Consumer Purchase Intentions After Seeing Ads Generated by AI:
The Role of Trust and the Theory of Planned Behavior

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Abstract

This study investigates how consumer trust in generative artificial intelligence advertisements (GenAI ads) shapes purchase intention via the Theory of Planned Behavior (TPB). Despite the growing use of GenAI ads, prior research has focused on consumer acceptance and attitude, overlooking purchase intention. This study extended the TPB by treating trust in the GenAI ad as an antecedent to address this gap. Data were gathered via a questionnaire in which 147 participants viewed a GenAI ad and then reported their trust, TPB beliefs, and purchase intention. Partial least squares structural equation modeling revealed that higher trust in the GenAI ad led to more favorable attitudes, stronger perceived social norms, and greater perceived behavioral control. Trust also exerted a significant indirect influence on intention. In turn, both attitude and, most strongly, subjective norms predicted purchase intention, while perceived control had no significant effect. These findings show that building trust is the first step in GenAI ad campaigns, after which TPB drivers, particularly social proof, translate that trust into purchase intention. The results indicate that marketers should foreground trust-building and social proof in their GenAI ads, while future research using experimental and longitudinal designs should confirm causality and explore dynamics across product categories.

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1 Introduction

The recent advancements in machine learning have led to the creation of large language models (LLMs) (Raiaan et al., 2024). This advancement, in turn, has resulted in the rapid adoption of generative artificial intelligence (GenAI), which refers to a technological innovation that uses machine learning and LLMs, trained on massive datasets, to generate new content by both consumers and businesses (Bick et al., 2024). The adoption curve is faster than that of computers and the internet, with 40 percent of the U.S. population aged 18-64 using GenAI in late 2024, and it is quickly becoming the next big thing (Bick et al., 2024). Marketers are not staying behind and are embracing this innovation, utilizing it throughout the customer journey to create more in-depth consumer profiles, improve targeting in search results, and even post-purchase support with chatbots (Kietzmann et al., 2018). Now, marketers generate advertisements in text, picture, and video formats using different GenAI tools (Huang & Rust, 2020; Liu & Yu, 2023).

This rapid integration of GenAI into marketing means millions of consumers now come into daily contact with these novel ads, giving rise to a critical question for academics and practitioners: What do consumers think about GenAI ads, and how do they react to them? Research has shown that consumers' perceived eeriness hurts their willingness to accept GenAI ads because it gives them a feeling of strangeness and unease (Gu et al., 2024). However, perceived intelligence, the consumers' overall evaluation of the ability of AI to automatically generate advertisements, has a positive effect (Gu et al., 2024). Consumers then perceive the ad as higher quality, finding it more trustworthy. Chen et al. (2024) showed that consumers believe that AI is more rational and logical and has a higher cognitive level than themselves, meaning that when GenAI is used to make ads for products that increase personal agency, it has a positive effect. However, this becomes adverse when GenAI generates ads for communal or social products.

When GenAI makes a deepfake, referred to as a technology that can place or swap any person, usually a celebrity, into a video they never participated in, research has shown that consumers can perceive deception, which negatively impacts shopping intention (Sivathanu et al., 2022). Research has also shown that using GenAI to create faces for charitable ads harmed donation intention when participants were aware of the falsity, as that prohibited empathy and trust (Arango et al., 2023). Moreover, research showed that perceived sincerity mediates the relationship between awareness of falsity and online brand engagement (Aljarah et al., 2024). All these studies show that GenAI ads have numerous downsides. Many studied variables, like awareness of falsity, perceived sincerity, and perceived deception, can be seen as antecedents to low trust (Aljarah et al., 2024; Fang & Li, 2014; Perepelkin & Di Zhang, 2014), which negatively affects consumers' intention to shop online (Gefen et al., 2003; Lee & Turban, 2001; Pavlou & Fygenson, 2006; Sivathanu et al., 2022). Moreover, the upside is only in niche situations, like when promoting agentic products (Chen et al., 2024).

This context of uncertainty and potential distrust directly challenges established behavioral models. For instance, the Theory of Planned Behavior (TPB) is a robust framework for predicting intentions. However, its standard application presumes that consumers can form stable attitudes and normative beliefs from the information presented. If consumers perceive the GenAI ad itself as eerie, inauthentic, or deceptive (Arango et al., 2023; Gu et al., 2024), that perception can disrupt the formation of the core TPB beliefs before the model's predictive mechanism even begins. Similarly, while trust is a well-researched concept in e-commerce, prior studies have typically focused on trust in the human-led vendor or the transactional platform (Gefen et al., 2003; Lee & Turban, 2001). GenAI introduces a new and crucial object of evaluation: trust in the non-human creative source of the advertisement itself. Existing models do not adequately account for how trust (or distrust) in this generative technology precedes and fundamentally shapes the subsequent beliefs about the purchase.

That is where the purpose of this study comes in, as previous research has looked at GenAI ads in the form of consumer acceptance, consumer attitude, and online brand engagement. There is a glaring omission from that list: the actual purchase intention of a consumer. Will they trust and then buy from an ad they know is created using GenAI? This study closes the research gap explicitly stated by Gu et al. (2024) about how research was lacking on consumers' purchasing intention after seeing GenAI ads. Therefore, this study addresses the following research question: To what extent does trust in GenAI ads affect purchase intention, and how is this relationship mediated by attitude, subjective norms, and PBC?

This intention will be studied via the TPB (Ajzen, 1985), specifically, an extended version of the theory, which includes the variable of trust in GenAI ads as an antecedent to the variables of the TPB (Canova et al., 2020; Ngo-Thi-Ngoc et al., 2024; Pavlou & Fygenson, 2006). This study uses this well-established theory to examine human behavior, arguing that intention shapes behavior, and three core variables shape intention. These are attitude, which is the overall evaluation of the person performing the behavior; subjective norms, categorized as the pressure perceived by the person from others to perform the behavior; and perceived behavior control (PBC), which assesses the person's perception of their ability to perform the behavior in terms of skill, resource, and difficulty. GenAI ads can influence all these factors, determining the intention to perform a behavior. Which, in this study, is purchasing a product. This study adds trust because previous research has shown it is vital in online shopping behavior and might influence the three variables of the TPB (Gefen et al., 2003). A second aim of this study is to provide managerial relevance by providing insights on this innovation within advertising and how to navigate its use best, now and in the future.

This study collected data via an online survey that included a stimulus to ensure participants' exposure to a GenAI ad and relevant responses. The analysis employed Partial Least Squares Structural Equation Modeling to examine the dataset. This thesis reviews existing literature, explains the methodology, reports its findings by presenting results, discusses the implications, and draws a conclusion.

2 Theoretical Background

2.1 GenAI Ads

The adoption of generative artificial intelligence (GenAI) is unprecedented, showing a faster adoption rate than the computer and the internet (Bick et al., 2024). Researchers have responded to GenAI's rapid adoption by publishing many studies examining its use and effects. One of the sub-categories where research has been ramping up is in marketing, which coincides with marketers adopting GenAI, too. Marketers already use GenAI across the customer journey to generate customer profiles, personalize experiences, deploy chatbots, and perform other tasks (Kietzmann et al., 2018). This study focuses on using GenAI to make advertisements, which stems from the recent advances in GenAI to generate audio and visuals (Zhang et al., 2024). Wu and Wen (2021) define GenAI ads as "Advertisements that are either partially or completely created by AI programs" (p. 134). Campbell et al. (2021) define it as the third wave of manipulated advertising, after analog (i.e., make-up), digital (i.e., Photoshop), and now: "Ads that are generated or edited through the artificial and automatic production and modification of data" (p. 2).

This study uses an adapted definition of *GenAI ads* from Wu and Wen (2021) because it is the most relevant to this study and explains the concept clearly: advertisements that are entirely created using GenAI models. Thereby excluding deepfake ads and other AI-edited footage. Sivathanu et al. (2022) explain that deepfakes swap real faces onto real bodies, which constitutes editing existing footage rather than generating new content. Previous research on GenAI ads has already focused on deepfakes and purchase intention after seeing those ads, which is the reason for leaving it out of this study.

In an example of such research by Sivathanu et al. (2022), they found that perceived deception negatively impacted customers' online shopping intentions after seeing deepfake advertisements. They found that trust positively affected customers' online shopping intentions because the deepfake advertisement led the customer to an interesting product, which instilled trust. Similarly, Arango et al. (2023) found that perceived falsity (which led to distrust) negatively impacted donation intention in the context of GenAI-made faces in charity advertisements. Thus, in at least two studies, customers can detect that an advertisement is generated by AI, especially when an ad is supposed to evoke trust or empathy. Chen et al. (2024) corroborated these findings by demonstrating that GenAI ads negatively affect consumer attitudes toward products with communal appeal. Conversely, when the product the GenAI ad promoted had an agentic appeal, it positively affected consumer attitudes. Chen et al. (2024) attribute this effect to consumers' perception that AI possesses a higher cognitive level than themselves.

Shifting the focus from deepfakes and specific cases like charities, Gu et al. (2024) researched consumer acceptance of GenAI ads as a broader concept closely aligned with this study's definition. They found that perceived eeriness negatively affects consumers' willingness to accept GenAI ads. Mirroring deepfake research and confirming that consumers can detect AI-generated advertisements, even when the content does not try to depict an actual human. Subsequent research showed that perceived eeriness negatively impacts trust, further underscoring the importance of trust in consumer behavior (Song & Shin, 2022). Gu et al. (2024) also mentioned, "Although this study focuses on consumers' willingness to accept AI advertisements, it does not examine consumers' product purchase willingness and brand attitudes. These topics could be explored in future studies" (p. 2234). This study explores this suggestion via purchase intention.

2.2 Purchase Intention

Intention research and its antecedents to behavior were popularized in the Theory of Reasoned Action (TRA), which later evolved into the Theory of Planned Behavior (TPB), by Ajzen (1985). Intention is "The indication of how hard people are willing to try, and how much of an effort they are planning to exert, to perform the behavior" (Ajzen, 1985, p. 12). In other words, higher intention leads to a higher likelihood of the behavior occurring. A later empirical study by Ajzen and Madden (1986) showed that behavioral intention significantly predicted actual behavior, later corroborated by meta-analyses and longitudinal studies (Armitage & Conner, 2001; Morwitz et al., 1993; Sheppard et al., 1988).

