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Article

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Abstract

This study examines how consumers respond to personalized advertisements that appear to be derived from prior conversations with generative AI assistants in social commerce settings. Drawing on privacy calculus theory, trust theory, and the stimulus–organism–response framework, the study investigates whether GenAI-based advertising personalization simultaneously creates perceived personalization value and privacy concern, and how these evaluations shape algorithmic trust and social commerce purchase intention. A scenario-based survey was conducted with 435 social commerce users in Jordan. Respondents evaluated a situation in which a product advertisement appeared to match a previous conversation with a generative AI assistant. The data were analyzed using partial least squares structural equation modeling with SmartPLS 4. The findings show that perceived GenAI-based advertising personalization increases both perceived personalization value and privacy concern. Personalization value strengthens algorithmic trust, whereas privacy concern weakens it. Algorithmic trust, in turn, strongly enhances social commerce purchase intention. The mediation results confirm that personalization value and privacy concern explain the dual effect of GenAI-based advertising personalization on algorithmic trust. In contrast, algorithmic trust transmits these effects to purchase intention. Transparency disclosure does not significantly reduce privacy concern, but it strengthens the positive relationship between personalization value and algorithmic trust. The study contributes to digital marketing and social commerce research by showing that conversational-AI-derived advertising data can be perceived as both useful and intrusive. That transparency may support trust formation without necessarily eliminating privacy concerns.

Keywords: generative AI; GenAI-based advertising personalization; algorithmic trust; privacy calculus; transparency disclosure; social commerce; purchase intention; Jordan

1. Introduction

Digital marketing is entering a new phase in which consumer conversations, data analytics, and personalized advertising are becoming increasingly intertwined. In earlier forms of digital personalization, marketers mainly relied on observable behavioral traces, such as browsing history, clicks, searches, purchases, and social media interactions. Generative artificial intelligence changes this logic by introducing conversational data as a potentially rich source of advertising personalization. Through interactions with AI assistants, consumers may reveal preferences, intentions, doubts, financial constraints, emotional concerns, and purchase-related goals. However, consumers may not always recognize that such conversational inputs can become signals for personalized advertising.

This shift creates a different kind of personalization problem. Consumers are no longer profiled only through passive digital traces; they may also be profiled through active dialogue with AI systems. A person who asks an AI assistant for advice about a product may later see an advertisement that appears to reflect that conversation. In some cases, this may feel helpful because the

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advertisement is relevant and timely. In other cases, it may feel intrusive because the consumer realizes that a private or semi-private interaction may have been used for commercial purposes.

Research in marketing has shown that artificial intelligence is reshaping customer experience, advertising, personalization, content creation, and consumer engagement. AI can support prediction, automation, customer understanding, and personalized interaction (Davenport et al., 2020; Huang & Rust, 2021). Generative AI extends these capabilities because it can create adaptive content, support conversational interaction, generate marketing messages, and personalize communication using richer consumer inputs (Kshetri et al., 2024; Chan & Choi, 2025; Grewal et al., 2025; Hermann & Puntoni, 2024). Unlike earlier predictive systems, GenAI can respond to consumers' expressed needs in real time and produce individualized messages that appear closely aligned with their goals or decision context. This can increase the perceived usefulness of advertising, but it also raises concerns about privacy, surveillance, consumer vulnerability, data control, and the commercial use of conversational information (Duivenvoorde, 2025).

The issue is especially relevant in social commerce. Social commerce platforms combine social interaction, recommendations, user-generated content, influencer communication, advertising, and purchasing in one environment. Consumers often rely on platform cues, peer opinions, seller credibility, social proof, and algorithmically curated recommendations when forming purchase intentions (Wang et al., 2022). As GenAI becomes part of these platforms, AI systems may operate as assistants, recommenders, content generators, and advertising tools at the same time. This makes consumer evaluation more complex. A personalized advertisement may be judged not only by its relevance, but also by the way the platform appears to use AI-generated or AI-mediated data.

Prior research has examined AI-powered personalization, privacy concerns, algorithmic trust, and purchase intention in digital and social commerce. However, most existing studies focus on personalization based on behavioral, transactional, demographic, or platform-generated data. Research on the personalization–privacy paradox shows that consumers may appreciate relevant personalization while resisting the data collection practices behind it (Aguirre et al., 2015; Martin & Murphy, 2017; Martin et al., 2020). Yet relatively little is known about how consumers respond when they believe that their conversations with generative AI assistants are used as advertising data. This distinction matters because conversational data can feel more personal and intentional than ordinary behavioral traces. A click or search query may reveal interest, but a conversation with an AI assistant may reveal reasons, doubts, limitations, and plans.

Despite growing research on AI-based personalization, privacy concerns, algorithmic trust, and social commerce, limited attention has been paid to advertising personalization that is perceived to originate from consumers' conversations with generative AI assistants. This distinction is theoretically important because conversational data may contain not only behavioral signals but also context-rich and intention-revealing information, including consumers' goals, doubts, constraints, emotions, and plans. As a result, GenAI-conversation-derived advertising personalization may intensify both the perceived value and the perceived intrusiveness of personalization. Understanding this dual response is therefore essential for explaining how consumers evaluate personalized advertising when AI conversations appear to become advertising data.

This study attempts to bridge this gap by developing and testing a conceptual model of GenAI-driven advertising personalization in social commerce empirically. Specifically, drawing from Privacy Calculus Theory, Trust Theory, and the Stimulus–Organism–Response theory, the model suggests that GenAI-personalized advertisements will trigger two simultaneous evaluative responses. Firstly, personalization value could emerge as the degree of relevance and usefulness of the advertisement rises. Secondly, privacy concern would be experienced due to the implication that users' data obtained in AI conversations were gathered, analyzed, and monetized. Such evaluations would then determine algorithmic trust, which would in turn affect purchase intention in social commerce.

Furthermore, this study examines the effect of transparency disclosures as a potential boundary condition. While transparency has often been suggested as a possible solution to address privacy

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concerns about AI algorithms and data uses, there might be some non-trivial consequences. For instance, transparency could help consumers better understand how personalization was conducted using artificial intelligence and why this specific advertisement is served to them. On the other hand, disclosure would make it more apparent how the data collected in AI conversations were commercialized. Thus, the study intends to test whether the association between GenAI-personalized advertisements and privacy concern would weaken through the mediation of transparency disclosure, as well as how such transparency affects the association between personalization value and algorithmic trust.

Jordan emerges as an appropriate context for the investigation. It represents a relatively new Arab digital market, where people are actively engaged in social media, and digital commerce activities are rapidly expanding. Moreover, at present, GenAI marketing, privacy calculus, algorithmic trust, and AI-driven social commerce receive little attention in Arab emerging economies. Analyzing Jordan as an appropriate environment would thus contribute to the literature that predominantly focuses on Western countries and large Asian economies, providing insight into the conditions under which expectations of consumers towards AI technologies, privacy, transparency, and digital trust could vary.

Four key contributions arise from this study. Firstly, the extension of Privacy Calculus Theory to conversational-AI data, which links personalization to the interactive human-AI dialogue and not only behavioral data tracking. Secondly, algorithmic trust research could benefit from demonstrating the way in which personalization and privacy influence algorithmic trust. Thirdly, social commerce literature would gain insights into the influence of GenAI advertising personalization on purchase intention in emerging Arab markets. Finally, transparency disclosure would become better understood due to the exploration of how such transparency affects privacy concern and personalization.

2. Literature Review and Theoretical Background

2.1. GenAI-Based Advertising Personalization

AI has always supported digital marketing through prediction, segmentation, targeting, recommendation, and optimization. Behavioral data were initially used for AI-enabled personalization, which included clicks, browsing behavior, ratings, purchase behavior, and social media interaction. AI has been identified as an important strategic marketing technology tool that improves customer insights, automation, data-driven decisions, and personalized interactions (Davenport et al., 2020; Huang & Rust, 2021). In advertising, AI supports targeting, tailoring messages, media planning, and personalized content along the customer journey (Kietzmann et al., 2018; Kumar et al., 2019).

GenAI extends this perspective by using natural language interaction, contextual cues, and conversations to produce individualized responses and marketing content (Kshetri et al., 2024; Hermann & Puntoni, 2024; Grewal et al., 2025). Unlike traditional personalization, GenAI-driven advertising may be based on consumers' explicit conversations with AI assistants about their requirements, preferences, budget, and purchase problems. Thus, advertisements could become more relevant, timely, and valuable, thus saving searching efforts and making purchasing decisions more convenient (An & Ngo, 2025; Kumar et al., 2019). However, it is also associated with privacy concerns since the conversational data that increase the effectiveness of personalized advertising could show consumers that AI assistants record and infer from their conversations or use them commercially. Since these conversations could include intentions, limitations, uncertainty, emotions, and consumer preferences, GenAI-based personalized advertising represents a more sensitive case than regular digital advertising.

