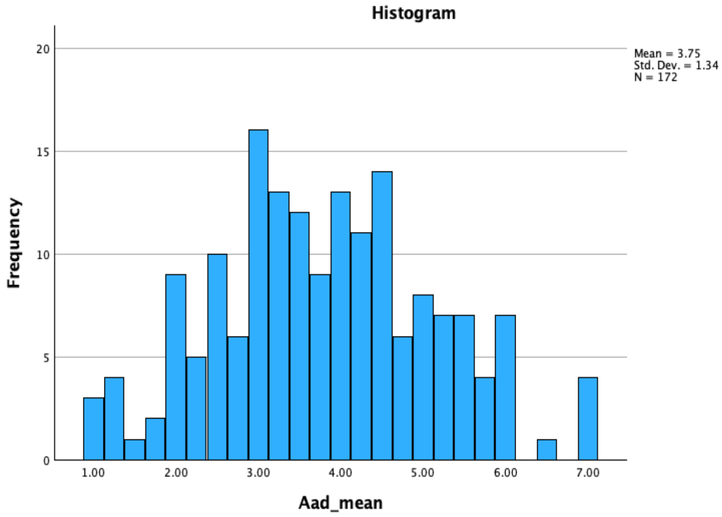
I feel that my privacy is being invaded when my personal data is used in advertising.	3.73	1.901	172
I am worried that the advertiser may share my personal information without my consent.	3.73	1.907	172

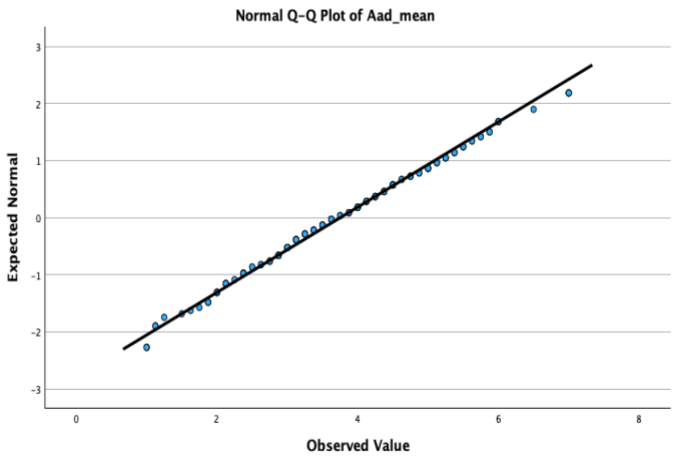
Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
I am concerned that my personal information could be misused by the advertiser.	7.47	12.788	.761	.866
I feel that my privacy is being invaded when my personal data is used in advertising.	7.03	11.905	.802	.831
I am worried that the advertiser may share my personal information without my consent.	7.03	11.917	.797	.836