More recent TPB literature adapts the intention variable to fit topic-specific contexts, as this study does. For example, prior studies have examined intentions of whistleblowing, visiting, and recycling participation (Han et al., 2009; Nigbur et al., 2009; Park & Blenkinsopp, 2008). In e-commerce adoption and marketing innovation research, purchase intention has been widely used (Hsu et al., 2016; Paul et al., 2015; Pavlou & Fygenson, 2006). This variable will also be used in this study, as it best captures the actual purchases of products by consumers, which is the topic of this study.

The definition of *purchase intention* that this study will use is adopted from Paul et al. (2015) to fit the topic of this study: purchase intention indicates the extent to which consumers are willing/ready to purchase products after seeing an advertisement generated by AI. That is because the definition encompasses previous research that showed that intention leads to behavior and suggests that higher *purchase intention* in this study would mean a higher willingness/readiness by the consumer to purchase a product after exposure to the central concept of this study: GenAI ads.

2.3 Theory of Planned Behavior

The theoretical framework this study uses to research purchase intention is the TPB. As mentioned, Ajzen (1985) developed the TPB as an extension of the TRA. TRA posits that individuals' intentions drive their behavior, and attitudes toward the behavior and subjective norms shape these intentions. However, as TRA assumed complete volitional control, full autonomy over performing a behavior, another variable, namely perceived behavioral control (PBC), was added to the TPB to combat that (Ajzen, 1985). In an empirical study, Ajzen and Madden (1986) found that adding this variable significantly increased the prediction of intentions. Quickly, the TPB became widely used to predict human behavior in many contexts and established itself as the dominant framework for understanding decision-making (Hasbullah et al., 2014).

Attitude determines whether an individual performs the behavior positively or negatively. A positive attitude would mean that the individual deems the outcome of the behavior as beneficial. Subjective norms refer to social pressure, as in whether the individual perceives that other important people would approve of them engaging in the behavior. In other words, they are less likely to engage in the behavior if they believe others would not do it. The latter added that PBC reflects the individuals’ belief in their ability to perform the behavior, which is closely related to self-efficacy. The TPB states that these three factors collectively influence behavioral intention, an antecedent to actual behavior. For example, actual behavior will occur when an individual thinks the behavior will have a beneficial outcome, others approve of him engaging in it, and the individual believes they have high control over the behavior (Ajzen, 1985). In this study, that would mean intending to purchase a product after seeing a GenAI ad that promotes it.

Researchers have applied the TPB to various disciplines, including health psychology. It has been used in studies on exercise, diet, and smoking (Hasbullah et al., 2014). Environmental studies have used it to look at behavior regarding recycling, energy conservation, and sustainable travel. Researchers have also used the TPB in digital contexts, similar to this study. Notably, Pavlou and Fygenson (2006) used an expanded version to explain consumer e-commerce adoption. They found that the TPB predictors effectively explained consumers' intention to shop online. Researchers have expanded the framework by adding variables such as trust in online vendors and predictors from the Technology Acceptance Model (Davis, 1989). This shows that the core variables remained robust even in extended versions. Later, numerous studies have shown the effectiveness of the TPB in predicting online purchase intention (Han et al., 2009; Hsu et al., 2016; Paul et al., 2015). Researchers have also demonstrated that TPB can predict university students' intention to use GenAI (Wang et al., 2024).

The following reasons justify why this study uses the TPB. That is, first, because of its well-regarded ability to predict intentions, an antecedent to actual behavior. Second, because of its wide usage in studies, in many fields, specifically online shopping and AI. Third, because of its ability to be extended and not lose prediction power, allowing variables to be added based on the specific contexts of studies. Lastly, in meta-analyses and longitudinal studies, it has repeatedly withstood stress tests and the advent of time (Armitage & Conner, 2001; Hagger & Hamilton, 2023; McEachan et al., 2011). Therefore, this study will use an extended version of the TPB with trust as an antecedent.

2.4 Trust and the TPB

Trust is added to the TPB in this study because early work from Lee and Turban (2001) found that customers who do not trust an e-commerce vendor are unlikely to proceed with a purchase. Explaining that trust plays a crucial role in online transactions, Pavlou and Fygenson (2006) corroborated. They found that integrating trust into e-commerce adoption models significantly improved the prediction of customers' purchase intention. These findings further emphasize that this study should not overlook trust. Many studies used an extended form of the TPB, where trust had significant explanatory power (Canova et al., 2020; Ngo-Thi-Ngoc et al., 2024; Pavlou & Fygenson, 2006; Sivathanu et al., 2022).

Although some studies use trust as a separate variable next to the three variables of the TPB, like Pavlou and Fygenson (2006), this study uses it as an antecedent to those variables. This approach resembles the theoretical framework used by Ngo-Thi-Ngoc et al. (2024), Canova et al. (2020), and Wu and Chen (2005). This study adopted this approach because trusting something can strongly affect an individual's attitude toward it. Also, if individuals trust something, they are more likely to accept the subjective norms around it. Lastly, individuals who trust something will have more perceived behavioral control. Since the TPB variables already capture consequent aspects of trust, this study does not assess trust as a separate variable to avoid redundancy. The studies mentioned earlier validate this reasoning, as they used trust as an antecedent and demonstrated its significant explanatory power regarding the three TPB variables.

This study adapts Hobbs and Goddard's (2015) definition of trust for *Trust in GenAI ads*: a heuristic that might be used when a lack of knowledge, experience, or familiarity with GenAI-based advertising hampers decision-making. This heuristic-based view is particularly appropriate for this research, as it frames trust as a crucial shortcut for judgment. It is how consumers must operate when confronted with advertisements created by a novel and uncertain technology like GenAI.

2.5 Hypotheses Development

Consequently, as assumed by TPB, and because trust in GenAI ads is proposed as an antecedent, this study proposes the subsequent six hypotheses.

H1: Trust in GenAI ads positively affects consumers' attitudes towards them. The hypothesized positive effect of trust on attitude is grounded in established e-commerce literature, which identifies trust as a crucial factor in shaping consumer attitudes during online purchases (Lee & Turban, 2001). This principle becomes especially important in the context of GenAI advertising, where the potential for deception or falsified content can create significant consumer uncertainty (Pavlou & Fygenson, 2006). Therefore, this study proposes that trust in the credibility and accuracy of the GenAI ad serves to mitigate this perceived risk, which in turn translates directly into a more favorable attitude toward the intention, consistent with prior extended TPB models (Canova et al., 2020; Wu & Chen, 2005)."

H2: Trust in GenAI ads positively affects subjective norms. Subjective norms reflect an individual's perceived social pressure to perform a given behavior (Ajzen & Madden, 1986). In the novel context of GenAI advertising, this study proposes that trust is a critical precursor to forming these normative beliefs. When consumers encounter an unfamiliar technology that can evoke suspicion, establishing trust in the ad's credibility is a key first step. This study hypothesizes that this trust influences subjective norms through two mechanisms. First, trust acts as a signal of social legitimacy; if consumers perceive GenAI ads as reliable, they are more likely to infer that this is a mainstream, socially accepted form of communication that their important referents would approve of. Second, trust mitigates the perceived social risk of engaging with a potentially eerie or deceptive technology (Gu et al., 2024). By reducing this risk, consumers can more confidently assume that their social circle would endorse the purchase. Therefore, as consumers' trust in a GenAI ad increases, they will perceive stronger positive subjective norms. Similar technology adoption models support this relationship (Wu & Chen, 2005).

H3: Trust in GenAI ads positively affects perceived behavioral control. PBC reflects an individual's perceived ease or difficulty in performing a behavior (Ajzen & Madden, 1986). This study proposes that trust in a GenAI ad positively influences PBC by reducing the uncertainty and perceived risk associated with the transaction prompted by the GenAI ad. When a novel information source like a GenAI ad is trusted, consumers are less likely to be concerned about potential deception or unforeseen complexities in the purchase process (Sivathanu et al., 2022). This alleviation of uncertainty increases a consumer's sense of control over the behavior, making the entire purchase journey feel more straightforward and manageable, consistent with prior models of trust in technology adoption (Wu & Chen, 2005).

H4: Attitude toward a GenAI ad positively influences purchase intention. Attitude toward the behavior, a central predictor in the TPB, refers to an individual's overall favorable or unfavorable evaluation of performing that behavior (Ajzen, 1985). In an advertising context, a consumer's positive evaluation of the advertisement itself is a well-established precursor to forming a positive attitude about the purchase. Therefore, a favorable response to the GenAI ad will lead to a more positive attitude toward purchasing the advertised product. Consistent with extensive meta-analytic evidence on the TPB, this more favorable attitude toward the behavior is, in turn, a direct and robust predictor of a greater intention to perform it (Armitage & Conner, 2001).

H5: Subjective norms positively affect intentions to purchase a product after seeing a GenAI ad. Subjective norms reflect an individual's perception of social pressure to perform a behavior (Ajzen & Madden, 1986). This study expects this influence to be potent in the context of GenAI advertising. Social Comparison Theory (Festinger, 1954) posits that when faced with uncertainty, individuals look to others to evaluate the appropriateness of their judgments and actions. This principle is central to technology adoption, where influential models like the extended Technology Acceptance Model show that social influence is a key driver of intention, especially in the early stages when users have limited personal experience (Venkatesh & Davis, 2000). Given that GenAI ads can evoke feelings of uncertainty and eeriness (Gu et al., 2024), it is proposed that consumers will rely heavily on perceived peer approval to validate their purchase intentions.