2.2. Privacy Calculus and the Personalization–Privacy Tension

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The Privacy Calculus Theory explains the behavior of consumers with regard to personalized digital interactions based on balancing anticipated benefits against privacy threats. As consumers, people may be motivated by personalized and convenient interactions on one side, but be reluctant to information gathering, profiling, and ambiguous targeting practices, for instance. As a result, a personalization vs. privacy trade-off is observed, in which relevance is appreciated despite being associated with privacy issues (Aguirre et al., 2015; Martin & Murphy, 2017; Martin et al., 2020; Cloarec et al., 2024; McKee et al., 2024).

Privacy threats in personalized advertising are associated with the impression that the platform is a service gathering too much information about users, making inferences about the sensitivity of information gathered, and using it for some purposes without a user's permission, etc. Typically, information privacy concerns are associated with personal information gathering and control as well as the knowledge of how information is utilized (Malhotra et al., 2004). Research studies in marketing also show that privacy has an impact on the consumer-trust relationship with organizations (Martin & Murphy, 2017; Martin et al., 2020). When it comes to digital media and advertising, such aspects as information intrusiveness, consumer-control perceptions, relations between consumer and brand, and appropriateness of information use also contribute to privacy evaluations (Boerman et al., 2023; Hayes et al., 2021).

When it comes to personalization based on GenAI conversation, privacy issues are amplified since more information can be disclosed in the process. People's interests, uncertainties, financial difficulties, personal issues, and plans can be revealed during conversation. Therefore, the current study will view perceived personalization value and privacy concern as separate consumer responses to GenAI advertising personalization. The former refers to the consumer benefits of personalization, while the latter implies consumers' discomfort with privacy and perceived lack of control.

2.3. Algorithmic Trust in GenAI-Personalized Social Commerce

Trust plays an important part in social commerce, since consumers decide whether to buy or not under conditions of uncertainty. Such conditions include, but are not limited to, the behavior of sellers and platforms themselves, as well as the operation of algorithms responsible for the curation of content, product recommendations, advertisement placement, seller ranking, and consumer purchase journey. The significance of trust in social commerce purchase intention is confirmed in the literature review (Wang et al., 2022). In an era of AI, algorithmic trust becomes increasingly important.

Algorithmic trust refers to consumers' willingness to engage with algorithmic systems through perceptions of their competence, reliability, usefulness, fairness, and trustworthiness. Consumer acceptance of algorithmic judgment is determined by its usefulness, appropriateness, legitimacy, and capability to enhance consumers' decision quality (Puntoni et al., 2021; Longoni & Cian, 2022; Yalcin et al., 2022). People will accept an algorithm if it can be seen as helpful, while resistance to it emerges if the use of algorithmic systems is seen as potentially harmful to their interests (Logg et al., 2019; Puntoni et al., 2021).

GenAI's ability to personalize advertising implies that algorithmic trust is influenced by consumers' perceptions of personalization as being helpful or intrusive. While helpful personalization is likely to increase trust by signaling the platform's understanding of consumer needs, privacy concerns may undermine algorithmic trust because of the impression that the consumer is being used for the purposes of the platform. In other words, the current study sees algorithmic trust as the key mediator of the relationship between personalization value/privacy concern and purchase intention.

2.4. Transparency Disclosure as a Boundary Condition

Transparency disclosures have been suggested as a way of improving consumers' knowledge about the role of AI and the use of data in the process, as well as in advertising personalization. Transparency and explainability could help alleviate the uncertainty by shedding light on the

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functioning of the algorithm, its decisions, and the ways in which consumers' data are utilized (Shin, 2021; Larsson, 2020). In terms of advertising, disclosure could aid consumers in comprehending the reason behind a particular message and the algorithmic processes involved in the creation of the advertising experience (Baek et al., 2024; Grigsby et al., 2025).

However, transparency does not necessarily lead to positive outcomes. Transparency associated with the use of AI could exacerbate the level of skepticism, undermine the authenticity, and decrease trust when algorithmic involvement becomes more noticeable (Brüns & Meißner, 2024; Grigsby et al., 2025; Schilke & Reimann, 2025). The problem arises because disclosing information about the use of AI in the process of creating ads would mean that consumers will be reminded that their conversation is being used for commercial purposes. In regard to protecting consumers, there could be several risks related to GenAI marketing, including personalization, persuasion, vulnerability, and the use of conversational data (Duivenvoorde, 2025).

Thus, transparency is conceived of as a boundary condition in the current research. On the one hand, transparency could disrupt the link between GenAI-based personalization and privacy concern because of increased control and awareness of consumers. On the other hand, it could intensify the connection between the value of personalization and algorithmic trust.

2.5. Theoretical Integration and Study Positioning

The suggested model integrates the Privacy Calculus Theory, Trust Theory, and the Stimulus-Organism-Response (SOR) approach. GenAI-based perceived advertising personalization serves as a stimulus. Value and privacy are considered the organism's perceptions, thus accounting for the positive and negative sides of privacy calculus. The psychological concept of algorithmic trust bridges evaluations of personalization and privacy and represents a response. Transparency disclosure is considered a potential moderating factor that can affect privacy and trust constructs.

The significance of the research includes explaining the psychological mechanism behind the impact of GenAI-based personalized advertising on purchase intention, taking into account its dual value-privacy nature. The paper also explains how algorithmic trust arises out of personalization value and privacy concerns. Even though prior literature explores the topics of AI-based personalization, privacy, trust, transparency disclosure, and social commerce individually, the relationship between these aspects when AI-generated communication serves as advertising data is not studied sufficiently.

3. Conceptual Framework and Hypotheses Development

A conceptual framework is proposed in this research for understanding the impact of GenAI-based personalized advertising on purchase intentions in social commerce. Based on Privacy Calculus Theory, Trust Theory, and the Stimulus–Organism–Response model, the proposed conceptual framework proposes GenAI-based personalized advertising as a stimulus, which results in two types of evaluations: perceived value from personalization and privacy concerns. The former refers to the benefits, while the latter refers to risks in the privacy calculus. Algorithmic trust is suggested to be the mediating variable between both evaluations and social commerce purchase intention.

3.1. GenAI-Based Advertising Personalization and Perceived Personalization Value

Personalized advertising is considered valuable when consumers feel it is relevant, useful, timely, and consistent with their needs. Personalized advertising in digital marketing might help reduce information overload, facilitate decision convenience, and enhance advertising relevance. Based on the current literature on the positive impact of personalized advertisements on consumer satisfaction, which are generated using AI tools (An & Ngo, 2025), it might be possible that GenAI advertising might have even greater value.

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This idea is supported by the fact that it is based on the analysis of richer input data, namely, conversations, rather than just clicks, browsing behavior, and purchasing habits. Consumers who communicate with AI assistants about their needs, preferences, budget, concerns, and decision intentions might get a feeling of increased personal relevance and usefulness of advertisements appearing after such a conversation. As a result:

H1: Perceived GenAI-based advertising personalization positively influences perceived personalization value.

3.2. GenAI-Based Advertising Personalization and Privacy Concern

Personalized services created through Generative AI could create value, but they might also pose privacy threats. Personalized advertising is an area where people usually feel fear when they believe that personalization means that platforms know everything about them or use data that exceeds their expectations and control (Boerman et al., 2023; Cloarec et al., 2024; Hayes et al., 2021). This threat seems even more likely to occur when personalization is done based on AI-mediated communication, not regular behavioral data. Communication with AI assistants can expose people's tastes, requirements, emotions, economic limitations, personal issues, and future intentions. Although such advertisements may be useful, consumers may feel uneasy when they realize that their AI-assisted conversations have been transformed into advertising data. Hence, GenAI-based personalized advertisements could be both beneficial and invasive. Thus:

H2: Perceived GenAI-based advertising personalization positively influences privacy concern.

3.3. Perceived Personalization Value and Algorithmic Trust

Algorithmic trust refers to the consumers' trust in the capability, reliability, usefulness, and appropriateness of an algorithmic system. In the case of AI-based social commerce, consumers depend on the algorithmic system for product recommendation, advertisement personalization, ranking, and buying assistance. Since consumers are unable to see how the system operates, trustworthiness becomes crucial.

Perceived personalization value may increase the level of algorithmic trust since it demonstrates that the AI system embedded in the platform recognizes consumers' needs and assists them meaningfully by offering relevant personalization. Based on earlier findings in consumer experiences in AI-based social commerce, consumers are likely to develop more trust towards the AI systems if they find them useful, reliable, and competent in improving their decision-making process (Ameen et al., 2021; Teodorescu et al., 2023). Therefore:

H3: Perceived personalization value positively influences algorithmic trust.

3.4. Privacy Concern and Algorithmic Trust

Privacy-related issues will be expected to weaken trust because they suggest vulnerability in the consumer-platform transaction relationship. Trust becomes hard to maintain when consumers feel that the platform gathers or uses personal information in an invasive, unclear, or inappropriate manner. Regarding personalized social commerce based on GenAI technology, consumers will consider the motives behind the use of AI interactions for advertising purposes when there is insufficient information available and no consumer control. Moreover, the use of sensitive conversational data in the personalization process can render the algorithm unfair, less transparent, and less consumer-focused. In accordance with Trust Theory, risk perceptions and vulnerabilities can lead to decreased trust when consumers do not see the exchange partner as reliable, benevolent, or credible.

H4: Privacy concern negatively influences algorithmic trust.

