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RESEARCH ARTICLE

AI-Driven Personalization and Purchase Intention: The Mediating Role of Algorithmic Fairness Perception

Roby Nur Akbar [1*] | Kamaluddin [2] | Nirwana [3] | Adi Suprayitno [4]

[1*,2,3,4] Study Program of Management, Faculty of Economics and Business, Universitas Merdeka Malang, Indonesia.

Correspondence
[1] Study Program of Management, Faculty of Economics and Business, Universitas Merdeka Malang, Indonesia.
Email. roby.akbar@unmer.ac.id.

Funding information
Universitas Merdeka Malang.

Abstract
Artificial intelligence (AI)-driven personalization has revolutionized digital commerce by enabling platforms to provide highly tailored recommendations, customized content, and adaptive shopping experiences. Although prior research has established that AI personalization positively influences consumer responses through dimensions such as trust, usefulness, and satisfaction, there has been limited exploration of how consumers assess the fairness of algorithmic decision-making prior to forming purchase intentions. Furthermore, few studies have integrated AI-driven personalization, brand experience, perceived value, and social proof into a cohesive framework that elucidates consumer behavior through the lens of algorithmic fairness perception. To address this gap, the present study examines the mediating role of algorithmic fairness perception in elucidating how AI-enabled marketing stimuli affect purchase intention. A quantitative cross-sectional survey was conducted involving 400 consumers with experience using AI-enabled e-commerce platforms, and the proposed model was analyzed utilizing Partial Least Squares Structural Equation Modeling (PLS-SEM). The results indicate that AI-driven personalization, brand experience, perceived value, and social proof significantly enhance algorithmic fairness perception. Additionally, AI-driven personalization, brand experience, perceived value, and algorithmic fairness perception substantially increase purchase intention, while social proof does not exhibit a significant direct effect. Nevertheless, algorithmic fairness perception serves as a significant mediator in the relationships between all antecedent variables and purchase intention. The originality of this study lies in positioning algorithmic fairness perception as the central psychological mechanism that translates AI-enabled marketing strategies into consumer purchase intention within a Stimulus–Organism–Response (SOR) framework. These findings contribute to the growing body of literature on AI marketing by shifting the analytical focus from technological effectiveness to ethical algorithmic evaluation, offering practical guidance for the development of transparent, responsible, and consumer-oriented AI systems that promote sustainable customer relationships.

Keywords
Ai-Driven Personalization; Algorithmic Fairness Perception; Brand Experience; Perceived Value; Social Proof; Purchase Intention; PLS-SEM.

1 | INTRODUCTION

Why does this platform seem to know what I want before I search for it This question encapsulates a pivotal shift in digital marketing: the increasing dominance of artificial intelligence (AI) in shaping consumer choices (Cho & Rha, 2026; Hildebrand & Bergner, 2019). As e-commerce platforms, social media applications, streaming services, and digital marketplaces increasingly rely on algorithmic systems (Shim & Kim, 2026), consumers are no longer presented with neutral product displays. Instead, they encounter personalized recommendations, curated reviews, targeted promotions, and adaptive interfaces designed to predict and influence their preferences (Zhang *et al.,* 2026; Sun *et al.,* 2025). This transformation indicates that AI is no longer merely a technological support tool; it has evolved into an active participant in the consumer decision-making process (Duan *et al.,* 2019; Bader & Kaiser, 2019).

AI-driven personalization refers to the utilization of algorithmic systems to customize product recommendations (Shirkhani *et al.,* 2023; Gowri, 2024), promotional content, search results, and digital interactions based on consumers' behavioral data, preferences, browsing history, and previous transactions. In contemporary digital commerce, platforms such as Amazon, Netflix, TikTok, Shopee, and Tokopedia increasingly employ recommendation systems and consumer analytics to deliver individualized experiences (Suryawan *et al.,* 2024; Turki, 2025). These systems aim to reduce information overload, enhance decision efficiency, and improve purchase relevance. Similar to how virtual influencers represent a new phase of AI-mediated branding (Tseng & Ou, 2025), AI-driven recommendation systems signify a new era of algorithm-mediated consumption, where digital platforms do not merely respond to consumer demand but actively shape what consumers see, evaluate, and ultimately purchase (Arachchi & Samarasinghe, 2025). The reference article also illustrates that AI-based marketing technologies increasingly influence trust, attitudes, and purchase intentions through consumers' perceptions of technological and social attributes (Turki, 2025).

While AI-driven personalization offers substantial marketing advantages, its growing influence also generates ethical and psychological tensions (Duan *et al.,* 2019). Personalized recommendations may assist consumers in discovering relevant products, yet they may also raise concerns regarding privacy, algorithmic bias, manipulation, and transparency. Consumers may question whether the recommendations they receive genuinely align with their needs or are primarily designed to maximize platform profits (Liao & Sundar, 2022; Arachchi & Samarasinghe, 2025). This tension mirrors the ethical concerns highlighted in AI-based influencer marketing (Hashem, 2025), where the boundary between authentic and synthetic communication becomes blurred, raising questions about disclosure, deception, manipulation, and credibility (Zhang *et al.,* 2026). In digital commerce, a similar boundary is obscured when algorithmic systems curate product visibility, reviews, ratings, and promotional offers without clearly explaining how such content is selected (Jin & Viswanathan, 2025).

These concerns are increasingly pertinent in the context of e-commerce and digital platforms. TikTok's algorithmic feed shapes the content users repeatedly encounter, while Amazon and Netflix personalize recommendations based on behavioral traces. Shopee and Tokopedia display products, promotions (Qadri & Moustafa, 2026), ratings, and reviews through algorithmic curation. Consequently, consumers do not solely evaluate products, prices, or brands; they also assess the system underlying the platform (Chang & Yu, 2026). When consumers perceive recommendations as relevant, transparent, and unbiased, personalization can strengthen trust and purchase intention. Conversely, when consumers suspect that recommendations are biased, overly commercial, or manipulative, personalization may diminish credibility and weaken the intention to purchase (Loi *et al.,* 2021).

This scenario underscores the significance of algorithmic fairness perception in AI-based digital marketing (Bader & Kaiser, 2019). Algorithmic fairness perception refers to consumers' assessment of whether an algorithm operates fairly, transparently, objectively, and without manipulation in presenting recommendations, promotions, reviews, and product information (Gowri, 2024). In AI-mediated environments, fairness emerges as a crucial psychological mechanism, as consumers increasingly depend on systems that they cannot fully observe or control (Oncioiu, 2026). The reference article demonstrates that consumers' responses to AI-based marketing are shaped not only by functional evaluations such as usefulness and ease of use but also by trust, privacy concerns, social perceptions, and broader ethical considerations (Loi *et al.,* 2021). This suggests that algorithmic evaluation is no longer purely technical; it is deeply psychological, social, and ethical (Klaus & Zaichkowsky, 2022).