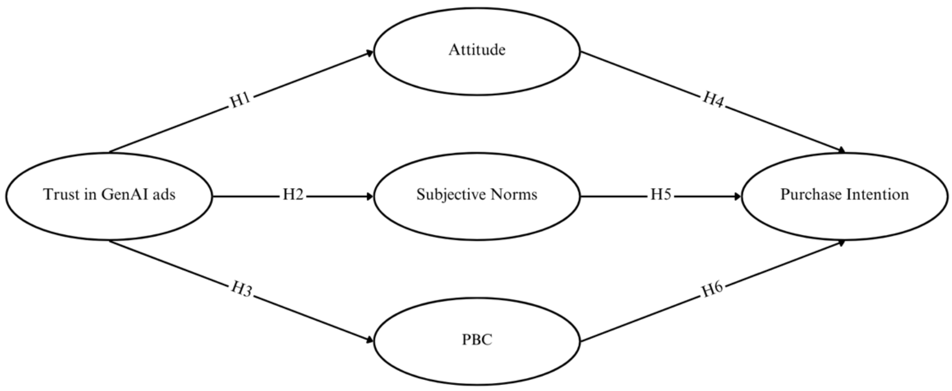
H6: Perceived behavioral control affects intentions to purchase a product after seeing a GenAI ad. PBC reflects an individual's perceived ease or difficulty of performing a behavior, encompassing their sense of self-efficacy and control over potential barriers (Ajzen & Madden, 1986). In established online purchasing contexts, PBC is a significant predictor of intention, as consumers must feel confident in their ability to successfully navigate the transaction (Pavlou & Fygenson, 2006). While the mechanics of online checkout are now familiar to many, the novel context of an advertisement generated by AI can introduce new perceptual barriers and risks. Consumers might question the legitimacy of the offer, the security of the transaction initiated by a non-human source, or the reliability of the fulfillment process. Therefore, a higher level of PBC in this context reflects not just the technical ability to make an online payment, but also a consumer's confidence that they can complete the entire purchase journey prompted by the GenAI ad without encountering these unique, technology-driven obstacles. As such, it is hypothesized that greater perceived behavioral control will positively influence purchase intention.

2.6 Theoretical Framework

Figure 1 presents the conceptual model that integrates the study's hypotheses into a single framework. The model argues that in the context of GenAI advertising, a consumer's decision-making process begins with establishing trust in the ad. This foundational trust is hypothesized to positively shape their subsequent beliefs: their Attitude, perception of Subjective Norms, and PBC (H1-H3). In turn, these TPB constructs are proposed to be the determinants of purchase intention (H4-H6).

Figure 1

Proposed Theoretical Framework



Note. PBC, Perceived Behavioral Control.

3 Methodology

3.1 Research Design

This study used a survey research design and Structural Equation Modelling with Partial Least Squares for data analysis. This approach is grounded in the epistemological belief that knowledge about consumer behavior can be generated by objectively measuring key constructs and statistically testing the hypothesized relationships between them. This approach was ideal because it allowed the gathering of quantitative data regarding the latent constructs this study looked at, namely, trust, attitude, subjective norms, perceived behavioral control (PBC), and purchase intention; as this study is about intent, a self-administered questionnaire allowed for efficient capture of that antecedent to behavior across a large and diverse sample. This setup makes it suitable for testing the hypotheses of this study and generalizing using quantitative methods.

The target population for this study consisted of Dutch consumers. Given this study's use of convenience sampling via social media, the findings are most generalizable to the subset of this population active on these networks. To ensure a controlled exposure to a GenAI ad for this population, a 30-second video stimulus was developed. This advertisement was generated using Runway Gen 3.7, Midjourney 8, and Eleven Labs for a water bottle brand called 'PATH.' It featured a time-lapse of the New York skyline, a park with a plastic bag appearing, a road that turns into an aquarium, which transitions into an underwater scene where the brand logo appears. The water bottle emerges from a wave, ending with a diver coming to the surface in the cutout of the water bottle and a call to action, with a voice-over from a woman talking about freedom, choices, and living life to the fullest. Before viewing the stimulus, a screening question confirmed participants' consent to watch a short video. Afterward, a recognition question was included to gauge whether participants identified the ad as AI-generated, which was crucial for ensuring the study's validity.

The data collection procedure went as follows. First, a small pilot test was conducted with 10 respondents, consisting of close friends and family. This pilot was done to ensure clarity of instructions and concepts. Their feedback was used to revise wording for clarity in the final questionnaire. The questionnaire was constructed using Qualtrics, where, first, respondents were informed of the concepts, and data privacy and anonymity were ensured. Afterward, they were sent to a prompt asking them to imagine they wanted to purchase a water bottle within the next month. The stimulus ad, followed by items about demographics, trust, and the Theory of Planned Behavior (TPB) variables, ends with questions to measure purchase intention and being thanked for their contribution (see Appendix D). Subsequently, the questionnaire was sent out using social media platforms. Several days later, a reminder was issued to these same social media platforms. This represents the use of the convenience sampling method in this study.

This study's minimum required sample size was determined a priori using the Inverse Square Root Method (Kock & Hadaya, 2018). This modern approach is recommended over traditional heuristics like the '10-times rule' for its statistical rigor (Hair et al., 2021). Following convention, the analysis targeted a statistical power of 80% at a 5% significance level. These parameters yielded a target sample size of 155. The final collected and usable sample consisted of 147 participants. Although this number is marginally below the initial target, a post-hoc analysis confirms the sample remains statistically robust. Specifically, the achieved sample of 147 provides statistical power of approximately 78%, a minimal deviation from the 80% target. Furthermore, detecting path coefficients of 0.14 or greater is sufficient, confirming its adequacy for identifying the small-to-medium effects. Therefore, the sample is considered sufficiently powered for the hypothesis testing.

3.2 Operationalization

3.2.1 Trust in GenAI Ads

To operationalize trust in GenAI ads, this study adapted items from a scale developed by Jian et al. (2000). This scale was selected over more general measures because it was explicitly designed and empirically validated for assessing human trust in automated systems, making it exceptionally well-suited for the context of GenAI advertising. For the present study, a subset of seven exclusively positively framed items was selected. This decision was made to avoid using reverse-coded items, which can potentially compromise scale reliability by confusing respondents (Swain et al., 2008). A sample item presented to participants was, “The advertisement is reliable.” The response was measured on a 7-point Likert scale, ranging from 1 (strongly disagree) to 7 (strongly agree). The complete list of adapted items for the trust scale is available in Appendix A.

3.2.2 Attitude

Attitude was measured using a four-item semantic differential scale based on the standard TPB approach (Ajzen & Madden, 1986). The specific items were adopted explicitly from Canova et al. (2020). This recent operationalization was selected for two reasons: first, for its proven validity in a purchase intention context, and second, to maintain methodological consistency with prior research that has successfully extended the TPB with trust. As adapted from their study, attitude was measured by presenting participants with the statement: “To buy this water bottle in the next month would be...” and asking them to respond on four 7-point semantic differential scales (e.g., unpleasant–pleasant). The complete list of adapted items for the attitude scale is available in Appendix A.

3.2.3 Subjective Norms

This study adapted a four-item scale developed by Paul et al. (2015) to measure subjective norms based on the standard TPB approach (Ajzen & Madden, 1986). A good multi-item scale captures different facets of a construct. The Paul et al. (2015) scale uses four items, providing a more stable and reliable measure than a scale with fewer items, such as Canova et al. (2020). A representative sample item presented to participants was, "Most people who are important to me think I should purchase this water bottle," measured on a 7-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree). The complete list of adapted items for the subjective norms scale is available in Appendix A.

3.2.4 Perceived Behavioral Control

This study adapted a four-item scale developed by Paul et al. (2015) to measure PBC based on the standard TPB approach (Ajzen & Madden, 1986). This scale was specifically chosen because it provides a comprehensive measure of PBC, with items that tap into the self-efficacy and controllability dimensions (Ajzen & Madden, 1986). Furthermore, its validation in a purchase intention context ensured its high relevance and suitability for this study. A representative sample item is "I believe I have the ability to purchase this water bottle," which was measured on a 7-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree). The complete list of adapted items for the PBC scale is available in Appendix A.

3.2.5 Purchase Intention

This study adapted a three-item Canova et al. (2020) scale to measure purchase intention. This scale was selected primarily to maintain strong methodological consistency with Canova et al. (2020), which serves as a key precedent for the extended TPB framework employed in this thesis. The scale has also been successfully validated in a context of purchase intention, ensuring its relevance and applicability. A representative sample item is "I intend to buy this water bottle within the next month," with responses recorded on a 7-point scale with anchors appropriate to the question (e.g., from 1 extremely unlikely to 7 extremely likely). The complete list of adapted items for the purchase intention scale is available in Appendix A.

3.3 Data Analysis

As mentioned, this study used Structural Equation Modelling, in particular the Partial Least Squares approach (PLS-SEM), which was developed by Jöreskog and Wold (1982) and refined by Lohmöller (1989). PLS-SEM is often used for complex models with multiple constructs and indicators, such as the TPB, whilst providing reliable estimates, even with smaller sample sizes. For data analysis, Hair et al. (2021) were used as a guide on data preparation, assessing the measurement model, and lastly, assessing the structural model.

3.3.1 Data preparation

The raw dataset was systematically screened for missing data, outliers, and normality using IBM SPSS Statistics (Version 30). Missing values per item ranged from 11 % to 15 % (see Appendix B, Table B1). Little's MCAR test showed no significant departure from MCAR, $\chi^2(37) = 51.07$, $p = .062$; accordingly, cases with any missing value on the core constructs were removed via listwise deletion. Univariate outliers, defined as $|z| > 3.29$, flagged eight responses; inspection of raw logs indicated these values were genuine and they were retained. Multivariate screening using Mahalanobis distance at $p < .001$ ($\chi^2(18) = 79.08$) identified one potential outlier (see Appendix B, Figure B1). Running the PLS-SEM with and without this case produced virtually identical path estimates, so the case was kept to preserve variability. Shapiro–Wilk tests (all $p < .001$) pronounced non-normality on several constructs (max skew = 2.14, kurtosis = 5.07) (see Appendix B, Table B2). This further justified the use of distribution-free PLS-SEM, which does not assume multivariate normality (Hair et al., 2021).

3.3.2 Measurement Model Assessment

A confirmatory factor analysis was conducted to verify that each indicator loads significantly onto its respective latent construct (e.g., *trust, attitude, subjective norms,* PBC, *and purchase intention*). Reliability was assessed via Cronbach's alpha, with values of 0.70 or higher deemed acceptable. Convergent validity was confirmed by ensuring that the Average Variance Extracted (AVE) for each construct exceeded 0.50, and discriminant validity was verified using the Fornell–Larcker criterion, which mandates that the AVE of each construct is greater than the squared correlations between constructs (Fornell & Larcker, 1981; Hair et al., 2021).