3.5. Algorithmic Trust and Social Commerce Purchase Intention

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Trust is a key driver of purchase intention in social commerce because consumers make decisions in an environment shaped by seller interactions, user-generated content, social proof, influencer communication, platform recommendations, and algorithmically curated advertisements. Prior social commerce research shows that trust is central to purchase intention, especially when consumers rely on platform-based cues and recommendation mechanisms (Wang et al., 2022).

Algorithmic trust can increase purchase intention by reducing uncertainty and increasing consumers' willingness to rely on AI-personalized advertisements and recommendations. When consumers trust the platform's algorithmic system, they are more likely to view personalized advertisements as credible, relevant, and useful, which can encourage product consideration and purchase. Therefore:

H5: Algorithmic trust positively influences social commerce purchase intention.

3.6. The Mediating Role of Perceived Personalization Value

The influence of GenAI-driven personalized advertising in terms of algorithmic trust is not expected to emerge spontaneously. Consumers are expected to judge whether the personalized ad adds any value before building trust. In situations where GenAI-driven personalized ads are considered valuable and helpful to consumers, people could attribute more competence and support intention to the algorithmic system behind them. This is in line with the value-based route of the privacy calculus approach, which suggests that personalization improves trust through value. Therefore:

H6: Perceived personalization value mediates the relationship between perceived GenAI-based advertising personalization and algorithmic trust.

3.7. The Mediating Role of Privacy Concern

AI-powered advertising personalization might impact algorithmic trust through issues related to privacy. If consumers feel like their ads are personalized through information collected during AI-conversation sessions, they might wonder how the information was being used, understood, and sold. As a result, they might lose trust in the algorithmic mechanism used by the platform. In other words, such an instance might represent a privacy calculus risk path, since personalization might undermine the trust consumers have in the algorithmic platform due to issues surrounding privacy. Therefore:

H7: H7: Privacy concern mediates the relationship between perceived GenAI-based advertising personalization and algorithmic trust, such that the indirect effect is negative.

3.8. The Mediating Role of Algorithmic Trust

Algorithmic trust is theorized to be the mediator that affects both the effects of perceived personalization value and privacy concerns on social commerce purchase intention. If individuals find GenAI-personalized advertisements valuable, they might have more trust in the algorithm used by the platform and, thus, increase their intention to make purchases through the social commerce platform. On the other hand, if individuals have high levels of privacy concern, their purchase intention will likely be decreased because of their reduced trust in the algorithms of the platform. Based on S-O-R Therefore:

H8a: Algorithmic trust mediates the relationship between perceived personalization value and social commerce purchase intention.

H8b: H8b: Algorithmic trust mediates the relationship between privacy concern and social commerce purchase intention, such that the indirect effect is negative.

3.9. The Moderating Role of Transparency Disclosure

Transparency disclosure is often suggested to help increase consumers' awareness regarding AI utilization, data processing, and advertising personalization. Transparency could reduce uncertainty

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by providing consumers with clarity about the way AI systems function and how consumer data can be used. Explainable AI literature suggests that consumers' trust and acceptance would grow due to algorithmic processes becoming comprehensible and justified (Shin, 2021). Similarly, disclosure would assist consumers in understanding the reasons for the presentation of a certain message and the role of algorithmic systems in advertisement delivery (Baek et al., 2024; Grigsby et al., 2025).

However, transparency does not necessarily bring about a positive effect. AI transparency could lead to greater suspicion, decrease perceptions of genuineness, or make the presence of an algorithm more prominent (Brüns & Meißner, 2024; Grigsby et al., 2025; Schilke & Reimann, 2025). In the context of discussion on the use of conversation data generated by artificial intelligence in advertising personalization, the above statement acquires a particular meaning. Although transparency disclosure could provide clarification in regard to data usage, it may also serve as a reminder that conversations are being commodified. Similarly, consumer protection literature stresses that issues of GenAI-based marketing include, inter alia, the need for proper disclosure, addressing consumers' vulnerabilities, persuasive strategies, and empowerment (Duivenvoorde, 2025).

Despite this complexity, improved transparency disclosure could reduce privacy concerns in GenAI-based advertising personalization because it could decrease uncertainty and promote control perceptions. Therefore:

H9: Transparency disclosure moderates the relationship between perceived GenAI-based advertising personalization and privacy concern, such that the positive relationship is weaker when transparency disclosure is high.

Transparency disclosure may also strengthen the relationship between perceived personalization value and algorithmic trust. When consumers perceive GenAI-personalized advertising as valuable, transparency may help them interpret this value as the result of a reliable and understandable algorithmic system rather than hidden surveillance or manipulation. Trust in algorithmic systems is shaped not only by usefulness, but also by whether the system's role is perceived as appropriate, explainable, and legitimate (Puntoni et al., 2021; Shin, 2021; Yalcin et al., 2022). Therefore:

H10: H10: Perceived transparency disclosure moderates the relationship between perceived personalization value and algorithmic trust, such that the relationship is stronger when perceived transparency disclosure is high.

3.10. Proposed Conceptual Model

The proposed model explains social commerce purchase intention through a dual-path privacy calculus mechanism. Perceived GenAI-based advertising personalization is expected to increase both perceived personalization value and privacy concern. Personalization value represents the benefit side and is expected to strengthen algorithmic trust, while privacy concern represents the risk side and is expected to weaken it. Algorithmic trust then serves as the key mechanism through which these evaluations shape social commerce purchase intention.

Transparency disclosure is positioned as a boundary condition. It is expected to weaken the effect of GenAI-based advertising personalization on privacy concern and strengthen the effect of perceived personalization value on algorithmic trust. Together, these relationships explain how GenAI-personalized advertising value creation can be simultaneously privacy-threatening, trust-shaping, and purchase-relevant in social commerce.

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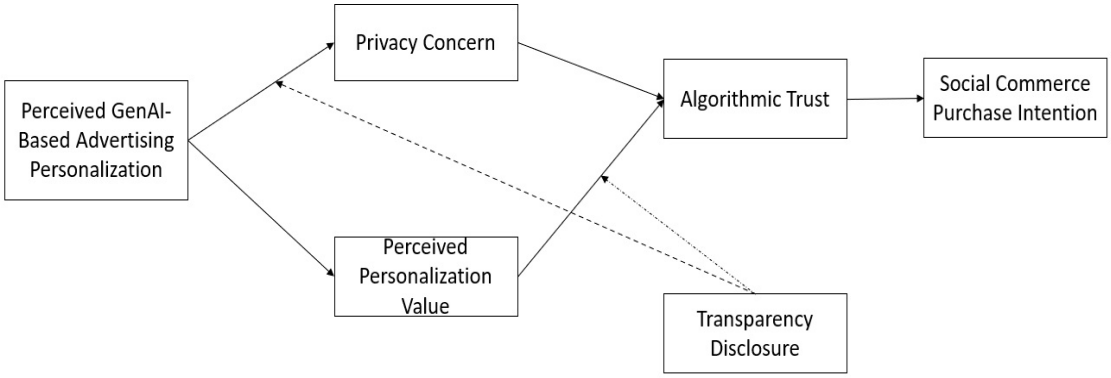

Figure 1. Proposed Conceptual Model.

4. Methodology

4.1. Research Design

This research utilized a quantitative design using the scenario method to explore consumer behavior regarding GenAI-generated advertisement personalization in social commerce. Quantitative analysis was suitable for testing relationships among latent variables such as GenAI-based advertising personalization, perceived personalization value, privacy concern, algorithmic trust, transparency disclosure, and social commerce purchase intention. Since the proposed model includes direct, indirect, and interaction effects among the variables, the use of a survey would allow collecting standard data for model testing via structural equation modeling.

The scenario approach was appropriate because GenAI-based advertising personalization is still an emerging concept that all consumers may not equally experience. The scenario helped provide a basis for measurement after the respondents were asked about their perceptions and behavioral intentions related to GenAI-conversation advertising personalization. Transparency disclosure was considered a moderating variable in terms of perception rather than an experimental one because this study examined how informative and understandable disclosures were perceived by consumers.

4.2. Scenario Development and Procedure

The scenario represents a practical example of social commerce, which involves the use of a generative AI assistant and a personalized advertisement. The participants were asked to imagine themselves using an AI assistant on a social media website to get help with making decisions about the products they want to purchase. In turn, they explained to the AI assistant what their preferences, budget, and requirements were. Afterward, when browsing the same website, they were faced with an advertisement that resembled the previous dialogue with the AI assistant.

The scenario was framed as follows:

Imagine that you are using a social media website that contains a generative AI assistant. You ask the assistant for help in making decisions about the products that you would like to purchase. You tell the assistant your preferences, budget, and requirements. Later, while browsing the same social media website, you come across an advertisement for a product that resembles the topics you have discussed with the AI assistant.

Afterward, the participants were asked to evaluate several constructs, such as the degree of perceived personalization of the advertisement, its value, issues related to privacy, trust in the algorithm, perception of transparency, and purchase intention. It was also important to check whether respondents fully understood the scenario and the connection between the advertisement and the AI assistant.