The rise of AI-driven personalization also alters the meaning of brand experience (Hardcastle *et al.,* 2025). Traditionally, brand experience is shaped by product quality, service encounters, communication, and visual identity (Tseng & Ou, 2025). However, in AI-based platforms, consumers experience brands through automated systems such as recommendation engines, chatbots, adaptive interfaces, personalized search results, and curated promotional content (Hildebrand & Bergner, 2019). Thus, the algorithm becomes an integral part of the brand encounter. A seamless, relevant, and transparent algorithmic interaction may enhance positive brand experience, whereas an intrusive or manipulative algorithmic interaction may impair consumers' perception of the brand (Hardcastle *et al.,* 2025). This logic aligns with the reference article, which explains that AI-mediated interactions can shape consumer trust, brand attitudes, and purchase intentions by integrating technological, social, and psychological evaluations (Arachchi & Samarasinghe, 2025).

AI-driven platforms also redefine perceived value (Qadri & Moustafa, 2026). In traditional consumer research, perceived value is typically associated with the balance between benefits and sacrifices, encompassing functional, economic, and emotional advantages. In AI-mediated digital commerce, however, perceived value increasingly hinges on the quality of algorithmic interaction (Yin & Qiu, 2021). Consumers may perceive higher value when recommendations help them save time, reduce search effort, discover relevant products, and make informed purchasing decisions (Arachchi & Samarasinghe, 2025; Hardcastle *et al.,* 2025). Conversely, perceived value may diminish when consumers believe that the platform exploits their data, narrows their choices, or promotes sponsored products under the guise of personalization. In this context, perceived value in AI-based marketing encompasses not only product benefits but also the perceived usefulness, fairness, and consumer orientation of the algorithmic process (Jacobides *et al.,* 2021).

Similarly, AI alters the dynamics of social proof in digital commerce. Online reviews, ratings, testimonials, purchase numbers, and influencer recommendations have long served as crucial cues in consumer decision-making (Tseng & Ou, 2025). However, in algorithmic platforms, social proof is not solely generated by users; it is also curated, ranked, filtered, and displayed by algorithms (Bader & Kaiser, 2019). Consumers may not encounter all reviews chronologically or neutrally but are instead exposed to reviews and ratings selected by the platform. This raises a new question: do consumers trust social proof when its visibility is algorithmically controlled? (Zhang *et al.,* 2026). If consumers perceive that reviews or ratings are selectively displayed to favor certain products, the credibility of social proof may weaken. Conversely, if the platform is viewed as fair and transparent, social proof may bolster confidence and purchase intention (Yin & Qiu, 2021).

Despite the rapid growth of research on AI marketing, digital personalization, and consumer behavior, several significant gaps persist (Liao & Sundar, 2022). Prior studies have predominantly examined AI-based marketing through established constructs such as perceived usefulness, perceived ease of use, trust, satisfaction, attitude, and technology acceptance. While these constructs are valuable, they may not fully capture consumers' ethical and psychological evaluations of algorithmic systems. In AI-driven platforms, consumers may not immediately develop trust or purchase intention after receiving personalized recommendations; instead, they may first assess whether the algorithm operates fairly, transparently, and without manipulation (Hashem, 2025). This distinction is crucial, as personalization can be perceived as not only helpful and relevant but also invasive, biased, or commercially exploitative (Jin & Viswanathan, 2025). Therefore, algorithmic fairness perception offers a more contextually relevant mechanism for explaining how consumers respond to AI-driven personalization in digital commerce (Gowri, 2024).

Despite the rapid advancement of artificial intelligence (AI) in digital marketing, several important theoretical and empirical gaps remain. First, previous studies have predominantly explained the effectiveness of AI-driven personalization through technology-oriented constructs such as perceived usefulness, perceived ease of use, trust, satisfaction, and technology acceptance. Although these perspectives successfully elucidate consumers' functional evaluations of AI-enabled services, they provide limited insight into how consumers assess the ethical quality of algorithmic decision-making before forming behavioral intentions. In increasingly algorithm-driven marketplaces, consumers are no longer passive recipients of personalized recommendations; rather, they actively evaluate whether recommendation systems operate fairly, transparently, and without commercial manipulation. Consequently, existing studies have not fully captured the psychological processes through which consumers transform algorithmic evaluations into purchase decisions.

Second, algorithmic fairness perception has garnered growing scholarly attention within the broader fields of artificial intelligence, recommender systems, algorithm governance, and responsible AI. However, prior studies have generally investigated algorithmic fairness from technological, legal, or ethical perspectives, emphasizing issues such as transparency, accountability, explainability, or algorithm legitimacy. Comparatively few studies have positioned algorithmic fairness perception as a consumer-centered psychological mechanism capable of explaining how AI-enabled marketing strategies influence purchase intention. As a result, the role of algorithmic fairness remains fragmented across different research streams and has yet to be fully integrated into consumer behavior theory within digital marketing contexts.

Third, previous studies have generally examined AI-driven personalization, brand experience, perceived value, and social proof as independent predictors of consumer behavior. While each construct has been shown to influence purchase intention individually, limited research has integrated these variables into a comprehensive framework that reflects consumers' actual experiences when interacting with AI-enabled digital platforms. In contemporary e-commerce environments, consumers simultaneously receive personalized recommendations, evaluate digital brand experiences, assess perceived value, and interpret algorithmically curated reviews and ratings. Understanding consumer behavior, therefore, requires an integrated perspective capable of explaining how these multiple stimuli jointly influence purchase intention through consumers' evaluation of algorithmic fairness.

Based on these research gaps, this study aims to develop and empirically test an integrated behavioral model explaining how AI-driven personalization, brand experience, perceived value, and social proof influence consumers' purchase intention through the mediating role of algorithmic fairness perception. By doing so, this study seeks to provide a deeper understanding of the psychological mechanisms underlying consumer responses to AI-enabled digital commerce and to contribute to the development of more transparent, responsible, and sustainable AI-based marketing practices.