3.3.3. Structural Model Assessment

Once the measurement model was validated, the structural model was examined to test the hypothesized relationships among constructs. PLS-SEM estimated the path coefficients, and the model's explanatory power was determined by assessing the R^2 values for endogenous variables. In addition to path significance, the effect size (f^2) of each structural path was calculated to assess its substantive impact, with values of 0.02, 0.15, and 0.35 representing small, medium, and large effects, respectively (Cohen, 2013; Hair et al., 2021). To assess the statistical significance of the path coefficients, a bootstrapping procedure with 10,000 subsamples was employed. This process generates standard errors and t-values for the structural paths, allowing the calculation of p-values to test the research hypotheses (Hair et al., 2021).

3.4 Research Ethics

This study followed the ethical standards outlined by the American Psychological Association regarding plagiarism, data collection, and analysis. In addition, the student and the supervisor signed an integrity form stating that the code of academic integrity from Radboud University will be upheld. All participants in the study were asked for consent and were fully informed about the study’s purpose, procedures, and potential risks. Confidentiality, data protection, and proper handling of sensitive information were considered throughout the research process.

3.5 Limitations

Inevitably, this research design faces certain methodological limitations. These are reported to enhance transparency and support an accurate interpretation of the findings. First, data were collected using a self-administered questionnaire, which introduces the possibility of self-reporting bias. Respondents may consciously or unconsciously provide inaccurate answers due to social desirability or misinterpretation. To mitigate this, anonymity was assured, all items were neutrally phrased, and the questionnaire was pre-tested for clarity. Second, this study employed convenience sampling, limiting the findings' statistical generalizability to the broader Dutch consumer population. While efforts were made to capture a diverse sample, the results represent the specific population subset accessible via the social networks used for distribution. They should be interpreted with this context in mind. Finally, a potential limitation pertains to the study's statistical power. The sample size was robust and sufficient for detecting medium and small-to-medium-sized effects ($f^2 \geq 0.05$). However, the study may have been underpowered to reliably detect very small effects ($f^2 < 0.02$). Consequently, while the statistically significant relationships found in this study are considered robust, the non-significant findings should be interpreted cautiously, as the possibility of a Type II error cannot be entirely ruled out.

4 Results

4.1 Demographic Information

Initially, a total of 185 responses were collected via the Qualtrics survey. The dataset was first screened for quality and completeness. A total of 12 responses were removed because they failed the attention check question, indicating a lack of attentive participation. An additional 26 responses were discarded due to being substantially incomplete. This data cleaning process resulted in a final, valid sample of N=147 for the subsequent analysis. The demographic characteristics of the valid participants are presented in Table 1. The sample included 70 males (47.6%) and 75 females (51.0%), while 2 (1.4%) preferred not to say. Most respondents were 55 and above (25.9%), followed by people between 18 and 25 (20.4%). The most frequently reported categories regarding education were (combined HBO and WO) bachelor's degree (35.4%), vocational (29.9%), and master's degree (20.4%). Most respondents were employed full-time (44.9%), followed by part-time (17.7%). Most respondents (65.3%) made between €25,000 and €99,000 annually. The most cited category was €50,000 to €74,999 (20.4%). Furthermore, a recognition check confirmed the validity of the GenAI stimulus; on a 7-point scale, participants reported a strong belief that the ad was created by artificial intelligence (M = 4.93, SD = 1.649).

4.2 Descriptive Statistics

Table 2 presents the mean (M) and standard deviation (SD) of individual items and each construct, as well as the reliability of the constructs. The means and standard deviations reflect the final set of items utilized in the study following an initial scale assessment and refinement process, which will be detailed in the subsequent section on the measurement model. Construct mean and standard deviation were calculated using composite scores' averages. Results showed sufficient internal consistency: Cronbach's Alpha was above .700 for all constructs, and composite reliabilities (CRs) ranged from .832 to .940.

Table 1

Demographic Information

Demographic	Frequency	%
Age (years)		
18-25	30	20.4
26-35	26	17.7
36-45	27	18.4
46-55	26	17.7
55 and above	38	25.9
Gender		
Male	70	47.6
Female	75	51.0
Prefer not to say	2	1.4
Education level		
No education completed	1	07
Primary education	2	1.4
Secondary education	17	11.6
Vocation education (MBO)	44	29.9
Bachelor’s degree (HBO)	36	24.5
Bachelor’s degree (WO)	16	10.9
Master’s degree (WO)	30	20.4
Doctorate (PhD)	1	0.7
Employment status		
Full-time job	66	44.9
Part-time job	26	17.7
Self-employed	14	9.5
Student	16	10.9
Unemployed	25	17.
Income level		
€15,000 and under	14	9.5
€15,000-€24,999	9	6.1
€25,000-€34,999	21	14.3
€35,000-€49,999	25	17.0
€50,000-€74,999	30	20.4
€75,000-€99,999	20	13.6
€100,000-€149,999	12	8.2
€150,000 and above	5	3.4
Not applicable/unknown	11	7.5

Note. N = 147 for all constructs.

Table 2

Descriptive statistics and reliability coefficients of trust, TPB constructs, and items

Construct and items	*M*	*SD*	Cronbach's alpha	CR
Trust in GenAI ads	4.244	1.299	.932	.932
I am confident in the advertisement.	4.259	1.571		
The advertisement provides security.	4.027	1.530		
The advertisement has integrity.	4.367	1.490		
The advertisement is dependable.	4.170	1.401		
The advertisement is reliable.	4340	1.492		
I can trust the advertisement.	4.306	1.533		
Attitude	4.573	1.549	.922	.924
Unpleasant–pleasant	4.789	1.518		
Useless–useful	4.483	1.874		
Negative–positive	4.565	1.771		
Crazy–wise	4.456	1.701		
Subjective Norms	3.603	1.613	.929	.931
Most people who are important to me think I should purchase this water bottle.	3.367	1.728		
Most people who are important to me would want me to purchase this water bottle.	3.436	1.821		
People whose opinions I value would prefer that I purchase this water bottle.	3.714	1.787		
My friend's positive opinion influences me to purchase this water bottle.	3.898	1.770		
PBC	5.006	1.481	.832	.832
I believe I have the ability to purchase this water bottle.	4.939	1.627		
I see myself as capable of purchasing this water bottle.	5.075	1.575		
Purchase Intention	3.260	1.761	.941	.940
I intend to buy this water bottle within the next month.	3.190	1.841		
How likely is it that you will form the intention to buy this water bottle within the next month?	3.415	1872		
How likely is it that you will actually buy this water bottle within the next month?	3.177	1.875		

Note. M, Mean; *SD*, Standard Deviation; CR, Composite Reliabilities; PBC, Perceived Behavioral Control. Every construct was scored on a 7-point Likert scale. N = 147 for all constructs.

4.3 Measurement Model

4.3.1 Scale Assessment and Refinement

All items were examined before assessing the measurement model to ensure overall measurement quality. Items were evaluated for factor loadings and internal consistency. This was done using their standardized factor loadings derived from a preliminary Partial Least Squares Structural Equation Modeling (PLS-SEM) estimation via ADANCO 2.4.1 and their impact on construct reliability using Cronbach's Alpha, based on established criteria of between .708 and 1 for factor loadings, and > .700 for Cronbach's Alpha (Hair et al., 2021).

First, the *trust in GenAI ads* (TRUST) scale, comprising seven items, was examined. While the scale exhibited a high Cronbach's Alpha of .913, item TRUST7 presented a factor loading of .638, below the recommended threshold of .708 in the preliminary PLS-SEM estimation (see Appendix C, Figure C1). Furthermore, TRUST7 demonstrated a low corrected item-total correlation (CITC = .471), whilst all other items scored above .672. Removing TRUST7 would also increase the overall Cronbach's Alpha from .913 to .926 (see Appendix C, Table C1). Considering its weaker factor loading, lower CITC, and increase in Cronbach's Alpha, TRUST7 was deleted to enhance scale homogeneity. This gave the final TRUST scale a Cronbach's Alpha of .926 with six items.

Second, an examination of the *perceived behavioral control* (PBC) scale, initially including four items, revealed issues with PBC2 and PBC4 during the preliminary PLS-SEM estimation (see Appendix C, Figure C1). These two items exhibited inadmissible factor loadings exceeding |1| (PBC2 = 1.066; PBC4 = 1.207). Such loadings indicate multicollinearity (Hair et al., 2021), necessitating their removal. Improvements in internal consistency further supported the decision to remove these items. The initial 4-item PBC scale yielded a Cronbach's Alpha of .800. After removing PBC2 and PBC4, the final two-item scale yielded a Cronbach's Alpha of .832 (see Appendix C, Table C2).

No items were removed from the *attitude, subjective norms*, or *purchase intention* scales as they all demonstrated satisfactory factor loading and internal consistency. Therefore, they were retained with all initially selected items described in the operationalization. The subsequent analyses presented in this chapter are based on these final scales for all constructs, as seen in Table 2.

4.3.2 Convergent Validity

Standardized factor loadings (λ) should ideally exceed .708, indicating that the construct explains at least 50% of an item's variance (Hair et al., 2021). As shown in Table 3, all items exhibited strong loadings on their intended constructs. Specifically, all standardized factor loadings were above .726, with most loadings being substantially higher, up to .941.

Further evidence for convergent validity was sought by examining each construct's Average Variance Extracted (AVE). The AVE should be .500 or higher, signifying that the construct explains, on average, at least 50% of the variance in its measurement items (Fornell & Larcker, 1981; Hair et al., 2021). As detailed in Table 3, the AVE ranged from .698 to .841, well above the .500 threshold.

Table 3

Measurement model: Standardized factor loadings

Constructs	Parcels/Items	λ	AVE
Trust in GenAI ads	TRUST1	.915	.698
	TRUST2	.817	
	TRUST3	.834	
	TRUST4	.733	
	TRUST5	.854	
	TRUST6	.848	
Attitude	ATT1	.865	.753
	ATT2	.864	
	ATT3	.829	
	ATT4	.911	
Subjective norms	SN1	.941	.773
	SN2	.931	
	SN3	.901	
	SN4	.726	
PBC	PBC1	.867	.714
	PBC3	.821	
Intention	INT1	.938	.841
	INT2	.882	
	INT3	.930	

Note. PBC, Perceived Behavioral Control. AVE, Average Variance Extracted. λ, Standardized factor loading.