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4.3. Population and Sampling

The target group for the study included Jordanian social commerce users who regularly interacted on social media sites and had prior experience with e-commerce transactions or an intention to make purchases on social platforms. The choice of Jordan was based on its status as a developing country in the Arab region that demonstrates high social media usage, growth in digital commerce, and familiarity with AI-enhanced platforms. Moreover, Arab emerging economies continue to be less studied in relation to GenAI marketing strategies, privacy calculus theory, algorithmic trust building, and AI-driven social commerce.

The selection of participants involved using a purposive sampling method, ensuring that the sample would be able to assess the hypothetical situation. The inclusion criteria were living in Jordan, having active accounts on social media websites, past purchases or intention to purchase from these platforms, and some knowledge about AI-based products like ChatGPT, Gemini, Copilot, Meta AI, or similar AI tools.

4.4. Sample Size and Respondent Profile

Following the screening process and data cleaning, a total of 435 valid answers remained. Ineligible responses included those that were incomplete, did not pass the screening process, did not meet attention control tests, contained straight-lining patterns, exhibited careless filling, and had unreasonably short answer times. Sample size was considered sufficient for the planned PLS-SEM model based on the inclusion of several latent constructs, mediating effects, and moderation processes.

Sample adequacy was assessed based on modern recommendations in PLS-SEM practice, which stress that researchers should consider model complexity, estimated effect sizes, power analysis, and the most complex structural relations, instead of relying on simple guidelines like the 10-times rule (Hair et al., 2022; Hair et al., 2024). Variables measured at the demographic level included gender, age, educational attainment, use of social media, frequency of online purchases, social commerce experience, and AI awareness.

4.5. Questionnaire Development and Measures

Questionnaire development started with adapting previously used and validated scales according to the current topic of personalizing GenAI-based advertising in social commerce. Following the process of translation and back-translation of the original version into Arabic, academic reviewers knowledgeable about marketing, online consumer behavior, and measurement instruments have confirmed its validity, consistency, and relevance. Phrasing revisions were made based on their feedback before launching the study survey.

In terms of questionnaire structure, the developed instrument consisted of a series of screener questions, the scenario, measurement questions, a marker variable, control variables, and demographic questions. Every construct was reflective and was operationalized by means of multi-item scales on a 7-point Likert scale (1 = strongly disagree, 7 = strongly agree). For the present study, six concepts were measured: GenAI-based perceived advertising personalization, personalization value, privacy concern, algorithmic trust, transparency disclosure, and social commerce purchase intention (Appendix A).

The privacy concern scale was based on previous research regarding digital advertising privacy and information privacy concerns, focusing on collection, control, and awareness issues (Malhotra et al., 2004; Martin & Murphy, 2017; Hayes et al., 2021; Cloarec et al., 2024). The algorithmic trust scale measured respondents' confidence in GenAI-based advertising, taking into account usefulness, competence, reliability, and appropriateness of algorithmic decision-making (Ameen et al., 2021; Puntoni et al., 2021; Teodorescu et al., 2023; Yalcin et al., 2022). The transparency disclosure scale was related to the clarity, understandability, and informativeness of AI-based data use (Shin, 2021; Baek et al., 2024; Grigsby et al., 2025; Schilke & Reimann, 2025).

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A marker variable measuring preference for interface appearance was added as a way to detect potential problems with common method variance. It did not relate to any of the constructs studied and had only instrumental meaning.

4.6. Pilot Study

A pilot study that included 50 individuals representing the target population was carried out ahead of the primary data collection. Issues that were assessed during the pilot were whether the scenario was clear, the wording used, the time required to complete it, its relation to social commerce, and context-appropriateness. The pilot also served to evaluate the realism and understanding of the situation by asking individuals whether they understood and found the scenario realistic within the context of today's social media, AI assistants, and personalized advertisements. Pilot results revealed that the respondents understood the scenario and found it relevant.

4.7. Data Collection Procedure and Ethical Considerations

The data were obtained using an online survey conducted among Jordanian users of social commerce who use social media and social commerce platforms. It was suitable to collect data using the web because the research focused on digital consumer behavior and aimed to gather data from those who use social media and online commerce platforms actively. Participation in the survey was voluntary, confidential, and anonymous. Before participants started completing the questionnaire, they were informed about the research objectives, the approximate duration of the survey, the fictional situation provided in the survey, and the right to drop out. The questionnaire did not ask participants for their personal identification, such as name, telephone number, or email address. Due to the use of AI and issues related to privacy and advertising, participants were informed that no real AI conversation data were collected, and their answers would be used for academic purposes only.

4.8. Common Method Bias

Since the study involved self-reports, common method variance was addressed through procedural and statistical measures. First, respondents were assured of anonymity and confidentiality; clear language was used on the survey; Clear instructions separated the scenario and measurement items, and respondents were reminded that there were no right or wrong answers; respondents' attention and understanding were checked; and the order of constructs was set up such that respondents could not easily infer the proposed relationships.

Second, common method variance was measured using Harman's single-factor test, full collinearity variance inflation factors, and the marker-variable technique. The marker variable was correlated with the endogenous constructs to see whether it explained any unique variance. The lack of correlation between the marker variable and the endogenous variables, no change in R^2, and no alteration in the path coefficients were taken as signs that common method variance would not affect the findings significantly.

4.9. Data Analysis Technique

The data analysis process involved the use of Partial Least Squares Structural Equation Modeling (PLS-SEM), implemented in SmartPLS 4. This choice of analysis method was justifiable considering that the prediction-focused model involved several latent constructs and explored direct, mediated, and moderated relationships in an emerging research context.

Here are the steps in the analytical process. Firstly, the data set was screened for any missing values, careless responses, straightlining, outliers, and unusual response patterns. Secondly, the descriptive statistics and respondent demographics were reported. Thirdly, the reflective measurement model was validated with regard to indicator loadings, reliability, convergent validity, and discriminant validity. It was expected that the loading factor would be greater than 0.708, the

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composite reliability would exceed 0.70, and the average variance extracted (AVE) would exceed 0.50. Discriminant validity was tested using the heterotrait-monotrait (HTMT) ratio.

Finally, the structural model was validated by checking for collinearity, path coefficient values, R^2, f^2, Q^2, and predictive performance. Both direct and indirect relationships were established through bootstrapping analysis using 10,000 subsamples. Mediation was tested by analyzing bootstrapped confidence intervals for indirect effects, while moderation was examined using interaction terms in SmartPLS. Predictive performance was validated using PLSpredict.

4.10. Robustness Checks

Robustness tests were also conducted. Nonresponse bias was checked through comparisons made between early and late respondents. Results were tested by conducting a regression after excluding careless answers to check their stability. Control variables such as age, gender, education, frequency of social media usage, online shopping behavior, experiences of social commerce, and knowledge of AI were considered to see if the relationships proposed still hold true. Common method variance was also examined via the marker-variable approach and collinearity statistics.

The base model was also compared with the marker-variable model. When there is no meaningful change in R^2 values and when it does not influence the strength and/or direction of the path between key variables, the results were considered robust.

5. Results

5.1. Data Screening and Descriptive Statistics

Partial least squares structural equation modeling (PLS-SEM) was adopted via the use of SmartPLS 4 to analyze the research model being developed. It is reasonable to adopt PLS-SEM considering the fact that it involves a number of reflective constructs, direct relationships, mediation processes, and moderation effects. At the same time, the study aims to explain and predict purchase intentions in the emerging social commerce setting where ads can be personalized based on GenAI conversations. A two-step process of analysis, according to which (1) the measurement model is evaluated for reliability and validity and (2) the structural model is analyzed to test direct, indirect, and moderation relationships, has been followed (Hair et al., 2022; Hair et al., 2024).

Pre-analysis procedures included a missing values check, incomplete cases detection, failed screening, failed attention check, straight-lining, careless responding, and unrealistically fast response time check. After pre-processing, 435 valid responses were obtained and retained for subsequent data analysis. Such a sample size can adequately estimate a fairly complex PLS-SEM model involving a number of predictors and mediators as well as interaction terms.

Results of descriptive analysis suggest that respondents assessed the constructs involved in the research model quite moderately. The mean values varied between 3.997 and 4.133, meaning that respondents were neither very positive about nor very negative about the use of AI-conversations for personalized ad purposes. Such an attitude is reasonable in a scenario-type investigation of a potentially controversial topic like that. Privacy concern received the highest mean rating, indicating high importance of this aspect. Standard deviation values varied between 0.934 and 1.058. They indicate good variability among responses for estimation. Both skewness and excess kurtosis of variables are relatively low.

Table 1. Descriptive statistics.

Construct	Mean	Median	Standard deviation	Excess kurtosis	Skewness
AT	3.998	4.000	1.012	-0.360	0.237
PGBA-P	4.004	4.009	0.984	-0.557	-0.085
PC	4.133	4.180	0.934	-0.418	-0.119
PPV	4.021	4.000	1.013	-0.838	0.042
SCPI	4.037	4.000	0.980	-0.448	0.155

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TD	3.997	3.903	1.058	-0.817	0.161

5.2. Common Method Bias

Since data were obtained through a single self-reported survey instrument, procedural and statistical solutions have been used to mitigate common method variance. As part of the procedural solution, anonymity and confidentiality assurances were made to minimize concerns about evaluation apprehension and socially desirable responses. The survey instrument used straightforward wording, included attention checks and comprehension checks, and separated the scenario from the measures. The constructs were also ordered such that the respondents would not be able to infer the proposed relationships among them.