The novelty of this study lies in three significant aspects. First, this research shifts the dominant perspective of AI-driven marketing from technology-centered evaluation toward fairness-centered evaluation by positioning algorithmic fairness perception as the primary psychological mechanism through which AI-enabled marketing activities influence purchase intention. Second, unlike previous studies that examined AI personalization, brand experience, perceived value, and social proof separately, this study integrates these constructs into a unified behavioral framework, thereby providing a more holistic explanation of consumer decision-making in AI-mediated digital commerce. Third, this study adopts the Stimulus–Organism–Response (SOR) Theory as the overarching theoretical foundation, positioning AI-driven personalization, brand experience, perceived value, and social proof as environmental stimuli, algorithmic fairness perception as the internal psychological organism, and purchase intention as the behavioral response. This theoretical integration offers a more comprehensive explanation of how consumers cognitively and ethically evaluate AI-enabled marketing systems before making purchasing decisions.

Furthermore, limited research has integrated AI-driven personalization, brand experience, perceived value, and social proof into a single framework to explain purchase intention through algorithmic fairness perception. In actual digital platform experiences, consumers encounter these elements simultaneously: they receive personalized recommendations, evaluate the platform's brand experience (Tseng & Ou, 2025), assess the value offered by the recommendation system, and interpret social proof such as ratings, reviews, and product popularity (Sun *et al.,* 2025). Because these cues are increasingly mediated by algorithms, understanding their combined influence requires a framework that places algorithmic fairness perception at the center of consumer evaluation (Cho & Rha, 2026). To address these gaps, this study proposes an integrated model explaining how AI-driven personalization, brand experience, perceived value, and social proof shape purchase intention through algorithmic fairness perception. By doing so, this study extends digital marketing and consumer behavior literature by shifting the discussion of AI personalization from relevance and usefulness toward fairness, transparency, and ethical evaluation.

This study contributes to the literature in several ways. Theoretically, it extends AI marketing and consumer behavior research by demonstrating that consumers' responses to AI-enabled platforms are determined not only by the functional performance of personalization technologies but also by their ethical evaluation of algorithmic fairness. By integrating the Stimulus–Organism–Response (SOR) framework with algorithmic fairness perception, this study provides a new theoretical perspective that bridges AI marketing, algorithm governance, and consumer psychology. Practically, the findings offer guidance for digital platform managers and AI developers in designing recommendation systems that emphasize fairness, transparency, accountability, and consumer orientation as strategic resources for enhancing purchase intention and fostering long-term customer relationships.

2 | BACKGROUND THEORY

2.1 AI-Driven Personalization and Algorithmic Fairness Perception

AI-driven personalization has become a central feature of digital marketing as platforms increasingly rely on algorithms to tailor recommendations, promotional offers, product rankings, and content exposure to individual consumers (Lee & Sharma, 2025). Unlike traditional personalization, which often depends on broad demographic segmentation (Yin & Qiu, 2021), AI-driven personalization operates dynamically by processing behavioral data, browsing history, prior purchases, and real-time interactions. In e-commerce platforms, these systems assist consumers in navigating extensive product assortments by presenting options that appear more relevant to their needs (Turki, 2025). While personalization enhances convenience and decision efficiency, its persuasive power is not without tension. Consumers may appreciate personalized recommendations when they are accurate, useful, and consistent with their preferences; however, they may also question whether such recommendations genuinely serve their interests or primarily aim to maximize platform revenue, promote sponsored products, or steer them toward specific choices (Aguirre *et al.,* 2015; Teepapal, 2025). This tension reflects broader concerns in AI-mediated marketing, where technological systems can enhance engagement while simultaneously raising issues related to manipulation, transparency, privacy, and credibility (Hu & Min, 2025; Rahman, 2026). In this context, algorithmic fairness perception becomes particularly important, as consumers are more likely to judge an algorithm as fair when personalized recommendations are perceived as relevant, consistent, transparent, and unbiased (Xu & Chen, 2025). Conversely, when personalization feels excessive, intrusive, or commercially distorted, consumers may interpret the system as manipulative, thereby undermining trust and purchase intention (Gong *et al.,* 2026). Therefore.
H1. AI-driven personalization will positively influence algorithmic fairness perception.

AI-driven personalization may also directly influence purchase intention. Personalized recommendations reduce search costs, simplify product evaluations, and assist consumers in discovering products that align with their preferences (Shim & Kim, 2026; Lo *et al.,* 2026). When consumers perceive that a platform understands their needs, they are more likely to consider the recommended products and proceed with a purchase (An & Ngo, 2025).

Consequently, AI-driven personalization is expected to positively influence purchase intention. Therefore.
H2. AI-driven personalization will positively influence purchase intention.

2.2 Brand Experience and Algorithmic Fairness Perception

Brand experience refers to consumers' sensory, affective, cognitive, and behavioral responses generated through interactions with a brand. In digital environments, brand experience is no longer shaped solely by products, advertising, service encounters, or brand communication; it increasingly emerges from platform-mediated interactions such as recommendation systems, AI-enabled customer service, chatbots, adaptive interfaces, personalized search results, and curated promotional content. Prior studies indicate that customer experience in digital and AI-enabled environments plays a crucial role in shaping satisfaction, trust, continued use, and purchase intention, suggesting that consumers evaluate brands based on the quality of their technology-mediated interactions rather than relying solely on traditional brand cues (Chen & Yang, 2021; Wang *et al.,* 2024). In AI-based platforms, algorithms become integral to the brand encounter, as consumers interpret the quality of algorithmic interaction as a signal of the platform's professionalism, competence, and consumer orientation. A seamless, enjoyable, and responsive digital experience can create the impression that the platform operates reliably and responsibly, whereas irrelevant recommendations, confusing navigation, or intrusive personalization may weaken brand evaluations and increase suspicion toward the platform's algorithmic logic. Research on AI and recommender systems in e-commerce suggests that these systems can enhance user experience, decision-making, satisfaction, and purchase intention when perceived as useful and well-integrated into the consumer journey. Extending this logic, consumers who have positive experiences with a platform may infer that its underlying algorithm is reliable, transparent, and fair (Lo *et al.,* 2026; Valencia-Arias *et al.,* 2024). Therefore.
H3. Brand experience will positively influence algorithmic fairness perception.

Brand experience is also expected to directly influence purchase intention. Positive brand experiences foster favorable emotional and cognitive responses, reduce uncertainty, and strengthen consumers' willingness to interact with and purchase from the platform (Chen & Yang, 2021; Wang *et al.,* 2023). In AI-based digital commerce, a pleasant and efficient brand experience can enhance consumers' confidence in completing transactions, as AI-enabled interactions, website quality, service quality, and consumer trust collectively shape online purchase intention (Bilal *et al.,* 2024; Chau *et al.,* 2025; Hanaysha *et al.,* 2025). Therefore, brand experience is anticipated to positively influence purchase intention. Thus.
H4. Brand experience will positively influence purchase intention.