4.3.3 Discriminant Validity

The Heterotrait-Monotrait ratio of correlations (HTMT) values for all pairs of constructs, along with their 95% bias-corrected bootstrap confidence intervals, are presented in Table 4. To establish discriminant validity, HTMT point estimates should be below .850 or the more liberal threshold of .900 (Henseler et al., 2016). All HTMT point estimates were below the conservative 0.850 threshold; the highest point estimate was .810. Furthermore, the upper bound of the 95% confidence interval for this highest HTMT value was .871, which is below the 0.900 threshold.

The inter-construct correlations were reviewed, as these inform the Fornell-Larcker criterion. Table 5 details these correlation coefficients, standard errors, and statistical significance. Common guidelines suggest interpreting correlation magnitudes: .100-.290 as small, .300-.490 as moderate, and .500-1 as strong (Cohen, 2013). All observed inter-construct correlations were positive. The Fornell-Larcker criterion stipulates that each construct's Average Variance Extracted (AVE) must be greater than its squared correlations with all other constructs in the model (Fornell & Larcker, 1981). Table 6 presents this analysis, with AVE values on the diagonal and squared inter-construct correlations in the off-diagonal cells. The AVE for every construct exceeded all its respective squared correlations with other constructs.

Table 4

Heterotrait-Monotrait Ratio of Correlations (HTMT) with 95% Confidence Intervals

Constructs	Trust in GenAI ads	Attitude	Subjective norms	PBC	Intention
Trust in GenAI ads	-	-	-	-	-
Attitude	0.708(0.804)	-	-	-	-
Subjective norms	0.706(0.782)	0.716(0.801)	-	-	-
PBC	0.363(0.520)	0.363(0.513)	0,328(0.471)	-	-
Intention	0.676(0.754)	0.652(0.738)	0,810(0.871)	0,203(0.345)	-

Note. HTMT point estimates are reported, with the upper bound of the 95% bias-corrected bootstrap confidence interval in brackets.

Table 5

Correlations between latent factors

Constructs	Trust in GenAI ads	Attitude	Subjective norms	PBC	Intention
Trust in GenAI ads	-	-	-	-	-
Attitude	0.708 (0.06)	-	-	-	-
Subjective norms	0.704 (0.04)	0.713	-	-	-
PBC	0.366 (0.09)	0.363	0.324	-	-
Intention	0.676 (0.05)	0.653 (0.08)	0.811 (0.07)	0.205 (0.05)[a]	-

Note. Standard errors in parentheses. All coefficients are significant with $p < 0.05$, except the one denoted by “a” for which $p = 0.094$.

Table 6

Fornell-Larcker Criterion (AVE and Squared Inter-Construct Correlations)

Constructs	Trust in GenAI ads	Attitude	Subjective norms	PBC	Intention
Trust in GenAI ads	**0.698**	-	-	-	-
Attitude	0.501	**0.753**	-	-	-
Subjective norms	0.496	0.509	**0.773**	-	-
PBC	0.134	0.132	0.105	**0.714**	-
Intention	0.457	0.426	0.657	0.042	**0.841**

Note. Diagonal elements (in bold) are the Average Variance Extracted (AVE). Off-diagonal elements are the squared correlations between the constructs.

4.4 Structural Model

4.4.1 Explanatory Power and Model Fit

The explanatory power of the structural model was evaluated by examining the coefficient of determination (R^2) for each endogenous construct. The R^2 value indicates the proportion of variance in an endogenous variable explained by its predictor constructs. The model explained 67.6% of the variance in *purchase intention* (R^2 = .676), 50.2% of the variance in *attitude* (R^2 = .502), 49.6% of the variance in *subjective norms* (R^2 = .496), and 13.4% of the variance in Perceived Behavioral Control (R^2 = .134). According to benchmarks by Hair et al. (2021), the R^2 value for Purchase Intention can be considered substantial, while those for *attitude* and *subjective norms* are moderate, and the R^2 for PBC is weak. To test for potential confounding variables, demographic factors including *Age*, *Gender*, *Education*, *Employment Status*, and *Income* were included as control variables in the initial model. However, none of these five controls were statistically significant (β between −0.09 and −0.01, $p > 0.05$), and their removal did not meaningfully change R^2 for *purchase intention*. Therefore, all five were omitted from the final analysis to maintain a parsimonious model. The overall fit of the estimated PLS path model was assessed using the Standardized Root Mean Square Residual (SRMR). The obtained SRMR value was .076. This value is below the threshold of .080 (Hair et al., 2021; Henseler et al., 2016), indicating an acceptable fit of the model to the data.

4.4.2 Path Analysis

To test the proposed research hypotheses, the path coefficients (β), their statistical significance, and effect sizes (f^2) were examined. Figure 2 visually represents the estimated structural model, displaying the standardized path coefficients and their significance. Table 7 presents the detailed statistical results for each hypothesized path, including standardized path coefficients

(β), standard errors (*SE*), t-values, p-values, Cohen's f^2 effect sizes, and the decision regarding hypothesis support.

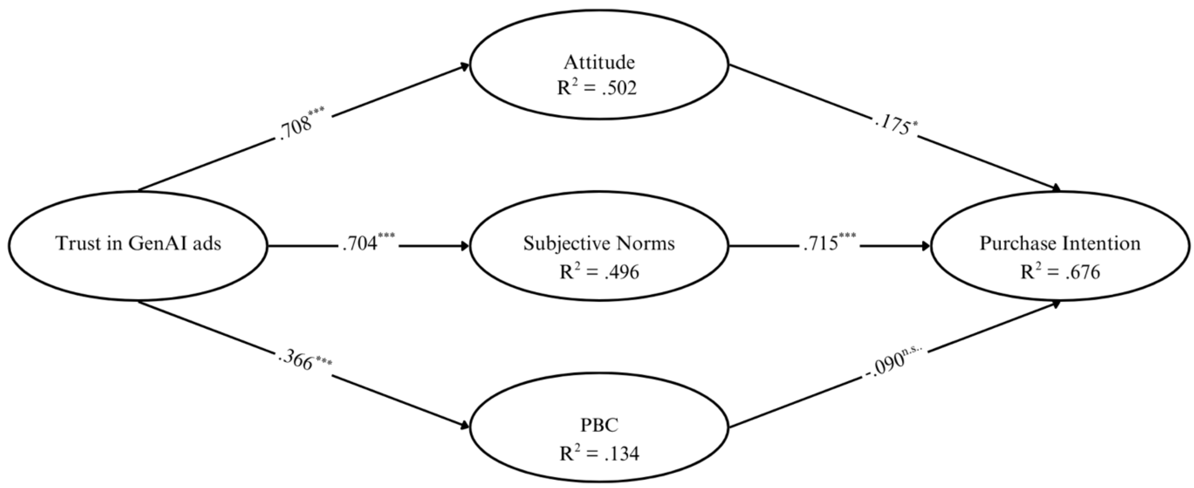
Hypothesis 1 (H1) proposed that *trust in GenAI ads* positively influences *attitude*. This path was found to be positive and statistically significant (β = .708, p < 0,001), with a large effect size (f^2 = 1,007). Therefore, H1 was supported. Hypothesis 2 (H2) posited that *trust in GenAI ads* positively influences *subjective norms*. The results indicate that this relationship was positive and statistically significant (β = .704, p < .001), accompanied by a large effect size (f^2 = .983). Thus, H2 was supported. Hypothesis 3 (H3) suggested that *trust in GenAI ads* positively influences Perceived Behavioral Control. This path was also found to be positive and statistically significant (β = .366, p < .001), with a medium effect size (f^2 = .155). Consequently, H3 was supported. Hypothesis 4 (H4) predicted that *attitude* would positively influence *purchase intention*. The analysis revealed this path as positive and statistically significant (β = .175, p = .035), with a small effect size (f^2 = .044). Therefore, H4 was supported. Hypothesis 5 (H5) proposed that *subjective norms* positively influence *purchase intention*. This was the strongest direct predictor of Purchase Intention, with a positive and statistically significant relationship (β = .715, p < .001) and a large effect size (f^2 = .766). H5 was therefore strongly supported. Hypothesis 6 predicted a positive relationship between Perceived Behavioral Control and Purchase Intention. The analysis revealed that this path was not statistically significant (β = -.090, p = .094), and the effect size was small (f^2 = .021). Consequently, H6 was not supported.

4.4.3 Indirect effect

In addition to the direct effects, the indirect effect of *trust in GenAI ads* on *purchase intention*, mediated by *attitude, subjective norm*s, and PBC, was examined. The results indicated *trust in GenAI ads'* significant and positive indirect effect on Purchase Intention (β = .595, t = 10.564, p < .001). This suggests trust influences purchase intention by impacting *attitude*, *subjective norms*, and PBC as mediating variables.

Figure 2

Standardized path coefficients



Note. Standardized path coefficients. *p < .05, **p < .01, ***p < .001. PBC, Perceived Behavioral Control.

Table 7

Hypothesis Testing Summary

Hypothesis	Path	Predicted	β	*SE*	t-value	p-value	f^2	Decision
H1	TRUST → ATT	+	$.708^{***}$	0.063	11.160	< .001	1.007	Supported
H2	TRUST → SN	+	$.704^{***}$	0.048	14.400	< .001	0.983	Supported
H3	TRUST → PBC	+	$.366^{***}$	0.096	3.794	< .001	0.155	Supported
H4	ATT → INT	+	$.175^{*}$	0.083	2.101	.035	0.044	Supported
H5	SN → INT	+	$.715^{***}$	0.076	9.325	< .001	0.766	Supported
H6	PBC → INT	+	$-.090^{n.s.}$	0.053	-1.674	.094	0.021	Not Supported

Note. ^{NS}, not significant. β, Standardized Path Coefficient. *SE*, Standard Error. Trust in GenAI ads (TRUST), Attitude (ATT), Subjective Norms (SN), Perceived Behavioral Control (PBC), Purchase Intention (INT). Significance levels determined via bootstrapping with 10,000 subsamples. Significance levels based on 2-sided p-values: *p < .05, **p < .01, ***p < .001. Cohen's f^2 effect sizes: 0.02 (small), 0.15 (medium), 0.35 (large).