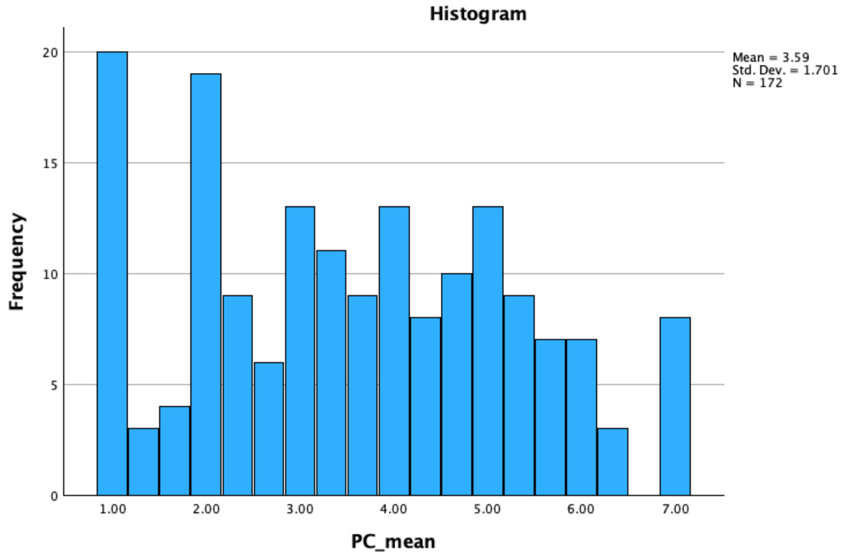
Normality

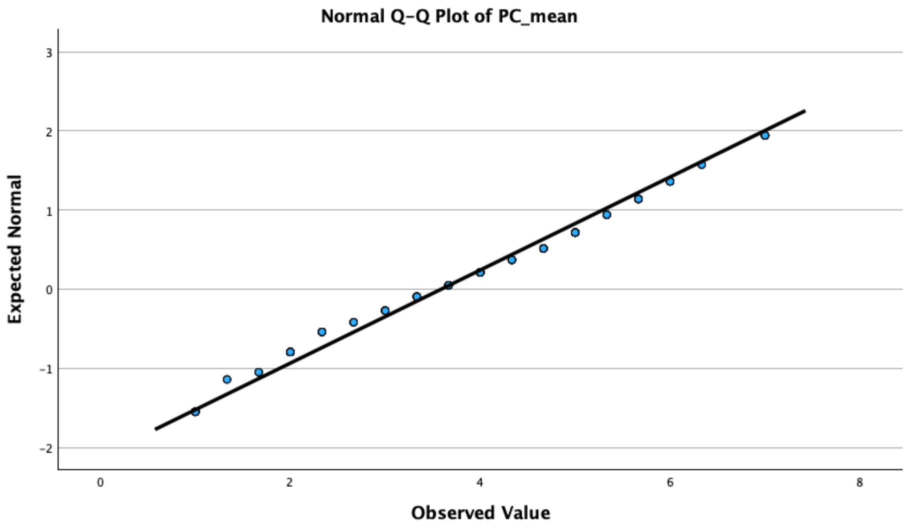
Normality Test Aad



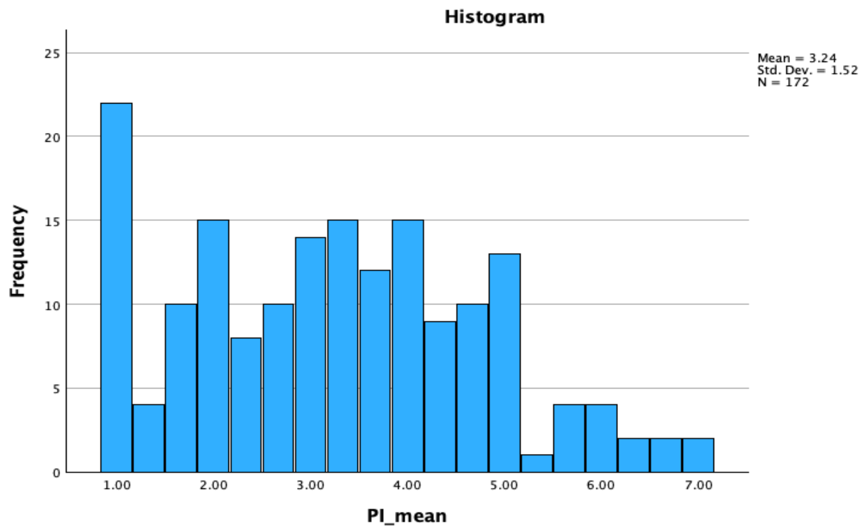


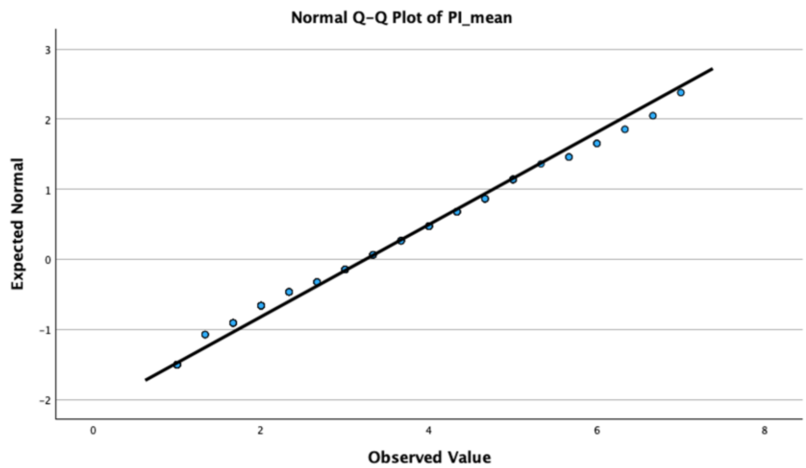
Normality Test PC





Normality Test PI





Hypothesis Testing

ANOVA Aad (H1a, H2a, H3a)