2.3 Perceived Value and Algorithmic Fairness Perception

Perceived value reflects consumers' overall assessment of the benefits they receive relative to the sacrifices they make. In digital commerce, these sacrifices may include money, time, effort, attention, personal data, and perceived risk. AI-based platforms can enhance perceived value by offering convenience, efficiency, relevant recommendations, reduced search effort, and more enjoyable shopping experiences. Prior studies indicate that high-quality personalized recommendation systems can enhance perceived value and purchase intention, while recommendation systems in e-commerce assist consumers in finding appropriate products, reducing search friction, and improving decision-making efficiency (Lo *et al.,* 2026; Wang *et al.,* 2023). Therefore. In AI-mediated environments, perceived value is closely tied to the quality of algorithmic interaction. Consumers may perceive higher value when recommendation systems help them identify suitable products, compare alternatives, and make faster decisions. However, perceived value may decline when consumers feel that the platform collects personal data or captures their attention without providing meaningful benefits in return. This value judgment may influence fairness evaluation, as consumers are more likely to view algorithmic systems as consumer-oriented and fair when the benefits they receive are proportional to the data, time, and attention they provide. Conversely, when the exchange feels exploitative, the algorithm may be perceived as biased or unfair. This argument aligns with privacy calculus research, which explains that consumers evaluate personalization by weighing perceived benefits against privacy risks and information disclosure costs (Zhu *et al.,* 2017; Hayes *et al.,* 2021). Therefore.
H5. Perceived value will positively influence algorithmic fairness perception.

Perceived value may also directly shape purchase intention, as consumers are more likely to purchase when they believe that a platform provides meaningful functional, economic, and experiential benefits. In digital commerce, perceived value can arise from convenience, price benefits, product quality, service quality, time-saving orientation, and reduced perceived risk. Prior studies demonstrate that perceived value positively influences purchase intention, while perceived risk tends to diminish consumers' willingness to buy in e-commerce contexts (Wang *et al.,* 2023). In AI-based digital commerce, personalized recommendation systems can further enhance perceived value by assisting consumers in saving time, reducing search effort, simplifying product evaluation, and making better choices (Lo *et al.,* 2026). Moreover, AI-powered personalization can increase purchase intention when recommendations are perceived as relevant, useful, and aligned with consumer needs (An & Ngo, 2025). Therefore,

perceived value is expected to positively influence purchase intention. Thus.
H6. Perceived value will positively influence purchase intention.

2.4 Social Proof and Algorithmic Fairness Perception

Social proof refers to consumers' tendency to rely on the opinions, behaviors, and experiences of others when evaluating products or services. In digital platforms, social proof is typically represented by online reviews, ratings, testimonials, product popularity, purchase numbers, user-generated content, and influencer recommendations. These cues help consumers reduce uncertainty, especially when direct product evaluation is limited. Prior studies indicate that online reviews significantly affect purchase intention, while trust, perceived risk, perceived security, and electronic word-of-mouth (e-WOM) also shape e-commerce purchasing decisions (Qiu & Zhang, 2024; Handoyo, 2024). Additionally, social influence and perceived information quality positively relate to consumers' online social shopping intention (Fu *et al.,* 2020). Therefore.
H7. Social proof will positively influence algorithmic fairness perception.

However, in AI-based platforms, social proof is not merely user-generated; it is also algorithmically curated. Reviews, ratings, and popularity indicators may be ranked, filtered, highlighted, or suppressed by platform algorithms. Consequently, consumers evaluate not only the content of social proof but also the fairness of how such information is displayed. If consumers believe that reviews and ratings are presented objectively, social proof may strengthen perceptions of platform credibility; if they suspect selective curation, social proof may trigger concerns about manipulation. Customer reviews, website quality, perceived service quality, and product assortment have been shown to influence online purchase intention through trust (Hanaysha *et al.,* 2025), while higher ratings in online reviews can positively impact purchase intention as they signal buyer satisfaction (Park *et al.,* 2021). Thus, credible and transparently presented social proof may enhance consumers' purchase confidence by reducing uncertainty and strengthening perceived credibility. Therefore.
H8. Social proof will positively influence purchase intention.

2.5 Algorithmic Fairness Perception and Purchase Intention

Algorithmic fairness perception refers to consumers' belief that a platform's algorithm operates fairly, transparently, objectively, and without manipulation. This perception is increasingly important in digital commerce, as consumers rely on algorithms to access product recommendations, promotional offers, reviews, ratings, and search results, while the processes behind these algorithmic outputs are often invisible. Prior research on fairness-aware recommender systems emphasizes that fairness is closely related to the trustworthiness of recommendation services (Jin *et al.,* 2023), while studies on commercial AI applications demonstrate that consumers' perceptions of algorithmic fairness, accountability, and transparency strengthen perceived structural assurance (Yuan *et al.,* 2024). Similarly, research in e-commerce platforms reveals that algorithmic fairness, accountability, and transparency positively affect algorithmic legitimacy, which in turn increases continuous usage intention (Liu & Sun, 2024). When consumers perceive an algorithm as fair, they are more likely to trust the platform and follow its recommendations because fairness signals that the platform does not manipulate choices, hide relevant alternatives, or exploit consumer data. Conversely, perceived unfairness may generate skepticism, resistance, and lower purchase intention. This logic aligns with AI-mediated marketing research showing that AI transparency and privacy assurance strengthen consumer trust and purchase intention in digital retail personalization (Rahman, 2026). Therefore:
H9. Algorithmic fairness perception will positively influence purchase intention.

2.6 Stimulus–Organism–Response (SOR) Theory

The theoretical foundation of this study is grounded in the Stimulus Organism–Response (SOR) Theory, originally proposed by Mehrabian and Russell (1974), which explains how environmental stimuli influence individuals' internal psychological states and subsequently shape behavioral responses. The SOR framework has been widely adopted in consumer behavior, retailing, digital marketing, and e-commerce research because it provides a comprehensive explanation of how external environmental cues are cognitively and emotionally processed before resulting in consumer behavior (Donovan & Rossiter, 1982; Eroglu *et al.,* 2001). Unlike traditional behavioral models that assume a direct relationship between external stimuli and behavioral outcomes, the SOR framework posits that consumers first evaluate and interpret external information through internal psychological processes before making behavioral decisions. Within the SOR perspective, stimuli (S) represent external environmental factors capable of influencing consumers' perceptions and evaluations. These stimuli may include technological features, marketing communications, platform characteristics, service quality, social interactions, and digital experiences. The organism (O) represents consumers' internal cognitive and affective evaluations that emerge after exposure to external stimuli. These psychological evaluations include beliefs, emotions, trust, perceived fairness, attitudes, and other cognitive responses that determine how consumers interpret environmental information. Finally, the response (R) reflects the behavioral outcomes resulting from these internal evaluations, including purchase intention, adoption intention, satisfaction, loyalty, continued usage, or other forms of consumer behavior.