The marker variable procedure was used as a statistical solution to common method variance. The marker variable, which is not theoretically related to the research constructs, was used only for diagnostic purposes and was correlated with privacy concern, perceived personalization value, algorithmic trust, and social commerce purchase intention. The analysis showed that adding the marker variable did not substantially increase the explained variances in the endogenous constructs. Privacy concern, for example, showed an increase in R^2 of only 0.004 (0.053 to 0.057), while perceived personalization value and algorithmic trust remained constant at 0.234 and 0.293, respectively. Social commerce purchase intention showed a slight increase of 0.002 (0.328 to 0.330). Such a small change in variance (below the ΔR^2 of 0.10) indicates that the method variance did not appreciably increase the variance in the model.

The structural paths also remained stable after the marker variable was included. The effect of perceived GenAI-based advertising personalization on perceived personalization value remained $\beta = 0.484$, $p < 0.001$. The negative effect of privacy concern on algorithmic trust remained $\beta = -0.330$, $p < 0.001$. The effect of algorithmic trust on social commerce purchase intention changed only marginally from $\beta = 0.573$ to $\beta = 0.572$. The indirect and moderating effects also remained substantively stable. Therefore, common method bias was unlikely to represent a serious threat to the validity of the findings.

Table 2. R^2 values of the baseline and marker-adjusted models.

Endogenous construct	Baseline model	Marker-adjusted model
PC	0.053	0.057
PPV	0.234	0.234
AT	0.293	0.293
SCPI	0.328	0.330

Table 3. Path coefficients and significance of the baseline and marker-adjusted models.

Relationship	Baseline model β	Baseline p-value	Marker-adjusted model β	Marker-adjusted p-value
PGBA-P → PPV	0.484	p < .001	0.484	p < .001
PGBA-P → PC	0.200	p < .001	0.196	p < .001
PPV → AT	0.370	p < .001	0.370	p < .001
PC → AT	-0.330	p < .001	-0.330	p < .001
AT → SCPI	0.573	p < .001	0.572	p < .001
PGBA-P → PPV → AT	0.179	p < .001	0.179	p < .001
PGBA-P → PC → AT	-0.066	p < .001	-0.065	p < .001
PPV → AT → SCPI	0.212	p < .001	0.212	p < .001
PC → AT → SCPI	-0.189	p < .001	-0.189	p < .001
TD × PGBA-P → PC	0.030	0.264	0.027	0.282
TD × PPV → AT	0.098	0.010	0.096	0.010

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5.3. Measurement Model Assessment

The measurement model was assessed before testing the structural model. Since all main constructs were modeled reflectively, reliability and convergent validity were examined using indicator loadings, composite reliability, and average variance extracted. As shown in Table 5, all item loadings exceeded the recommended threshold of 0.708, with loadings ranging from 0.719 to 0.869. This indicated that all indicators contributed adequately to their respective latent constructs and that no item needed to be removed.

Composite reliability values ranged from 0.864 to 0.895, exceeding the recommended minimum threshold of 0.70. These results confirmed satisfactory internal consistency reliability. In addition, average variance extracted values ranged from 0.581 to 0.716, exceeding the recommended threshold of 0.50. Therefore, convergent validity was established for all reflective constructs.

Specifically, algorithmic trust demonstrated strong reliability and convergent validity, with loadings ranging from 0.817 to 0.844, AVE = 0.681, and CR = 0.895. Perceived GenAI-based advertising personalization also showed acceptable measurement quality, with loadings ranging from 0.756 to 0.813, AVE = 0.615, and CR = 0.864. Privacy concern achieved loadings between 0.719 and 0.795, AVE = 0.581, and CR = 0.874. Perceived personalization value achieved loadings between 0.782 and 0.839, AVE = 0.671, and CR = 0.891. Social commerce purchase intention achieved loadings between 0.750 and 0.833, AVE = 0.633, and CR = 0.873. Finally, transparency disclosure showed strong measurement properties, with loadings ranging from 0.821 to 0.869, AVE = 0.716, and CR = 0.883.

Discriminant validity was assessed using the heterotrait–monotrait ratio. As shown in Table 6, all HTMT values were below the conservative threshold of 0.85. The highest HTMT value was between algorithmic trust and social commerce purchase intention, HTMT = 0.692, which remained below the recommended threshold. Therefore, discriminant validity was established. Overall, the measurement model demonstrated satisfactory reliability, convergent validity, and discriminant validity.

Table 4. Reliability and convergent validity.

Variable	Item	Loading	AVE	CR
AT	AT1	0.823	0.681	0.895
	AT2	0.818		
	AT3	0.844		
	AT4	0.817		
PGBA-P	PGBA-P1	0.808	0.615	0.864
	PGBA-P2	0.757		
	PGBA-P3	0.756		
	PGBA-P4	0.813		
PC	PC1	0.782	0.581	0.874
	PC2	0.785		
	PC3	0.795		
	PC4	0.728		
	PC5	0.719		
PPV	PPV1	0.836	0.671	0.891
	PPV2	0.839		
	PPV3	0.818		
	PPV4	0.782		
SCPI	SCPI1	0.800	0.633	0.873
	SCPI2	0.750		
	SCPI3	0.833		
	SCPI4	0.797		
TD	TD1	0.821	0.716	0.883
	TD2	0.869		

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	TD3	0.848

Table 5. Discriminant validity: HTMT scores.

Variable	AT	PGBA-P	PC	PPV	SCPI	TD
AT						
PGBA-P	0.139					
PC	0.346	0.244				
PPV	0.416	0.587	0.192			
SCPI	0.692	0.154	0.187	0.430		
TD	0.340	0.043	0.140	0.165	0.174	

5.4. Structural Model Assessment

After confirming the adequacy of the measurement model, the structural model was assessed to test the proposed hypotheses. The results are presented in Table 7. Perceived GenAI-based advertising personalization had a positive and significant effect on perceived personalization value, $\beta = 0.484$, $t = 12.620$, $p < 0.001$, supporting H1. This result indicates that when consumers perceived that an advertisement was personalized based on their AI conversation data, they were more likely to view the advertisement as relevant, useful, and valuable. The effect size was medium to large, $f^2 = 0.306$, suggesting that perceived GenAI-based advertising personalization was an important predictor of perceived personalization value.

Perceived GenAI-based advertising personalization also had a positive and significant effect on privacy concern, $\beta = 0.200$, $t = 4.396$, $p < 0.001$, supporting H2. Although the effect size was small, $f^2 = 0.042$, the finding is theoretically meaningful because it confirms the dual nature of GenAI-personalized advertising. The same personalization mechanism that increased perceived value also increased concern about the commercial use of AI conversation data.

Perceived personalization value had a positive and significant effect on algorithmic trust, $\beta = 0.370$, $t = 9.203$, $p < 0.001$, supporting H3. This finding suggests that consumers were more likely to trust the platform's algorithmic system when GenAI-personalized advertising was perceived as relevant, useful, and helpful. The effect size was moderate, $f^2 = 0.183$, indicating that personalization value was an important trust-building mechanism.

Privacy concern had a negative and significant effect on algorithmic trust, $\beta = -0.330$, $t = 8.352$, $p < 0.001$, supporting H4. This result indicates that concern about the use of AI conversation data weakened consumers' trust in the platform's algorithmic advertising and recommendation system. The effect size was also moderate, $f^2 = 0.147$, suggesting that privacy concern represented a meaningful risk-based mechanism in the model.

Algorithmic trust had a positive and significant effect on social commerce purchase intention, $\beta = 0.573$, $t = 17.668$, $p < 0.001$, supporting H5. This was the strongest direct effect in the model, with a large effect size, $f^2 = 0.489$. This result confirms that algorithmic trust played a central role in explaining consumers' willingness to purchase through social commerce platforms after exposure to GenAI-personalized advertising.

Table 6. Hypothesis testing.

Hypothesis	Relationship	Std. beta	Std. error	t-value	p-value	BCI LL	BCI UL	f^2
H1	PGBA-P → PPV	0.484	0.038	12.620	p < .001	0.414	0.541	0.306
H2	PGBA-P → PC	0.200	0.045	4.396	p < .001	0.120	0.269	0.042
H3	PPV → AT	0.370	0.040	9.203	p < .001	0.301	0.433	0.183
H4	PC → AT	-0.330	0.039	8.352	p < .001	-0.390	-0.260	0.147
H5	AT → SCPI	0.573	0.032	17.668	p < .001	0.514	0.622	0.489
H6	PGBA-P → PPV → AT	0.179	0.025	7.216	p < .001	0.139	0.220	0.032
H7	PGBA-P → PC → AT	-0.066	0.017	3.803	p < .001	-0.095	-0.038	0.004
H8a	PPV → AT → SCPI	0.212	0.027	7.738	p < .001	0.166	0.257	0.045

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H8b	PC → AT → SCPI	-0.189	0.026	7.296	p < .001	-0.230	-0.145	0.036
H9	TD × PGBA-P → PC	0.030	0.047	0.631	0.264	-0.047	0.107	0.001
H10	TD × PPV → AT	0.098	0.042	2.346	0.010	0.028	0.165	0.013

Note. Bootstrapping was conducted with 10,000 subsamples. Since the hypotheses were directional, one-tailed significance tests were used at the 5% level; therefore, 90% bootstrap confidence intervals are reported.