Descriptives

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
Aad_mean	172	1.00	7.00	3.7529	1.33982
PI_mean	172	1.00	7.00	3.2442	1.52000
PC_mean	172	1.00	7.00	3.5891	1.70095
Valid N (listwise)	172				

Univariate Analysis of Variance

Between-Subjects Factors

		N
AI Disclosure (0 = no, 1 = yes)	0	81
	1	91
Personalization (0 = no, 1 = yes)	0	92
	1	80

Descriptive Statistics

Dependent Variable: Aad_mean

AI Disclosure (0 = no, 1 = yes)	Personalization (0 = no, 1 = yes)	Mean	Std. Deviation	N
0	0	3.6827	1.02471	39
	1	4.2857	1.43223	42
	Total	3.9954	1.28139	81
1	0	3.4080	1.28792	53
	1	3.7171	1.45417	38
	Total	3.5371	1.36059	91
Total	0	3.5245	1.18531	92
	1	4.0156	1.46172	80
	Total	3.7529	1.33982	172

Tests of Between-Subjects Effects

Dependent Variable: Aad_mean

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	18.468[a]	3	6.156	3.585	.015	.060
Intercept	2407.317	1	2407.317	1401.840	<.001	.893
AI_Disclosure	7.514	1	7.514	4.376	.038	.025
Personalization	8.791	1	8.791	5.119	.025	.030
AI_Disclosure * Personalization	.913	1	.913	.532	.467	.003
Error	288.499	168	1.717			
Total	2729.469	172				
Corrected Total	306.967	171				

a. R Squared = ,060 (Adjusted R Squared = ,043)

ANOVA PI (H1b, H2b, H3b)

Between-Subjects Factors

		N
AI Disclosure (0 = no, 1 = yes)	0	81
	1	91
Personalization (0 = no, 1 = yes)	0	92
	1	80

Descriptive Statistics

Dependent Variable: PI_mean

AI Disclosure (0 = no, 1 = yes)	Personalization (0 = no, 1 = yes)	Mean	Std. Deviation	N
0	0	3.3162	1.38697	39
	1	3.6429	1.52378	42
	Total	3.4856	1.45969	81
1	0	3.0503	1.44026	53

	1	3.0000	1.70673	38
	Total	3.0293	1.54812	91
Total	0	3.1630	1.41637	92
	1	3.3375	1.63514	80
	Total	3.2442	1.52000	172

Tests of Between-Subjects Effects

Dependent Variable: PI_mean

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	11.136[a]	3	3.712	1.624	.186	.028
Intercept	1788.409	1	1788.409	782.548	<.001	.823
AI_Disclosure	8.727	1	8.727	3.819	.052	.022
Personalization	.807	1	.807	.353	.553	.002
AI_Disclosure * Personalization	1.501	1	1.501	.657	.419	.004
Error	383.942	168	2.285			
Total	2205.333	172				
Corrected Total	395.078	171				

a. R Squared = ,028 (Adjusted R Squared = ,011)

ANOVA PC (H4a, H4b, H4)

Between-Subjects Factors

		N
AI Disclosure (0 = no, 1 = yes)	0	81
	1	91
Personalization (0 = no, 1 = yes)	0	92
	1	80

Descriptive Statistics

Dependent Variable: PC_mean

AI Disclosure (0 = no, 1 = yes)	Personalization (0 = no, 1 = yes)	Mean	Std. Deviation	N
0	0	2.9573	1.47529	39
	1	4.2381	1.81873	42
	Total	3.6214	1.77306	81
1	0	3.3459	1.50066	53
	1	3.8596	1.80195	38
	Total	3.5604	1.64345	91
Total	0	3.1812	1.49432	92
	1	4.0583	1.80932	80
	Total	3.5891	1.70095	172

Tests of Between-Subjects Effects

Dependent Variable: PC_mean

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	39.176[a]	3	13.059	4.816	.003	.079
Intercept	2191.453	1	2191.453	808.142	<.001	.828
AI_Disclosure	.001	1	.001	.000	.984	.000
Personalization	34.031	1	34.031	12.550	<.001	.070
AI_Disclosure * Personalization	6.218	1	6.218	2.293	.132	.013
Error	455.569	168	2.712			
Total	2710.444	172				
Corrected Total	494.744	171				

a. R Squared = ,079 (Adjusted R Squared = ,063)

Oneway ANOVA (H4c)

Descriptives

PC_mean

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean Lower Bound	95% Confidence Interval for Mean Upper Bound	Minimum	Maximum
nPAI	53	3.3459	1.50066	.20613	2.9323	3.7595	1.00	6.00
PAI	38	3.8596	1.80195	.29232	3.2674	4.4519	1.00	7.00
nPnAI	39	2.9573	1.47529	.23624	2.4790	3.4355	1.00	7.00