Recent developments in AI-enabled digital commerce have further strengthened the relevance of the SOR framework. Digital marketplaces increasingly employ artificial intelligence to personalize product recommendations, organize product rankings, curate online reviews, and deliver adaptive shopping experiences. Consequently, consumers are exposed not merely to products or promotional messages but also to algorithmically generated interactions that actively shape their shopping experiences. In such environments, consumer behavior cannot be adequately explained solely by the functional performance of AI technologies, as consumers simultaneously evaluate whether these algorithmic systems operate transparently, objectively, and fairly. Therefore, the SOR framework provides an appropriate theoretical lens for explaining how AI-generated marketing stimuli are transformed into behavioral intentions through consumers' psychological evaluations.

In AI-mediated digital environments, consumers rarely observe the underlying decision-making processes performed by algorithms. Instead, they evaluate recommendation systems based on the experiences and signals they receive during platform interactions. Recommendation relevance, interface quality, perceived benefits, review credibility, and algorithmic transparency jointly shape consumers' internal judgments regarding whether the platform behaves fairly. Accordingly, consumers' behavioral intentions are influenced not only by the presence of AI personalization itself but also by the psychological interpretation of whether such personalization is implemented responsibly and ethically. Based on the SOR framework, this study conceptualizes AI-driven personalization, brand experience, perceived value, and social proof as environmental stimuli, as they represent external marketing cues delivered through AI-enabled digital platforms. These variables constitute the information environment surrounding consumers during online shopping activities and collectively influence how consumers interpret the quality of the platform. Although each stimulus represents a different aspect of digital marketing, all function as environmental inputs that initiate consumers' cognitive evaluation processes.

The organism component is represented by algorithmic fairness perception, reflecting consumers' internal psychological evaluation regarding whether AI algorithms operate fairly, transparently, objectively, and without manipulation. This construct represents a cognitive appraisal rather than a technological characteristic. Consumers do not directly evaluate the algorithm itself; instead, they develop subjective perceptions regarding the fairness of algorithmic decision-making after interacting with personalized recommendations, curated reviews, platform interfaces, and AI-generated marketing content. Consequently, algorithmic fairness perception functions as the central psychological mechanism translating external marketing stimuli into behavioral responses.

Finally, purchase intention represents the response within the SOR framework. After evaluating algorithmic fairness, consumers decide whether they are willing to purchase products recommended by the platform. When AI systems are perceived as fair, transparent, and consumer-oriented, consumers are more likely to trust the platform, accept algorithmic recommendations, and demonstrate stronger purchase intentions. Conversely, when recommendation systems are perceived as manipulative, commercially biased, or lacking transparency, consumers may resist algorithmic recommendations despite receiving highly personalized marketing content. Accordingly, the present study proposes that AI-enabled marketing does not influence purchase intention solely through technological effectiveness but through consumers' internal evaluations of algorithmic fairness. This perspective extends the traditional application of the SOR framework by introducing algorithmic fairness perception as a contemporary organism construct within AI-driven digital commerce. As artificial intelligence increasingly mediates interactions between firms and consumers, ethical evaluations of algorithms become essential psychological mechanisms explaining why identical AI technologies may produce different behavioral outcomes across consumers. Therefore, the proposed conceptual model positions AI-driven personalization, brand experience, perceived value, and social proof as stimuli; algorithmic fairness perception as the organism; and purchase intention as the response. This theoretical structure provides an integrated explanation of consumer decision-making in AI-mediated marketplaces and establishes a stronger conceptual foundation for the proposed hypotheses.

2.7 Conceptual Development

AI-based marketing stimuli may influence purchase intention both directly and indirectly. Directly, AI-driven personalization, brand experience, perceived value, and social proof may increase purchase intention by improving recommendation relevance, experience quality, perceived benefits, and social confidence. Prior studies indicate that AI-powered personalization can influence purchase intention through perceived relevance, usefulness, and trust, while personalized recommendations may also enhance decision efficiency but raise concerns about algorithmic dominance, user autonomy, and privacy (An & Ngo, 2025; Xu & Chen, 2025). Indirectly, these marketing stimuli may first shape consumers' evaluation of whether the platform's algorithmic system operates fairly, transparently, and non-manipulatively. Research on fairness-aware recommender systems emphasizes that fairness is closely related to the trustworthiness of recommendation services, while ethical AI personalization studies show that transparency and privacy assurance strengthen consumer trust and purchase intention (Jin & Viswanathan, 2025; Rahman, 2026).

Therefore, algorithmic fairness perception may explain how AI-driven personalization, brand experience, perceived value, and social proof are translated into purchase intention in digital commerce. Reviews, ratings, and e-WOM can strengthen purchase-related responses, but their persuasive power may depend on whether such information is perceived as credible and fairly presented by the platform (Chau *et al.,* 2025). Therefore.

H10. Algorithmic fairness perception will mediate the relationship between AI-driven personalization and purchase intention.

H11. Algorithmic fairness perception will mediate the relationship between brand experience and purchase intention.

H12. Algorithmic fairness perception will mediate the relationship between perceived value and purchase intention.

H13. Algorithmic fairness perception will mediate the relationship between social proof and purchase intention.

3.8 Conceptual Framework

Together, these hypotheses suggest that consumers' purchase intention in AI-based digital platforms is shaped through both direct and indirect mechanisms. Directly, AI-driven personalization, brand experience, perceived value, and social proof may enhance purchase intention by improving recommendation relevance, digital experience quality, perceived benefits, and social confidence. Prior research demonstrates that AI-powered personalization can influence purchase intention through perceived relevance, usefulness, and trust (An & Ngo, 2025), while online reviews and social proof significantly shape consumers' purchase-related responses in digital commerce (Qiu & Zhang, 2024; Feng *et al.,* 2024). Indirectly, these variables may first influence consumers' evaluation of whether the platform's algorithmic system operates fairly, transparently, and non-manipulatively. In this sense, algorithmic fairness perception functions as a central psychological mechanism that explains how AI-mediated marketing stimuli are translated into purchase intention, since fairness-aware recommender systems are closely related to trustworthiness (Jin & Viswanathan, 2025), and AI transparency as well as privacy assurance can strengthen consumer trust and purchase intention in digital retail personalization (Rahman, 2026). Thus, the proposed framework positions algorithmic fairness perception not merely as an ethical concern, but as a key evaluative process through which consumers decide whether to accept, trust, and act upon platform-generated recommendations.