5 Discussion

5.1 Summary of Key Findings

The rapid increase in the use of generative AI to create advertising raises questions about how consumers intend to purchase from this type of advertising. Recent studies on responses to GenAI advertising have highlighted perceptual barriers, such as perceived eeriness negatively impacting consumer acceptance (Gu et al., 2024) and awareness of falsity directly undermining trust in the context of charitable ads (Arango et al., 2023). However, researchers have not examined how consumer trust translates into actual purchase intentions within established decision-making frameworks. This study addressed this gap by extending the Theory of Planned Behavior (TPB), positioning trust in GenAI ads as an antecedent to attitude, subjective norms, and perceived behavioral control (PBC). The results reveal that trust is a foundational precursor, exerting medium to strong positive effects on all three TPB constructs. This trust ultimately has a significant indirect effect on purchase intention. In turn, when examining the direct drivers of intention, subjective norms proved to be the most potent predictor, with attitude playing a secondary yet significant role. In contrast to the TPB expectations, perceived behavioral control did not significantly predict purchase intention in the context of GenAI ads.

The results support that consumers' trust in GenAI ads is a critical precursor to forming the beliefs that shape their purchase intentions. The findings confirm that trust in GenAI ads is an influential antecedent in this extended TPB model, emerging as a strong, positive, and significant predictor of attitude, subjective norms, and PBC. This result not only corroborates foundational research on the importance of trust during online shopping but also adapts these established principles for advertising made by GenAI. Researchers have found that although trust has traditionally been the primary mechanism for facilitating online transactions, the trustworthiness of the advertisement itself has now become a significant factor in the context of GenAI advertising. Because GenAI ads are novel and can create uncertainty about their authenticity and reliability, consumers appear to use trust in the ad as a heuristic for decision-making under uncertainty, as described by Hobbs and Goddard (2015). Before consumers form an attitude toward purchasing, assess norms, or evaluate their control, they determine if the AI-generated message is trustworthy. By positioning trust as an antecedent to the TPB variables, this study provides empirical evidence for this specific model structure, as advanced by research like Wu and Chen (2005) and Canova et al. (2020).

A central finding of this study is the pronounced dominance of subjective norms in driving purchase intention. When comparing the direct paths, subjective norms exerted a significantly larger effect than attitude, reversing the typical TPB pattern in consumer research, where personal attitude most often dominates (Conner & Armitage, 1998). This shift reflects the novel character of GenAI advertising. This interpretation is grounded in how consumers react to the unfamiliarity. Prior studies document that GenAI ads can trigger feelings of eeriness and falsity (Arango et al., 2023; Gu et al., 2024), creating high uncertainty. In this context of high uncertainty, individuals naturally turn to social comparison to evaluate the appropriateness of their judgment (Festinger, 1954). Social comparison likely serves two key purposes: first, to mitigate the perceived risk of making a socially questionable choice, and second, to conform to the behavior of others. This explanation aligns strongly with established technology-adoption theory, which holds that social influence is especially potent during the early phases of novel technology use when personal experience is limited (Venkatesh & Davis, 2000).

In contrast to the standard TPB premise (Ajzen & Madden, 1986), PBC failed to be a significant predictor of purchase intention. This non-significant finding likely stems from the simple nature of the behavior studied: making an online purchase from an ad. For most respondents who also filled out the questionnaire online, the barriers to performing such a task are minimal and uniformly low. The measurement items for PBC in this study primarily captured self-efficacy, the belief in one's capability to act, and it is reasonable to assume that participants' self-efficacy for a simple online transaction was consistently high. However, while PBC did not directly influence purchase intention, trust in the GenAI ads still had a statistically significant positive effect on PBC. However, the magnitude of this effect was considerably smaller than the significant effects that trust in GenAI ads exerted on attitude and subjective norms.

5.2 Theoretical Implications

First, this study contributes to the literature on technology adoption and the TPB by empirically positioning trust as an antecedent to all core TPB constructs in GenAI advertising. Whereas earlier extensions of TPB treated trust as a parallel predictor of purchase intention or focused on trust in the vendor or platform, the model locates consumers' trust in the GenAI advertisement as the foundational belief from which attitude, subjective norms, and PBC derive. This study advances Pavlou and Fygenson's (2006) and Canova et al.'s (2020) demonstrations of trust's indirect effects via TPB variables in e-commerce and organic-food contexts by adapting Lee and Turban's (2001) e-commerce trust principles (e.g., structural assurances, perceived integrity, and system reliability) to GenAI advertising, showing how cues of authenticity, transparency, and social proof within the ad build that initial trust. This adaptation is crucial for GenAI, as prior research has identified that this specific technology can trigger consumer concerns about deception and authenticity. For example, studies on deepfakes have highlighted consumer perceptions of deception (Sivathanu et al., 2022), while research on AI-generated faces for ads has shown that awareness of falsity directly undermines trust (Arango et al., 2023). Therefore, modeling trust as the initial psychological hurdle, this study confirms that addressing these well-documented, trust-eroding concerns is the primary gateway to influencing consumer beliefs.

Second, the findings significantly contribute to the TPB by identifying a boundary condition for the predictive power of its core antecedents. Specifically, this study shows that subjective norms exerted the most potent direct effect on purchase intention for GenAI ads, reversing the typical hierarchy in consumer research where attitude dominates (Conner & Armitage, 1998). This study explains this inversion through the lens of technological novelty: as GenAI advertisements trigger heightened uncertainty and feelings of eeriness (Arango et al., 2023; Gu et al., 2024), consumers turn to social comparison and peer behavior to assess appropriateness and mitigate risk, consistent with Social Comparison Theory (Festinger, 1954) and Venkatesh and Davis's (2000) assertion that social influence is potent during early stages of novel technology adoption. This reliance on social norms may also be amplified by the nature of AI's perceived strengths. For instance, Chen et al. (2024) found that consumers respond more positively to GenAI ads for agentic products than communal products, suggesting a perceived deficit in GenAI's ability to convey empathic connection. It is plausible that consumers compensate for the GenAI's lack of perceived empathic connection by placing even greater weight on the social consensus of their peer group. This contribution thus refines the application of the TPB for emerging phenomena. It shows that when consumers face high uncertainty, the typical predictive hierarchy of the TPB may invert, with the subjective norms' pathway becoming a more powerful driver of intention than individual attitude.

Finally, a third contribution lies in clarifying the context-dependent nature of PBC within the TPB framework. The non-significant PBC pathway observed for the simple behavior of making an online purchase from a GenAI advertisement supports Ajzen's (1985) proposition that PBC most strongly influences intention when significant barriers exist. PBC becomes less influential in shaping behavioral intentions for low-barrier digital tasks where self-efficacy is uniformly high. This finding is particularly insightful when contrasted with earlier e-commerce adoption studies like Pavlou and Fygenson (2006), where PBC was a significant predictor of intention. The difference likely reflects the evolution of e-commerce itself, which was once a novel behavior with significant perceived barriers for some consumers and has now become a routine, low-complexity task for most. This study, therefore, suggests that as digitally native behaviors become more commonplace, the predictive salience of PBC within the TPB framework may diminish, even when a novel technology like GenAI is introduced as part of the process.

5.3 Managerial Implications

First, this study provides crucial insight for marketers because consumer trust in a GenAI ad is the foundational belief that shapes all subsequent attitudes and norms. Managing and building this trust becomes the primary strategy while using GenAI ads. The results demonstrate that trust in the GenAI ad directly and strongly influences consumers' attitudes toward it, their perception of social norms, and even their sense of control over the purchase process. Therefore, from a practical standpoint, marketers cannot effectively leverage the powerful influences of attitude and social norms if they have not first secured consumer trust in the GenAI ad. Marketers should label GenAI ads to signal openness and reduce suspicions of deception, embed trust signals within or alongside the ad, and align GenAI ads with core brand values and ethical guidelines to guard against uncanny or misleading imagery, thereby avoiding the perception of inauthenticity that Arango et al. (2023) and Sivathanu et al. (2022) show can erode trust.

Second, subjective norms dominate the prediction of purchase intention. This finding suggests that for novel GenAI ads, perceived subjective norms influence consumers more than their attitudes. Therefore, marketers should design campaigns to signal positive social norms around purchasing products featured in GenAI ads. Integrate user testimonials, star ratings, and short review snippets into the ad to create clear empathic connection signals that normalize and validate the purchase. Also, marketers should not let GenAI ads operate in a vacuum. To maximize impact, complement these campaigns with influencer collaborations that provide a crucial layer of human validation. A trusted creator reviewing the product, unboxing it, or reacting to the GenAI ad offers an authentic perspective that makes the purchase feel like a safe and socially endorsed choice for their followers. Feature live purchase counters or user testimonials in the ad description to show a shared, positive experience and cement the sense that buying from GenAI ads is the norm.

Finally, a third implication surrounds the non-significant effect of PBC on purchase intention, offering practical guidance on where marketers can de-emphasize their efforts. For simple online purchases, consumers already feel a high degree of control, so ad messaging that focuses heavily on the ease of the behavior is likely redundant. Instead, marketers should redirect resources toward the more impactful levers uncovered in this study: building ad credibility and utilizing social proof.

5.4 Research Limitations and Future Research

Readers should consider the findings of this research in light of its specific sample and context. Using a convenience sample drawn from a Dutch population limits the statistical generalizability of the results to other national or cultural settings. Furthermore, the study focused on a low-involvement product. The psychological drivers of purchase intention may differ significantly for purchases with more purchase complexity and perceived risk. Future research should replicate this extended TPB model using more diverse, representative samples from different cultural backgrounds, where trust in technology and social-influence dynamics may vary. Testing the model with high-involvement products, such as financial services, healthcare offerings, or complex electronics, would be a valuable extension to examine whether PBC becomes a more significant predictor when purchase complexity and perceived risk are higher.

This study relied on a single video advertisement as the GenAI stimulus. Although this approach provided high internal validity through controlled exposure, it necessarily limits the external validity of the findings. Future research should move towards experimental designs that systematically manipulate key stimulus characteristics to establish causality and understand the impact of specific ad features. For example, researchers might compare consumer responses to photorealistic versus highly stylized animated GenAI ads or directly test the impact of an explicit AI-generated disclosure versus no disclosure.