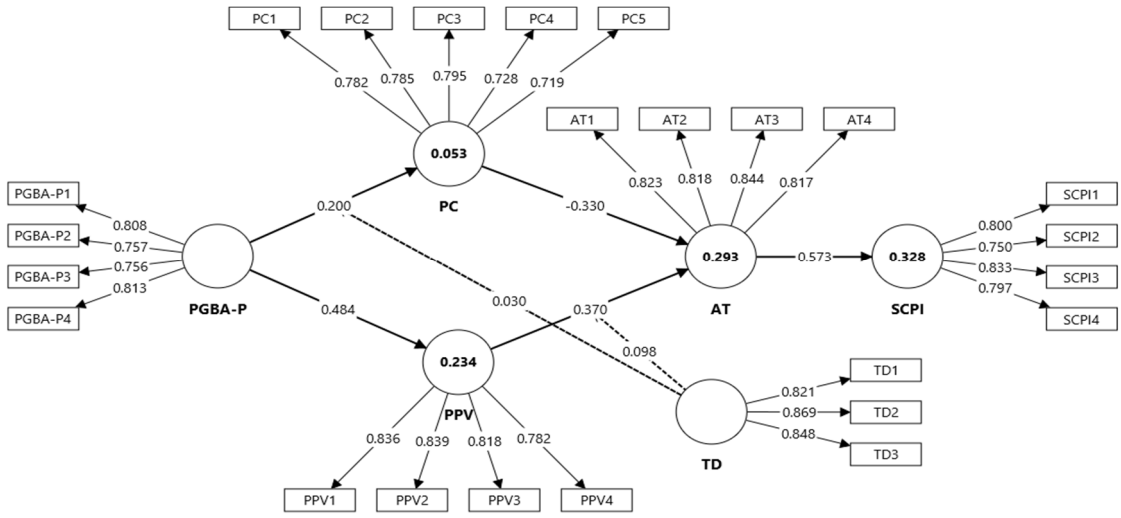

Figure 2. Structural model results.

5.5. Mediation Analysis

The results from the mediator analyses support the postulated dual-path privacy calculus framework. First, perceived personalization value mediates the association between perceived GenAI-based advertising personalization and algorithmic trust ($\beta = 0.179$, $t = 7.216$, $p < 0.001$), which supports H6. Specifically, this implies that the personalization value offered by GenAI-based advertising personalization partially mediates the effect of perceived personalization on algorithmic trust. It shows that consumers' trust in an algorithmic system cannot be increased solely because advertising is personalized. Rather, they will increase their trust in the algorithm when they see the value and importance of the personalization.

Privacy concern also acts as a mediator in the relationship between perceived GenAI-based advertising personalization and algorithmic trust ($\beta = -0.066$, $t = 3.803$, $p < 0.001$). Thus, H7 is supported by the findings. Importantly, this mediating effect exhibits a negative correlation and reflects the risks associated with privacy calculus mechanisms. In essence, this finding highlights that perceived GenAI-based advertising personalization increases the privacy concerns that, in turn, lead to diminished trust in the algorithmic system used by companies to personalize ads.

Moreover, algorithmic trust mediates the influence of perceived personalization value on social commerce purchase intention ($\beta = 0.212$, $t = 7.738$, $p < 0.001$), and this supports H8a. Hence, the analysis reveals that personalization value contributes to consumers' purchase intention, at least in part, due to higher trust in an algorithm. Finally, algorithmic trust significantly mediates the relationship between privacy concern and social commerce purchase intention ($\beta = -0.189$, $t = 7.296$, $p < 0.001$), which supports H8b.

In summary, the results from the mediators analysis support the idea that algorithmic trust serves as the key psychological mechanism involved in the relationships under study. Namely, GenAI-based advertising personalization affects trust via two paths that have different consequences—one enhancing personalization values, another generating privacy risks. Therefore, the findings support the notion that consumers rely on the benefits-and-risk approach while assessing conversational-AI-derived advertising personalization.

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5.6. Moderation Analysis

Regarding the moderation analyses, there was partial support for the proposed moderating role of transparency disclosure. Transparency disclosure did not moderate the positive relationship between the perception of GenAI-based advertising personalization and privacy concern, with the interaction effect being statistically insignificant ($\beta = 0.030$, $t = 0.631$, $p = 0.264$). Hence, H9 could not be accepted. This finding implies that transparency disclosure cannot reduce privacy concern resulting from the use of consumer data by businesses in the process of GenAI-based advertising personalization.

H9 was rejected. However, the above results have theoretical importance. First, the absence of a significant moderation effect implies that only transparency disclosure may not be enough to address privacy concerns related to AI conversation data used to personalize advertising. In other words, the use of such data is viewed by consumers as a more private activity than standard use of behavioral data, and, therefore, despite receiving relevant information via transparency disclosures, people still tend to be concerned about the commercialization of their conversations.

Second, unlike H9, the interaction between transparency disclosure and the perception of personalization value was positive and statistically significant ($\beta = 0.098$, $t = 2.346$, $p = 0.010$), and, therefore, H10 was accepted. This means that the positive relationship between perceived personalization value and trust in the algorithm was enhanced when transparency disclosure took place. In other words, increased transparency regarding GenAI-based personalization strengthened the trust consumers felt toward it.

In turn, Figure 3 illustrates the obtained findings as it shows the stronger positive relationship between personalization value and algorithmic trust among those consumers who were exposed to greater levels of transparency disclosure. Thus, in this case, transparency disclosure did not remove the privacy concerns associated with conversation data; however, it helped people to evaluate the personalization process more positively, as being valuable and trustworthy.

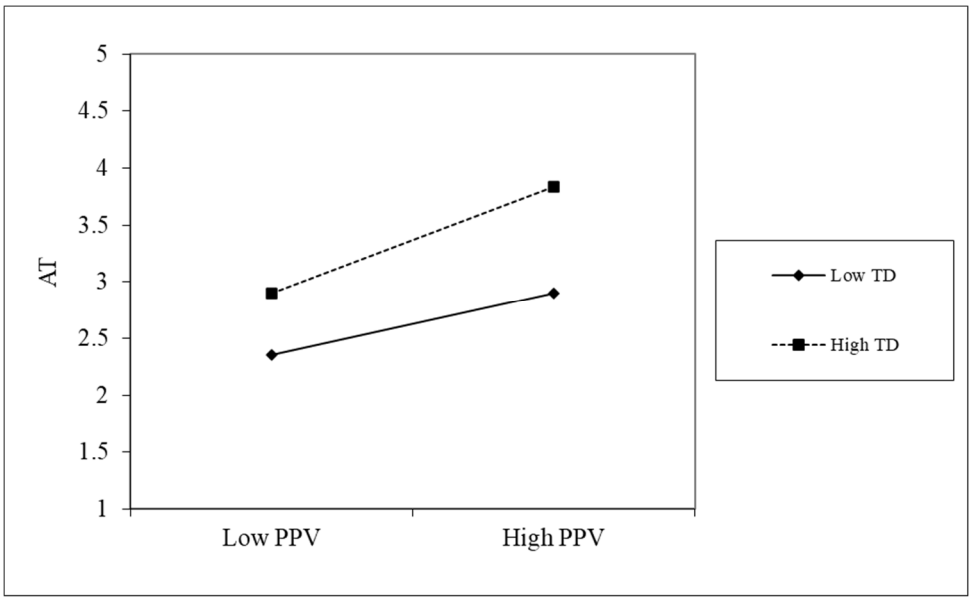

Figure 3. Moderating effect of transparency disclosure on the relationship between perceived personalization value and algorithmic trust.

5.7. Predictive Assessment

PLSpredict was used to evaluate the model's predictive performance for the indicators of social commerce purchase intention. As shown in Table 8, all Q^2predict values were positive, indicating that the model had predictive relevance for the SCPI indicators. The Q^2predict values ranged from

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0.012 to 0.029 across the four indicators, suggesting weak-to-modest but meaningful predictive relevance.

In addition, the PLS-SEM RMSE values were lower than the corresponding linear model benchmark RMSE values for all four SCPI indicators. The PLS-LM differences were negative across all indicators, ranging from −0.008 to −0.014. These results indicate that the PLS-SEM model produced slightly lower prediction errors than the benchmark linear model for each SCPI indicator. Therefore, the model demonstrated acceptable predictive performance for social commerce purchase intention.

This predictive evidence complements the explanatory results of the structural model. While the path coefficients and R^2 values showed that algorithmic trust explained a meaningful share of social commerce purchase intention, the PLSpredict results further indicated that the proposed model generated lower prediction errors than the benchmark linear model. Accordingly, the findings support both the explanatory and predictive relevance of the proposed model.