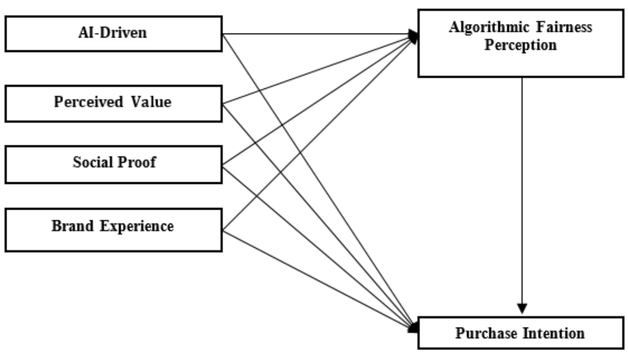

Figure 1. Research Model

3 | METHOD

This study employed a quantitative causal design utilizing a cross-sectional survey to examine the relationships among AI-driven personalization, brand experience, perceived value, social proof, algorithmic fairness perception, and purchase intention. A cross-sectional design was deemed appropriate because data for all constructs were collected at a single point in time, and the study aimed to test both direct and indirect relationships among latent variables. The model was tested using Partial Least Squares Structural Equation Modeling (PLS-SEM), as this approach is suitable for prediction-oriented analysis, complex structural models, latent variable estimation, and mediation testing (Hair *et al.,* 2022).

The target population consisted of consumers who had experience using digital platforms with algorithmic personalization features, particularly e-commerce and online shopping applications. These platforms commonly provide personalized product recommendations, targeted promotions, customized search results, and algorithmically curated reviews or ratings, which have become central features of digital commerce and personalized consumer experience (Tyrväinen *et al.,* 2020; Ampadu *et al.,* 2022). Given that the population size was unknown, this study aimed to recruit at least 400 respondents, which was considered adequate for PLS-SEM analysis involving multiple latent constructs and mediation paths (Hair & Alamer, 2022). Purposive sampling was employed to ensure that respondents had relevant experience with AI-based digital platforms. Participants were required to be at least 18 years old, to have used a platform with personalized recommendations or algorithmically curated content, and to have interacted with or made a transaction on the platform. These criteria ensured that participants could evaluate AI-driven personalization, brand experience, perceived value, social proof, algorithmic fairness, and purchase intention based on actual platform experience.

This study measures six latent constructs: AI-driven personalization, brand experience, perceived value, social proof, algorithmic fairness perception, and purchase intention. All items were adapted from prior studies in AI-based digital marketing, e-commerce, online purchase behavior, and algorithmic decision systems. AI-driven personalization was assessed through recommendation relevance, perceived usefulness, and the ability of AI systems to align with consumer preferences, following studies on AI-powered personalized advertising and personalized recommendation systems (An & Ngo, 2025; Lo *et al.,* 2026). Brand experience was evaluated through digital interaction quality, comfort, positive impressions, and engagement with AI-enabled platforms, consistent with studies on AI-enabled customer experience and e-commerce platform quality (Wang *et al.,* 2024; Hanaysha *et al.,* 2025). Perceived value was measured using indicators related to utilitarian value, convenience, efficiency, and economic benefits, while social proof was assessed through reviews, ratings, product popularity, and information credibility, as these factors are known to influence purchase-related responses in digital commerce (Wang *et al.,* 2023; Qiu & Zhang, 2024). Algorithmic fairness perception was evaluated through fairness, transparency, accountability, objectivity, non-bias, and non-manipulation, drawing from studies on algorithmic decision-making and ethical AI personalization (Aysolmaz *et al.,* 2023; Rahman, 2026). Finally, purchase intention was measured through intention to buy, willingness to follow platform recommendations, and willingness to continue purchasing through the platform, consistent with prior e-commerce and AI personalization research (An & Ngo, 2025; Wang *et al.,* 2024).

Data were collected through an online questionnaire distributed using Google Forms. Respondents were first informed about the purpose of the study and asked to confirm that they met the screening criteria before proceeding to the main questionnaire. Only respondents with experience using e-commerce or digital platforms featuring personalized recommendation capabilities were included. To minimize response bias and common method bias, participation was voluntary and anonymous, and the questionnaire was structured by separating predictor, mediator, and outcome variables into different sections. These procedures align with common method bias controls in survey-based research, where assurances of anonymity, clear questionnaire design, and separation of predictor and criterion variables are recommended to reduce potential bias (MacKenzie & Podsakoff, 2012; Kock *et al.,* 2021). Similar procedural remedies, including randomization of question order, anonymity assurance, and separation of predictor and criterion items, have also been implemented in recent e-commerce purchase intention research (Nguyen *et al.,* 2025).

Given that the study relied on self-reported survey data collected from a single source, common method bias was addressed using both procedural and statistical remedies. Procedurally, anonymity was guaranteed, the questionnaire avoided leading statements, and predictor and criterion items were separated across different sections, as prior methodological studies recommend procedural controls to reduce response bias and common method variance in survey-based research (Min *et al.,* 2016; Cooper *et al.,* 2020). Statistically, common method bias was assessed using Harman's single-factor test and full collinearity Variance Inflation Factor (VIF). Harman's single-factor test examined whether a single factor accounted for the majority of variance, while full collinearity VIF was applied as a more robust diagnostic approach in PLS-SEM. The model is considered free from serious common method bias when the first factor does not exceed 50% of total variance and all full collinearity VIF values remain below the conservative threshold of 3.3 (Ramayanti *et al.,* 2025; Sukhov *et al.,* 2023).

The hypotheses and conceptual model were tested using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS. The analysis followed a two-step procedure consisting of measurement model assessment and structural model assessment. First, the measurement model was assessed to evaluate reliability and validity. Indicator reliability was examined through outer loading values, with loadings of 0.70 or higher considered acceptable. Internal consistency reliability was evaluated using Cronbach's Alpha and Composite Reliability, with values above 0.70 indicating acceptable reliability. Convergent validity was assessed using Average Variance Extracted (AVE), with values above 0.50 indicating that the construct explains more than half of the variance of its indicators. Discriminant validity was evaluated using the Fornell–Larcker criterion and Heterotrait–Monotrait ratio (HTMT), with HTMT values below 0.90 indicating acceptable discriminant validity. Second, the structural model was assessed to test the proposed hypotheses. The evaluation included path coefficients, t-statistics, p-values, coefficient of determination (R^2), effect size (f^2), predictive relevance (Q^2), and mediation effects. The significance of direct and indirect relationships was examined using bootstrapping with 5,000 subsamples at a 5% significance level. A hypothesis was considered supported when the t-statistic was greater than or equal to 1.96 or the p-value was less than or equal to 0.05.