PnAI	42	4.2381	1.81873	.28064	3.6713	4.8049	1.00	7.00
Total	172	3.5891	1.70095	.12970	3.3331	3.8452	1.00	7.00

Tests of Homogeneity of Variances

		Levene Statistic	df1	df2	Sig.
PC_mean	Based on Mean	1.423	3	168	.238
	Based on Median	1.271	3	168	.286
	Based on Median and with adjusted df	1.271	3	158.664	.286
	Based on trimmed mean	1.371	3	168	.253

ANOVA

PC_mean

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	39.176	3	13.059	4.816	.003
Within Groups	455.569	168	2.712		
Total	494.744	171			

ANOVA Effect Sizes[a,b]

		Point Estimate	95% Confidence Interval Lower	95% Confidence Interval Upper
PC_mean	Eta-squared	.079	.011	.153
	Epsilon-squared	.063	-.007	.138
	Omega-squared Fixed-effect	.062	-.007	.138
	Omega-squared Random-effect	.022	-.002	.050

a. Eta-squared and Epsilon-squared are estimated based on the fixed-effect model.
b. Negative but less biased estimates are retained, not rounded to zero.

Post Hoc Tests (H4c)

Multiple Comparisons

Dependent Variable: PC_mean
Tukey HSD

(I) Preseted Condition	(J) Preseted Condition	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
nPAI	PAI	-.51374	.35004	.459	-1.4221	.3946
	nPnAI	.38865	.34741	.679	-.5129	1.2902
	PnAI	-.89218*	.34019	.047	-1.7750	-.0094

PAI	nPAI	.51374	.35004	.459	-.3946	1.4221
	nPnAI	.90238	.37536	.080	-.0716	1.8764
	PnAI	-.37845	.36868	.734	-1.3351	.5783
nPnAI	nPAI	-.38865	.34741	.679	-1.2902	.5129
	PAI	-.90238	.37536	.080	-1.8764	.0716
	PnAI	-1.28083*	.36619	.003	-2.2311	-.3306
PnAI	nPAI	.89218*	.34019	.047	.0094	1.7750
	PAI	.37845	.36868	.734	-.5783	1.3351
	nPnAI	1.28083*	.36619	.003	.3306	2.2311

*. The mean difference is significant at the 0.05 level.

Homogeneous Subsets

PC_mean

Tukey HSD[a,b]

		Subset for alpha = 0.05	
Preseted Condition	N	1	2
nPnAI	39	2.9573	
nPAI	53	3.3459	3.3459
PAI	38	3.8596	3.8596
PnAI	42		4.2381
Sig.		.061	.065

Means for groups in homogeneous subsets are displayed.
a. Uses Harmonic Mean Sample Size = 42.268.
b. The group sizes are unequal. The harmonic mean of the group sizes is used. Type I error levels are not guaranteed.

Exploratory Analysis: Aad x PC

Regression Analysis

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	PC_mean, Personalization (0 = no, 1 = yes)[b]	.	Enter

a. Dependent Variable: Aad_mean
b. All requested variables entered.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.215[a]	.046	.035	1.31622

a. Predictors: (Constant), PC_mean, Personalization (0 = no, 1 = yes)

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	14.184	2	7.092	4.094	.018[b]
	Residual	292.783	169	1.732		
	Total	306.967	171			

a. Dependent Variable: Aad_mean
b. Predictors: (Constant), PC_mean, Personalization (0 = no, 1 = yes)

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics
		B	Std. Error	Beta			Tolerance
1	(Constant)	3.234	.238		13.569	<.001	
	Personalization (0 = no, 1 = yes)	.411	.208	.153	1.973	.050	.933
	PC_mean	.091	.061	.116	1.493	.137	.933

Coefficients[a]

Model		Collinearity Statistics VIF
1	(Constant)	
	Personalization (0 = no, 1 = yes)	1.071
	PC_mean	1.071

a. Dependent Variable: Aad_mean

Collinearity Diagnostics[a]

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions (Constant)	Variance Proportions Personalization (0 = no, 1 = yes)	Variance Proportions PC_mean
1	1	2.527	1.000	.02	.06	.02
	2	.377	2.588	.08	.94	.06
	3	.096	5.143	.90	.00	.92

a. Dependent Variable: Aad_mean