Table 7. PLSpredict results.

Indicator	Q^2predict	PLS RMSE	LM RMSE	PLS-LM
SCPI1	0.029	1.209	1.223	-0.014
SCPI2	0.012	1.252	1.263	-0.011
SCPI3	0.025	1.182	1.190	-0.008
SCPI4	0.025	1.238	1.252	-0.014

Note. Negative PLS-LM values indicate lower prediction error for the PLS-SEM model than for the benchmark linear model.

5.8. Summary of Hypothesis Testing

Overall, the findings provided support for most of the proposed hypotheses. H1, H2, H3, H4, and H5 were supported, confirming the direct relationships in the model. The mediation hypotheses H6, H7, H8a, and H8b were also supported, confirming the dual-path privacy calculus mechanism and the central mediating role of algorithmic trust. Regarding moderation, H10 was supported, indicating that transparency disclosure strengthened the relationship between perceived personalization value and algorithmic trust. However, H9 was not supported, indicating that transparency disclosure did not significantly weaken the relationship between perceived GenAI-based advertising personalization and privacy concern.

Substantively, the results show that GenAI-based advertising personalization operates through two simultaneous psychological pathways. On the positive side, it increases perceived personalization value, which strengthens algorithmic trust and indirectly enhances social commerce purchase intention. On the negative side, it increases privacy concern, which weakens algorithmic trust and indirectly reduces purchase intention. These findings confirm that conversational-AI-derived advertising personalization should not be treated as purely beneficial or purely threatening. Rather, consumers appear to evaluate it through a privacy calculus process in which value and risk coexist.

The results also clarify the role of transparency disclosure. Transparency disclosure did not significantly reduce the privacy concern associated with GenAI-based advertising personalization. However, it strengthened the extent to which perceived personalization value translated into algorithmic trust. This suggests that transparency may be more effective as a trust-building mechanism than as a privacy-concern-reducing mechanism in contexts where advertising personalization is perceived to rely on AI conversation data.

Table 8. Summary of hypothesis testing.

Hypothesis	Relationship	Result
H1	PGBA-P → PPV	Supported
H2	PGBA-P → PC	Supported

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H3	PPV → AT	Supported
H4	PC → AT	Supported
H5	AT → SCPI	Supported
H6	PGBA-P → PPV → AT	Supported
H7	PGBA-P → PC → AT	Supported
H8a	PPV → AT → SCPI	Supported
H8b	PC → AT → SCPI	Supported
H9	TD × PGBA-P → PC	Not supported
H10	TD × PPV → AT	Supported

6. Discussion

This study examined how perceived GenAI-based advertising personalization influences social commerce purchase intention through perceived personalization value, privacy concern, and algorithmic trust. It also tested whether transparency disclosure moderates the effects of GenAI-based advertising personalization on privacy concern and of personalization value on algorithmic trust. Overall, the findings support the proposed dual-path model. GenAI-based advertising personalization increased both perceived personalization value and privacy concern, confirming that it can function as a value-creating and privacy-threatening mechanism at the same time.

The positive effect of GenAI-based advertising personalization on perceived personalization value shows that consumers may evaluate advertisements more favorably when they appear to reflect prior AI-assisted conversations. In this context, value does not come only from general algorithmic targeting, but from the perception that the advertisement is connected to consumers' stated needs, preferences, budgets, and purchase concerns. This suggests that conversational-AI-derived personalization can enhance marketing value when consumers interpret it as useful and decision-supportive.

At the same time, GenAI-based advertising personalization increased privacy concern. This finding confirms that conversational AI data are more privacy-sensitive than ordinary behavioral traces such as clicks, browsing history, or previous purchases. AI conversations may contain richer and more personally revealing information, including preferences, constraints, emotions, financial limits, and future intentions. Therefore, when consumers believe that such inputs are used for advertising personalization, they may experience discomfort, perceived loss of control, or concern about unexpected data use. This explains why GenAI-personalized advertising may produce both acceptance and resistance.

The results also show that perceived personalization value strengthened algorithmic trust, whereas privacy concern weakened it. This supports the integration of Privacy Calculus Theory and Trust Theory. Consumers are more likely to trust the platform's algorithmic advertising and recommendation system when personalization appears valuable, relevant, and useful. However, concern about the use of AI conversation data reduces that trust. Algorithmic trust, therefore, does not arise simply from personalization accuracy or technological sophistication; it depends on whether consumers view algorithmic personalization as beneficial, acceptable, and respectful of privacy boundaries.

Algorithmic trust had the strongest direct effect on social commerce purchase intention. This highlights the central role of trust in AI-mediated social commerce. Consumers may encounter personalized advertisements, seller content, peer recommendations, influencer communication, and algorithmically curated product suggestions. Still, their willingness to purchase depends strongly on whether they trust the platform's algorithmic system. Platforms therefore cannot rely only on personalization relevance or AI capability; they must also build confidence in how algorithmic systems operate, recommend products, and use consumer data.

The mediation results further support the dual-path logic. Perceived personalization value positively mediated the relationship between GenAI-based advertising personalization and algorithmic trust, while privacy concern negatively mediated it. Thus, GenAI-personalized

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advertising works through two competing routes: a value-enhancing route that increases perceived usefulness and strengthens trust, and a privacy-risk route that increases concern and weakens trust. Algorithmic trust also mediated the effects of personalization value and privacy concern on purchase intention. This confirms the S-O-R logic of the model, where GenAI-based advertising personalization acts as the stimulus, personalization value and privacy concern represent internal evaluations, algorithmic trust functions as a more immediate psychological state, and purchase intention represents the behavioral response.

The moderation results provide an important contribution. Contrary to expectation, transparency disclosure did not significantly weaken the relationship between GenAI-based advertising personalization and privacy concern. This suggests that transparency may not be sufficient to reduce privacy concern when the data source is perceived as sensitive. In the case of AI conversation data, disclosure may clarify the practice without making it feel less intrusive. Consumers may understand how data are used, yet still feel uncomfortable because the data come from conversational exchanges that seem personal, contextual, and revealing.

However, transparency disclosure strengthened the relationship between perceived personalization value and algorithmic trust. This indicates that transparency is more effective as a trust-enhancing mechanism than as a privacy-reducing mechanism in GenAI-personalized advertising. When consumers perceive personalization as valuable, transparency helps them interpret that value as the outcome of a more understandable and legitimate algorithmic process. In other words, transparency may not remove privacy concerns, but it can help useful personalization become more trustworthy.

Overall, the findings show that a dual evaluation process shapes consumer responses to GenAI-personalized advertising. Consumers may appreciate AI-personalized advertisements when they are relevant and helpful, while still feeling concerned when personalization appears to rely on AI conversation data. Algorithmic trust determines whether these evaluations translate into purchase intention. Transparency contributes to this process mainly by strengthening the trust-building effect of personalization value, rather than by directly reducing privacy concern.

7. Theoretical Contributions

The current study enriches the literature on digital marketing, social commerce, privacy calculus, algorithmic trust, and transparency disclosure. Firstly, the current study extends the Privacy Calculus Theory by analyzing advertising personalization based on data from conversational AI. Previous studies about privacy calculus focused mainly on personalization based on behavioral, transactional, demographic, or social media data. The current results suggest that personalization based on conversational AI data could lead to greater sensitivity, as this kind of data reveals customers' needs, concerns, and intentions. Hence, it has been found that GenAI-based advertising personalization enhances both personalization value perception and privacy concern, which indicates that the privacy calculus would become more complicated because personalization is associated with human-AI conversations.

Secondly, the current study makes a valuable contribution to the literature on AI-driven personalization. It distinguishes GenAI-based advertising personalization from traditional algorithmic personalization. The latter usually relies on browsing history, purchase history, demographic profiling, and platform use. Previous research has established that AI improves engagement, personalization, recommendation, and decision-making processes (Davenport et al., 2020; Huang & Rust, 2021; Kumar et al., 2019). At the same time, GenAI-based personalization is based on conversation, contextual factors, and concerns. Thus, GenAI-personalized advertising should not be perceived as an expansion of algorithmic personalization but as a new type of customer-technology communication.

Thirdly, this study contributes to algorithmic trust research by introducing algorithmic trust as the mediating factor between privacy calculus evaluations and the intention to make purchases through social commerce. Algorithmic trust is no longer considered an independent variable. Instead,

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competing evaluations determine it. For instance, personalization value fosters algorithmic trust, whereas privacy concern undermines it. That is why AI-driven personalization may lead to both acceptances and rejections. In turn, algorithmic trust depends not only on performance and effectiveness but also on usefulness, legitimacy, and respect for privacy.

Fourthly, this study enriches the theoretical framework of the S-O-R model. In particular, the current paper introduces a new stimulus (GenAI-based personalization) and internal consumer states (personalization value perception, privacy concern, and algorithmic trust). Thus, the present research applies Privacy Calculus Theory and Trust Theory within the conceptual S-O-R framework to better understand GenAI-based personalized advertising influence on purchase intentions.