4 | RESULTS AND DISCUSSION

4.1 Results

4.1.1 Measurement Model Assessment

The measurement model was assessed using indicator reliability, internal consistency reliability, convergent validity, and discriminant validity. All measurement items obtained outer loading values above the recommended threshold of 0.70, with loadings ranging from 0.835 to 0.917, indicating that each indicator adequately represents its corresponding latent construct. Therefore, no indicators were removed from the model.

Table 1. Indicator Reliability, Construct Reliability, and Convergent Validity

Construct	Items	Outer Loadings	Cronbach's Alpha	Composite Reliability	AVE
AI-Driven Personalization	AIP1; AIP2; AIP3; AIP4; AIP5	0.835-0.898	0.921	0.941	0.761
Algorithmic Fairness Perception	AFP1; AFP2; AFP3; AFP4; AFP5; AFP6	0.854-0.889	0.934	0.948	0.753
Brand Experience	BE1; BE2; BE3; BE4; BE5	0.854-0.914	0.939	0.953	0.804
Perceived Value	PV1; PV2; PV3; PV4; PV5	0.846-0.917	0.928	0.946	0.777
Social Proof	SP1; SP2; SP3; SP4; SP5	0.846-0.904	0.933	0.949	0.788
Purchase Intention	P1; P2; P3; P4; P5	0.848-0.889	0.919	0.940	0.757

Note: All loadings exceeded 0.70, Cronbach's alpha and composite reliability exceeded 0.70, and AVE exceeded 0.50. These results confirm indicator reliability, internal consistency reliability, and convergent validity.

As shown in Table 1, the Cronbach's alpha values range from 0.919 to 0.939, while composite reliability values range from 0.940 to 0.953, indicating strong internal consistency. The AVE values range from 0.753 to 0.804, exceeding the recommended threshold of 0.50. Therefore, the measurement model demonstrates satisfactory convergent validity.

Table 2. Discriminant Validity: HTMT Criterion

Construct	AIP	AFP	BE	PV	SP	PI
AI-Driven Personalization	-					
Algorithmic Fairness Perception	0.611	-				
Brand Experience	0.599	0.628	-			
Perceived Value	0.577	0.584	0.569	-		
Social Proof	0.520	0.581	0.562	0.548	-	
Purchase Intention	0.543	0.569	0.569	0.586	0.493	-

Note: AIP = AI-Driven Personalization; AFP = Algorithmic Fairness Perception; BE = Brand Experience; PV = Perceived Value; SP = Social Proof; PI = Purchase Intention. All HTMT values were below 0.90, supporting discriminant validity.

Discriminant validity was evaluated using the HTMT criterion. As presented in Table 2, all HTMT values were below 0.90, with the highest value being 0.628. This indicates that the constructs are empirically distinct. Therefore, the measurement model is adequate for further structural model assessment.

4.1.2 Structural Model Assessment

Before testing the hypotheses, collinearity among the predictor constructs was assessed using inner VIF values. The VIF values ranged from 1.599 to 1.971, indicating that the structural model was not affected by serious multicollinearity. The coefficient of determination further shows that the model explains 49.3% of the variance in algorithmic fairness perception and 42.1% of the variance in purchase intention. These results indicate moderate explanatory power and support the relevance of the proposed model in explaining purchase intention in AI-based digital commerce.

Table 3. Collinearity and Effect Size

Endogenous Construct	Predictor	VIF	f^2
Algorithmic Fairness Perception	AI-Driven Personalization	1.695	0.061
Algorithmic Fairness Perception	Brand Experience	1.765	0.073
Algorithmic Fairness Perception	Perceived Value	1.681	0.039
Algorithmic Fairness Perception	Social Proof	1.599	0.052
Purchase Intention	AI-Driven Personalization	1.798	0.017
Purchase Intention	Algorithmic Fairness Perception	1.971	0.025

Purchase Intention	Brand Experience	1.895	0.031
Purchase Intention	Perceived Value	1.746	0.055
Purchase Intention	Social Proof	1.682	0.007

Note: All VIF values were below the conservative threshold of 3.3. The f^2 values suggest small effect sizes, which are common in behavioral research involving multiple predictors.

Table 3 provides a critical assessment of collinearity and effect sizes for predictors related to algorithmic fairness perception and purchase intention. The Variance Inflation Factor (VIF) values, ranging from 1.599 to 1.971, indicate that multicollinearity is not a concern, as all values fall below the acceptable threshold of 3.3. Meanwhile, the effect size (f^2) values reflect small effects, which are not uncommon in behavioral studies involving multiple predictors. This analysis affirms that the predictors maintain their distinctiveness and do not compromise the model's integrity.

Table 4. Coefficient of Determination

Endogenous Construct	R^2	Adjusted R^2
Algorithmic Fairness Perception	0.493	0.488
Purchase Intention	0.421	0.414

Note: The R^2 values indicate moderate explanatory power for both endogenous constructs.

Table 4 outlines the coefficient of determination for algorithmic fairness perception and purchase intention. The R^2 values of 0.493 and 0.421 demonstrate a moderate ability to explain variance in these constructs. The adjusted R^2 values, 0.488 and 0.414, further confirm that the model effectively captures the relationships among the variables involved.

4.1.3 Direct Effect Hypothesis Testing

Direct effect hypothesis testing examines the relationships between predictors and outcomes within the model. The analysis revealed that most relationships were statistically significant, affirming the expected influences of AI-driven personalization, brand experience, perceived value, and algorithmic fairness perception on purchase intention. However, the lack of a significant effect from social proof indicates that its role in influencing purchase intention may be more complex in environments driven by algorithms. This finding invites further investigation into the nuances of social proof's impact.