The cross-sectional design of this research captures consumer perceptions and intentions at a single point in time. This static snapshot cannot account for the dynamic evolution of attitudes toward an emerging technology; as public discourse and familiarity with GenAI ads grow, the roles of trust, attitude, and subjective norms may shift. Therefore, a longitudinal study would be a valuable next step. Tracking a cohort of consumers over several months could reveal how the relative importance of these predictors changes as GenAI advertising moves from novelty to routine and how early trust levels influence later adoption and repeat behavior.

Finally, this study measured purchase intention as a proxy for actual behavior. While the TPB posits a firm intention–behavior pathway, a gap between what consumers say they will do and what they do is well-documented. The findings thus illuminate the drivers of consumers' willingness to purchase, not the final act of purchasing itself. Future research should incorporate behavioral metrics within a field experiment to extend these findings and establish causal links between ad type and consumer action. For instance, in an A/B test on an e-commerce site, GenAI ads could be compared directly with human-designed ones on the conversion rate to validate the intention-behavior pathway in this context.

6 Conclusion

Consumers now frequently encounter advertisements created by generative artificial intelligence (GenAI), placing them in a new and often uncertain position. While prior research identified consumer apprehensions, a model explaining how consumer trust in GenAI advertising translates into purchase intention through an established decision-making framework remained a critical gap. This study sought to address this gap by proposing and testing an extended Theory of Planned Behavior (TPB) model that positions trust in the GenAI ad as a foundational antecedent. The findings suggest that consumer decision-making in this context follows a straightforward process. The first stage establishes trust in the ad, a precondition shaping a consumer's attitude, subjective norms, and perceived behavioral control (PBC). In the next stage, these beliefs translate into purchase intention, with a clear hierarchy among the direct predictors. When the technology feels novel and uncertain, a consumer's peers, embodied in subjective norms, most powerfully drive their intention to act. This social influence is higher than the impact of personal attitude, while concerns related to PBC fall away in importance for simple online purchases. This study contributes to the body of knowledge for scholars and practitioners in three key ways. First, it repositions trust as a critical antecedent to the TPB in this context. Second, it reveals the boundary conditions under which subjective norms are most influential for predicting purchase intention. Finally, it clarifies the circumstances in which PBC becomes a non-significant predictor. The journey to influencing consumer purchase intention does not begin with persuasion but with credibility; marketers must first earn consumer trust and then leverage the power of social proof to guide consumers toward action.

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Appendix A
Measurement items

Construct	Definition	Original item	Adapted item	Scale	Source
Trust in GenAI ads	A heuristic that might be used in situations when a lack of knowledge, experience, or familiarity with GenAI-based advertising hampers decision-making.	I am confident in the system The system provides security The system has integrity The system is dependable The system is reliable I can trust the system I am familiar with the system	I am confident in the advertisement. The advertisement provides security. The advertisement has integrity. The advertisement is dependable. The advertisement is reliable. I can trust the advertisement. I am familiar with the advertisement.	1 = strongly disagree, 7 = strongly agree	Jian et al. (2000)
Attitude	Determines whether an individual performs the behavior positively or negatively.	To buy organic food products/organic fruit and vegetables in the next month would be...	To buy this water bottle in the next month would be...	Four 7-step semantic differential scales: Unpleasant–pleasant Useless–useful Negative–positive Crazy–wise	Canova et al., 2020
Subjective Norms	Reflects individuals' social pressure regarding whether to perform a given behavior.	Most people who are important to me think I should purchase green products when going for purchasing. Most people who are important to me would want me to purchase green products when going for purchasing. People whose opinions I value would prefer that I purchase green products. My friend’s positive opinion influences me to purchase green product.	Most people who are important to me think I should purchase this water bottle. Most people who are important to me would want me to purchase this water bottle. People whose opinions I value would prefer that I purchase this water bottle. My friend’s positive opinion influences me to purchase this water bottle.	1 = strongly disagree, 7 = strongly agree	Paul et al., 2015

PBC	Refers to individuals' sense of ease or difficulty in performing a behavior	I believe I have the ability to purchase green products. If it were entirely up to me, I am confident that I will purchase green products. I see myself as capable of purchasing green products in future. I have resources, time and willingness to purchase green products.	I believe I have the ability to purchase this water bottle. If it were entirely up to me, I am confident that I will purchase this water bottle. I see myself as capable of purchasing this water bottle. I have resources, time and willingness to purchase this water bottle.	1 = strongly disagree, 7 = strongly agree	Paul et al., 2015
Purchase Intention	Indicates the extent to which consumers are willing/ready to purchase products after seeing an advertisement generated by AI.	I intend to buy organic food products in the next month How likely is it that you will form the intention to buy organic food products in the next month? How likely is it that you will actually buy organic food products in the next month?	I intend to buy this water bottle within the next month. How likely is it that you will form the intention to buy this water bottle within the next month? How likely is it that you will actually buy this water bottle within the next month?	1 = strongly disagree/extremely unlikely, 7 = strongly agree/extremely likely	Canova et al., 2020

Appendix B

Missing Data, Outlier, and Normality Analysis

Table B1

Percentage of Missing Values per Item

				Missing		No. of Extremes[a]	
	N	Mean	Std. Deviation	Count	Percent	Low	High
Trust_1	154	4.20	1.610	19	11.0	0	0
Trust_2	154	3.97	1.546	19	11.0	0	0
Trust_3	154	4.29	1.541	19	11.0	0	0
Trust_4	154	4.14	1.407	19	11.0	0	0
Trust_5	154	4.29	1.528	19	11.0	0	0
Trust_6	154	4.24	1.593	19	11.0	0	0
Trust_7	154	3.10	1.746	19	11.0	0	4
Attitude_1	150	4.75	1.537	23	13.3	6	0
Attitude_2	150	4.44	1.898	23	13.3	0	0
Attitude_3	150	4.53	1.779	23	13.3	13	0
Attitude_4	150	4.41	1.723	23	13.3	13	0
Subjective_Norms_1	148	3.35	1.733	25	14.5	0	0
Subjective_Norms_2	148	3.42	1.826	25	14.5	0	0
Subjective_Norms_3	148	3.70	1.794	25	14.5	0	0
Subjective_Norms_4	148	3.89	1.771	25	14.5	0	0
PBC_1	148	4.92	1.639	25	14.5	6	0
PBC_2	148	3.70	1.861	25	14.5	0	0
PBC_3	148	5.05	1.605	25	14.5	6	0
PBC_4	148	4.34	1.752	25	14.5	0	0
Purchase_Intention_1_1	147	3.19	1.841	26	15.0	0	0
Purchase_Intention_2_1	147	3.41	1.872	26	15.0	0	0
Purchase_Intention_2_2	147	3.18	1.875	26	15.0	0	0

a. Number of cases outside the range (Q1 - 1.5*IQR, Q3 + 1.5*IQR).

Figure B1

Mahalanobis Distance Plot with Critical χ^2 Cut-off

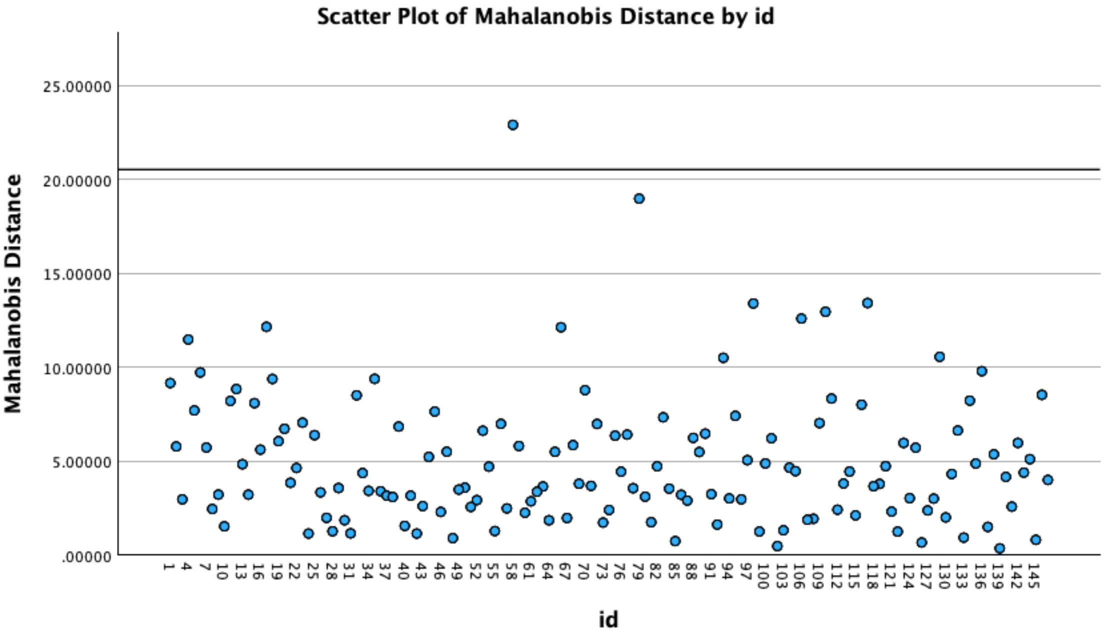


Table B2

Normality Diagnostics for Construct Scores

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
SN_Scale	.121	735	<.001	.948	735	<.001
PBC_Scale	.113	735	<.001	.967	735	<.001
PI_Scale	.112	735	<.001	.927	735	<.001
Attitude_Scale	.105	735	<.001	.963	735	<.001
Trust_Scale	.091	735	<.001	.982	735	<.001

a. Lilliefors Significance Correction

Note. Construct Scores were calculated using the mean of all corresponding items. SN, Subjective Norms. PBC, Perceived Behavioral Control. PI, Purchase Intention.