Fifthly, the study makes an important contribution to transparency disclosure research. Transparency disclosure has not decreased privacy concern. However, it has made a significant contribution by increasing the effect of personalization value on algorithmic trust. As a result, this study rejects the popular notion that transparency reduces privacy concern per se. In the case of GenAI-based personalized advertising, transparency disclosure helps reveal how AI uses conversational data without changing the nature of personalization as a highly sensitive process at the same time. Besides, the disclosure process increases personalization value, legitimacy, and understandability.

Finally, this study makes contextual contributions to GenAI marketing research by using the data collected in Jordan, an emerging digital market among Arabs. Most of the studies in the field analyze Western or large Asian markets. The current research enriches GenAI marketing research geographically and culturally by examining social commerce users in Jordan.

8. Practical Implications

Practical Implications for Social Commerce Platforms, Digital Marketers, AI System Designers, and Policymakers

First, social commerce platforms should recognize that GenAI-personalized advertising is likely both beneficial and worrisome. It is possible that consumers may enjoy seeing relevant and useful advertisements while at the same time worrying that their GenAI conversations could be used to target them. Hence, social commerce platforms should not assume that the higher personalization will always lead to greater acceptance. GenAI-personalized advertisements need to balance relevancy with privacy-sensitivity.

Second, marketers should emphasize the value of GenAI-personalized advertisements. According to the findings, the value of personalization can foster algorithmic trust and, subsequently, improve purchase intention. Therefore, advertisements need to be timely, relevant, useful, and targeted according to consumers' real needs and not just technically personalized.

Third, social commerce platforms should not solely rely on privacy disclosures for mitigating privacy issues. It is suggested by the findings that even disclosing that AI algorithms are using data can be insufficient when the data itself is deemed sensitive. Thus, social commerce platforms should implement more privacy controls and measures along with transparency, such as obtaining opt-ins from users before using their data and providing detailed explanations, customization settings, data deletion tools, and limits on the use of conversation data for advertisements.

Fourth, however, transparency still can be used to foster trust. If consumers find personalization valuable, then transparent disclosures will enable them to understand, legitimize, and trust the process. As such, social commerce platforms should provide clear explanations as to why a certain advertisement has been shown, what type of AI conversation data has been collected, and how consumers can control personalization.

Fifth, AI system designers should incorporate explainability and control of the process into GenAI-personalized advertising systems. Privacy concerns may undermine algorithmic trust that can, in turn, decrease purchase intention. Hence, the ability to view, control, or limit the usage of conversation data is crucial.

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From the managerial perspective, AI conversation data should be considered highly sensitive. Compared to general browsing and purchasing activity, conversation data can include information related to the goal, constraints, emotions, and intentions of consumers. Social commerce platforms should go above and beyond with privacy notices and offer layered explanations, opt-ins, personalization preferences, and options to limit usage of conversation data for advertisements. These steps should also be implemented because of potential privacy, persuasion, and autonomy issues in GenAI marketing (Duivenvoorde, 2025).

Lastly, privacy policymakers and regulators should treat conversational AI data as a special type of consumer data. Ethical GenAI advertising involves not only disclosure but also consent and consumers' rights to choose.

9. Limitations and Future Research Directions

Several limitations should be acknowledged. First, the study relied on self-reported survey data. Although procedural and statistical remedies were used to reduce common method bias, future research could use behavioral data, field experiments, or platform-based observations to examine actual click-through behavior, purchases, opt-out decisions, or data-sharing choices.

Second, the study used a scenario-based design. This was appropriate because GenAI-based advertising personalization based on AI conversation data is still emerging. Still, future studies could use experiments or field studies involving actual disclosure formats and real personalized advertisements.

Third, the study was conducted in Jordan. Although this provides evidence from an underrepresented Arab market, the findings may not fully generalize to other cultural, regulatory, or technological contexts. Future research could compare Jordan with other Arab markets, such as Saudi Arabia, the United Arab Emirates, Egypt, Qatar, or Morocco, as well as Western and Asian markets.

Fourth, the study focused on perceived GenAI-based advertising personalization rather than verified platform-level use of AI conversation data. Future research could examine actual AI-personalized advertising systems in controlled or field settings to determine whether consumers respond differently when they know with certainty that AI conversation data were used.

Fifth, transparency disclosure was examined as a measured moderator. Future research could experimentally manipulate disclosure type, timing, detail, and format, such as simple disclosure, detailed data-use explanations, consent-based disclosure, visual labels, or interactive "why am I seeing this ad?" explanations.

Sixth, the study did not examine boundary conditions such as AI literacy, perceived control, privacy sensitivity, trust propensity, regulatory knowledge, perceived intrusiveness, or persuasion knowledge. Future research could test whether these factors change how consumers respond to GenAI-based advertising personalization.

Finally, the study examined social commerce purchase intention as the main outcome. Future research could extend the model by examining advertising avoidance, platform trust, brand trust, willingness to share data, opt-in intention, customer engagement, complaint intention, or long-term loyalty.

10. Conclusion

This study examines consumer reactions to the use of GenAI in personalized advertisements in social commerce. Based on Privacy Calculus Theory, Trust Theory, and the S-O-R theory, this study examines the validity of a research model whereby GenAI-generated advertising personalization perception impacts purchase intention via personalization value, privacy risk, and algorithmic trust. This study finds that GenAI-generated advertising personalization perception creates both positive and negative effects. Specifically, it increases personalization value while heightening privacy risk at the same time. Personalization value boosts algorithmic trust, while privacy risk decreases it. In turn, algorithmic trust positively impacts purchase intention in social commerce. Transparency disclosure

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does not effectively lower privacy risk; however, it strengthens the positive relationship between personalization value and algorithmic trust. Using data from conversational-AI-based advertisements, this study contributes to the literature by applying the privacy calculus perspective and algorithmic trust theory to a new personalized context. Moreover, this study provides empirical evidence to inform how to design GenAI personalization-based advertisements that deliver high personalization value, are transparent, and are privacy-focused.

Appendix A:

Table A1. Measurement Scales, Items, and Marker Variable.

Construct	Code	Measurement Item	Source
Perceived GenAI-Based Advertising Personalization	PGBA-P1	The advertisement I saw seemed to be personalized based on my conversation with the AI assistant.	Adapted from Kumar et al. (2019); An and Ngo (2025); Hayes et al. (2021); Hermann and Puntoni (2024); Kshetri et al. (2024)
	PGBA-P2	The advertisement reflected the preferences and needs I expressed during the AI conversation.	
	PGBA-P3	The platform appeared to use my AI conversation to tailor the advertisement to me.	
	PGBA-P4	The advertisement seemed highly connected to the product information I discussed with the AI assistant.	
Perceived Personalization Value	PPV1	The personalized advertisement was relevant to my needs.	Adapted from An and Ngo (2025); Hayes et al. (2021)
	PPV2	The personalized advertisement was useful for my purchase decision.	
	PPV3	The personalized advertisement helped me find a product that matched my preferences.	
	PPV4	The personalized advertisement made the shopping process more convenient.	
Privacy Concern	PC1	I was concerned that my conversation with the AI assistant was used for advertising purposes.	Adapted from Malhotra et al. (2004); Martin and Murphy (2017); Hayes et al. (2021); Cloarec et al. (2024); McKee et al. (2024)
	PC2	I felt uncomfortable that information from my AI conversation may have been used to personalize the advertisement.	
	PC3	I was concerned about how the platform collected and used my AI conversation data.	
	PC4	I felt that using AI conversation data for advertising could reduce	

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		my control over my personal information.	
	PC5	I was worried that the platform may use my AI conversation data in ways I did not expect.	
Algorithmic Trust	AT1	I trusted the platform's AI-based advertising system.	Adapted from Ameen et al. (2021); Puntoni et al. (2021); Yalcin et al. (2022); Teodorescu et al. (2023)
	AT2	I believed that the platform's AI system provided reliable advertising personalization.	
	AT3	I felt confident in the platform's AI-driven recommendation and advertising system.	
	AT4	I believed that the platform's AI system acted in a trustworthy way when personalizing advertisements.	
Transparency Disclosure	TD1	The platform clearly explained whether AI conversation data were used for advertising personalization.	Adapted from Shin (2021); Baek et al. (2024); Grigsby et al. (2025); Schilke and Reimann (2025)
	TD2	The disclosure about the use of AI-related data for advertising was clear and understandable.	
	TD3	I understood how the platform used AI conversation data to personalize advertisements.	
Social Commerce Purchase Intention	SCPI1	I would consider purchasing the advertised product through the social commerce platform.	Adapted from Wang et al. (2022); Sadiq et al. (2025)
	SCPI2	I would be willing to click on the advertisement to learn more about the product.	
	SCPI3	I would consider interacting with the seller or brand through the platform.	
	SCPI4	I would be likely to purchase from the platform if the advertised product matched my needs.	
Marker Variable: Preference for Digital Interface Appearance	MV1	I prefer digital platforms with visually attractive layouts.	Adapted from marker-variable logic; Lindell and Whitney (2001); Podsakoff et al. (2012, 2024)
	MV2	I like websites and apps that use modern visual designs.	
	MV3	I prefer online platforms with well-organized screen layouts.	

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