Appendix C

Scale Reliability and Refinement Analysis

Table C1

Reliability and item analysis for TRUST (7 items)

Reliability Statistics

Cronbach's Alpha	N of Items
.919	7

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
Trust_1	24.36	56.389	.816	.900
Trust_2	24.59	57.708	.776	.904
Trust_3	24.25	57.437	.816	.900
Trust_4	24.45	60.466	.718	.910
Trust_5	24.28	57.041	.835	.898
Trust_6	24.31	57.177	.801	.902
Trust_7	25.47	60.481	.533	.932

Table C2

Reliability and item analysis for PBC (4 items)

Reliability Statistics

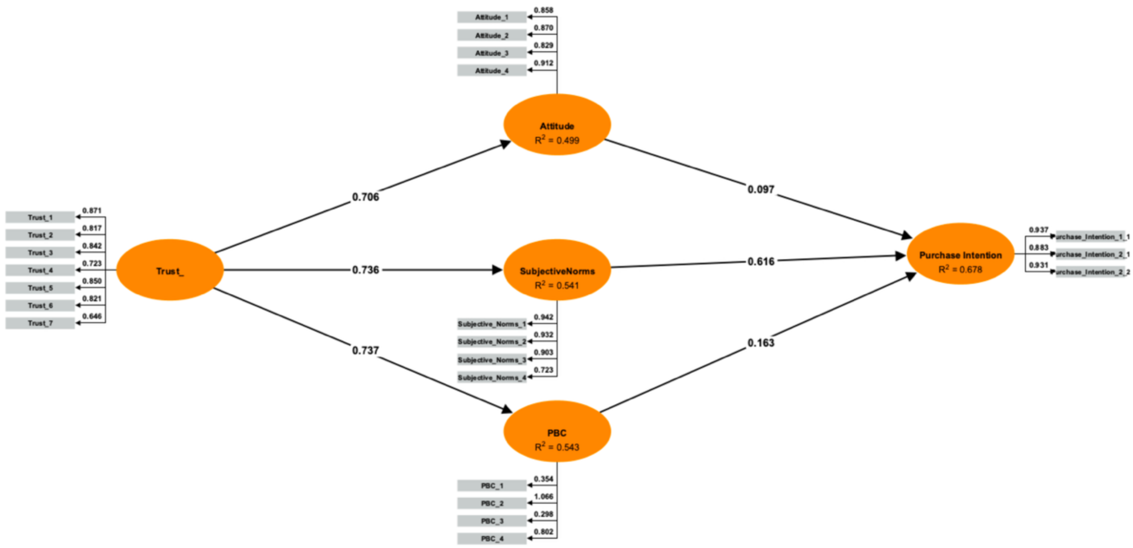
Cronbach's Alpha	N of Items
.800	4

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
PBC_1	13.12	17.328	.672	.722
PBC_2	14.35	18.281	.460	.829
PBC_3	12.99	18.896	.562	.773
PBC_4	13.72	15.188	.789	.656

Figure C1

PLS-SEM standardized outer loadings (initial run)



Note. Item PBC_2 displayed an inadmissible standardized loading above |1| (λ = 1.066). After PBC_2 was removed, PBC_4 rose to λ = 1.270, confirming multicollinearity; both indicators were deleted (Hair et al., 2021). Item TRUST 7 showed a sub-threshold loading of λ > .708 (λ = .646) and a low corrected item-total correlation, and its deletion raised the scale's Cronbach's alpha from .919 to .932, so it too was excluded from the final model.

Appendix D

Questionnaire

Dear participant, I appreciate your interest in this survey!   This survey is part of a master's thesis in Business Administration at Radboud University Nijmegen. This research aims to understand better how consumers respond to advertisements created using artificial intelligence (AI) and how this response is shaped by different factors that influence the purchasing intention of a specific product. While answering the questions, please reflect on your typical experiences with video advertisements, rather than focusing on one specific platform where you encounter ads or the specific product that will be shown. This helps us understand what we are interested in, which is, in general, how users think about this type of AI-based advertising. If your experience differs across platforms, please consider the platform(s) you use most often or feel most familiar with.

This survey will take around 5 to 10 minutes to complete. Participation is voluntary, and you may withdraw at any time. All responses are anonymous and confidential; your data will be solely used for academic purposes and stored securely in compliance with the Radboud University guidelines (see HERE). The data cannot be traced back to you. Your candid responses will help us understand how consumers evaluate AI-created ads and how this influences future purchase decisions, ultimately informing better advertising practices. If you have any questions, uncertainties, or concerns, please contact the researcher, Nils de Leeuw, at nils.deleeuw@ru.nl.

By clicking the "I agree to participate in this study" button below, you indicate that:
- You have read the information above.
- You consent to participating in the research study as described in the above information.
- You voluntarily agree to participate
- You understand that the research data will be available for at least 10 years for review and reuse in future scientific research.
- You agree that the data officer and designated data management staff of Radboud University may view your data.

○ I agree to participate in this study (1)

○ I do not agree to participate in this study (this ends the survey) (2)

Imagine you want to purchase a new water bottle within the next month. You will now watch a 30-second advertisement for such a product.

[VIDEO]

Remember: Please reflect on your typical experiences with video advertisements, rather than focusing on this specific product that will be shown. This helps us understand what we are interested in, which is, in general, how users think about this type of advertising. To ensure you watched the video, please select the color of the water bottle at the end of the advertisement below.

○ Red (1)

○ Blue (2)

○ Green (3)

○ Yellow (4)

Thank you for watching the video! Please answer the following questions about this advertisement on a scale from "Not at all" to "Completely".

	Not at all (1)	To a very small extent (2)	To a small extent (3)	To a moderate extent (4)	To a considerable extent (5)	To a great extent (6)	Completely (7)
To what extent do you believe this advertisement was generated by artificial intelligence? (1)	○	○	○	○	○	○	○

In this section, we look at your trust in the advertisement itself. We are interested in your judgment, not what you think others might assume. Remember: Please reflect on your experiences with these advertisements. You can always go back to rewatch the advertisement if needed. Please evaluate the following statements about your trust in this advertisement on a scale from "Strongly Disagree" to "Strongly Agree".

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
I am confident in the advertisement. (1)	○	○	○	○	○	○	○
The advertisement provides security. (15)	○	○	○	○	○	○	○
The advertisement has integrity. (16)	○	○	○	○	○	○	○
The advertisement is dependable. (17)	○	○	○	○	○	○	○
The advertisement is reliable. (18)	○	○	○	○	○	○	○
I can trust the advertisement. (19)	○	○	○	○	○	○	○
I am familiar with the advertisement (20)	○	○	○	○	○	○	○

This section gauges your overall evaluation of the action. We are interested in your view, not what you think others believe. Remember: Please reflect on your experiences with these advertisements. You can always go back to rewatch the advertisement if needed. Please evaluate the following statement about buying the water bottle you have just seen on the scale from the statement on the right to the statement on the left.

To buy this water bottle next month would be...

	1 (1)	2 (2)	3 (3)	4 (4)	5 (5)	6 (6)	7 (7)	
Unpleasant	○	○	○	○	○	○	○	Pleasent
Useless	○	○	○	○	○	○	○	Useful
Negative	○	○	○	○	○	○	○	Positive
Crazy	○	○	○	○	○	○	○	Wise

In the next section, we look at the social side: the degree to which you believe people approve or disapprove of you doing the action, and how much their opinions influence you. Remember: Please reflect on your experiences with these advertisements. You can always go back to rewatch the advertisement if needed. Please evaluate the following statements on a scale from "Strongly Disagree" to "Strongly Agree".

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
Most people who are important to me think I should purchase this water bottle. (1)	○	○	○	○	○	○	○
Most people who are important to me would want me to purchase this water bottle. (2)	○	○	○	○	○	○	○
People whose opinions I value would prefer that I purchase this water bottle. (3)	○	○	○	○	○	○	○
My friend’s positive opinion influences me to purchase this water bottle. (4)	○	○	○	○	○	○	○

The following section explores how easy or difficult you feel the action would be for you. It is about your sense of control, not the objective difficulty. Remember: Please reflect on your experiences with these advertisements. You can always go back to rewatch the advertisement if needed.

Please evaluate the following statements on a scale from "Strongly Disagree" to "Strongly Agree".

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
I believe I have the ability to purchase this water bottle. (1)	○	○	○	○	○	○	○
If it were entirely up to me, I am confident that I will purchase this water bottle. (2)	○	○	○	○	○	○	○
I see myself as capable of purchasing this water bottle. (3)	○	○	○	○	○	○	○
I have resources, time and willingness to purchase this water bottle. (4)	○	○	○	○	○	○	○

This next section explores your stated readiness or plan to act within a specified timeframe. It is the immediate mental step before action happens. Remember: Please reflect on your experiences with these advertisements. You can always go back to rewatch the advertisement if needed.   Please evaluate the following statements on a scale from "Strongly Disagree" to "Strongly Agree".

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
I intend to buy this water bottle within the next month. (1)	○	○	○	○	○	○	○

This next section focuses on the same subject but uses a different scale. Remember: Please reflect on your experiences with these advertisements. You can always go back to rewatch the advertisement if needed.   Please evaluate the following statements from "Extremely unlikely" to "Extremely likely".

	Extremely unlikely (1)	Moderately unlikely (2)	Slightly unlikely (3)	Neither likely nor unlikely (4)	Slightly likely (5)	Moderately likely (6)	Extremely likely (7)
How likely is it that you will form the intention to buy this water bottle within the next month? (1)	○	○	○	○	○	○	○
How likely is it that you will actually buy this water bottle within the next month? (2)	○	○	○	○	○	○	○

What is your age?

- < 18 (1)
- 18 - 25 (2)
- 26 - 35 (3)
- 36 - 45 (4)
- 46 - 55 (5)
- > 55 (6)

What is your gender?

- Male (1)
- Female (2)
- Non-binary/third gender (3)
- Prefer not to say (4)

What is your highest level of education?

- ○ No education completed (1)
- ○ Primary education (basisschool) (2)
- ○ Secondary education (voortgezet onderwijs) (3)
- ○ Vocational education (MBO) (4)
- ○ Bachelor's degree (HBO) (5)
- ○ Bachelor's degree (WO) (6)
- ○ Master's degree (WO) (7)
- ○ Doctorate (PhD) (8)

What is your current employment status?

- ○ Full-time job (1)
- ○ Part-time job (2)
- ○ Self-employed (3)
- ○ Student (4)
- ○ Unemployed (5)

What was your total household income (in euros) before taxes during the past 12 months?

○ < 15.000 (1)

○ 15.000 - 24.999 (2)

○ 25.000 – 34.999 (3)

○ 35.000 - 49.999 (4)

○ 50.000 – 74.999 (5)

○ 75.000 – 99.999 (6)

○ 100.000 – 149.000 (7)

○ > 150.000 (8)

○ Not applicable/unknown (9)