Table 5. Direct Effects and Hypothesis Testing

Hypothesis	Structural Path	β	STDEV	t-value	p-value	Result
H1	AI-Driven Personalization -> Algorithmic Fairness Perception	0.229	0.047	4.829	0.000	Supported
H2	AI-Driven Personalization -> Purchase Intention	0.134	0.058	2.324	0.020	Supported
H3	Brand Experience -> Algorithmic Fairness Perception	0.256	0.053	4.861	0.000	Supported
H4	Brand Experience -> Purchase Intention	0.184	0.055	3.347	0.001	Supported
H5	Perceived Value -> Algorithmic Fairness Perception	0.181	0.045	4.021	0.000	Supported
H6	Perceived Value -> Purchase Intention	0.237	0.053	4.476	0.000	Supported
H7	Social Proof -> Algorithmic Fairness Perception	0.206	0.048	4.321	0.000	Supported
H8	Social Proof -> Purchase Intention	0.083	0.054	1.553	0.120	Not supported
H9	Algorithmic Fairness Perception -> Purchase Intention	0.170	0.062	2.758	0.006	Supported

Note: Hypotheses were considered supported when $p < 0.05$. All direct effects were significant except for the relationship between Social Proof and Purchase Intention.

Table 5 shows that eight out of nine direct hypotheses were supported. AI-driven personalization, brand experience, perceived value, and social proof significantly influenced algorithmic fairness perception. Additionally, AI-driven personalization, brand experience, perceived value, and algorithmic fairness perception significantly influenced purchase intention. The only unsupported direct relationship was the effect of social proof on purchase intention, suggesting that social proof does not automatically translate into purchase intention in algorithmically mediated platforms.

4.2 Discussion

Focusing on the antecedents of algorithmic fairness perception, this study finds that brand experience contributes the most to algorithmic fairness perception ($\beta = 0.256$, $p < 0.001$), followed by AI-driven personalization ($\beta = 0.229$, $p < 0.001$), social proof ($\beta = 0.206$, $p < 0.001$), and perceived value ($\beta = 0.181$, $p < 0.001$). This ranking indicates that consumers do not assess algorithmic fairness solely based on technical personalization. Instead, their judgment of fairness is significantly influenced by the overall brand experience encountered on the platform. The prominent role of brand experience suggests that consumers interpret algorithmic fairness through the quality of their interactions with the platform. In AI-mediated commerce, the algorithm becomes part of the brand experience. A smooth interface, consistent recommendation quality, clear product presentation, and reliable transaction processes signal that the platform operates responsibly. Thus, algorithmic fairness is not merely a technical characteristic; it is also an outcome of consumer experience. AI-driven personalization positively impacts algorithmic fairness perception. This finding suggests that personalized recommendations are not automatically viewed as intrusive or manipulative. When consumers perceive that AI-driven recommendations align with their needs and preferences, they are more likely to regard the algorithm as useful and fair. In this context, personalization can serve as a positive indicator of algorithmic fairness by reducing search effort and enhancing decision efficiency. Social proof also significantly influences algorithmic fairness perception. This indicates that reviews, ratings, purchase counts, and popularity cues contribute to fairness evaluations when consumers believe such information is presented objectively. Since social proof on digital platforms is often curated or ranked by algorithms, consumers may assess the fairness of the system before relying on these cues. Perceived value further strengthens algorithmic fairness perception, meaning consumers are more inclined to view algorithms as fair when the platform provides benefits proportional to the data, time, attention, and effort they invest.

Table 7. Specific Indirect Effects

Hypothesis	Indirect Path	β	STDEV	t-value	p-value	Result
H10	AI-Driven Personalization -> Algorithmic Fairness Perception -> Purchase Intention	0.039	0.016	2.429	0.015	Supported
H11	Brand Experience -> Algorithmic Fairness Perception -> Purchase Intention	0.044	0.019	2.291	0.022	Supported
H12	Perceived Value -> Algorithmic Fairness Perception -> Purchase Intention	0.031	0.013	2.297	0.022	Supported
H13	Social Proof -> Algorithmic Fairness Perception -> Purchase Intention	0.035	0.016	2.249	0.025	Supported

Note: All indirect effects were significant at $p < 0.05$, confirming the mediating role of algorithmic fairness perception.

Importantly, this study reveals that the influence of AI-driven personalization, brand experience, perceived value, and social proof on purchase intention is partially mediated by algorithmic fairness perception. The specific indirect effect tests indicate that all indirect paths are significant. AI-driven personalization indirectly influences purchase intention through algorithmic fairness perception ($\beta = 0.039$, $p = 0.015$). Brand experience also has a significant indirect effect on purchase intention ($\beta = 0.044$, $p = 0.022$). Perceived value and social proof further demonstrate significant indirect effects through algorithmic fairness perception, with $\beta = 0.031$ ($p = 0.022$) and $\beta = 0.035$ ($p = 0.025$), respectively.

These mediation findings indicate that algorithmic fairness perception is a central psychological mechanism in AI-mediated digital commerce. Consumers' purchase intention is shaped not only by personalization, experience, value, or social proof but also by their evaluation of whether the algorithmic system is fair, transparent, and non-manipulative. This is particularly relevant for social proof; although it does not directly affect purchase intention, it significantly influences it through algorithmic fairness perception. Therefore, reviews and ratings become persuasive when consumers perceive that they are displayed in a fair and unbiased manner.

Table 8. Summary of Hypothesis Testing

Hypothesis	Relationship	Result
H1	AI-Driven Personalization -> Algorithmic Fairness Perception	Supported
H2	AI-Driven Personalization -> Purchase Intention	Supported
H3	Brand Experience -> Algorithmic Fairness Perception	Supported
H4	Brand Experience -> Purchase Intention	Supported
H5	Perceived Value -> Algorithmic Fairness Perception	Supported
H6	Perceived Value -> Purchase Intention	Supported
H7	Social Proof -> Algorithmic Fairness Perception	Supported
H8	Social Proof -> Purchase Intention	Not supported
H9	Algorithmic Fairness Perception -> Purchase Intention	Supported
H10	AIP -> AFP -> PI	Supported

H11	BE -> AFP -> PI	Supported
H12	PV -> AFP -> PI	Supported
H13	SP -> AFP -> PI	Supported

Source: Smart PLS3, 2026

Overall, twelve of the thirteen hypotheses were supported. The only unsupported hypothesis was the direct effect of social proof on purchase intention. However, the significant indirect effect of social proof through algorithmic fairness perception suggests that social proof remains relevant, operating through consumers' evaluations of the algorithmic system's fairness. This finding provides a nuanced understanding of how social proof functions in algorithmically mediated digital platforms. The bootstrapping output from SmartPLS is illustrated in Fig. 1. This figure, derived from the original bootstrapping output, displays the estimated path coefficients alongside the corresponding t-values for the structural relationships.

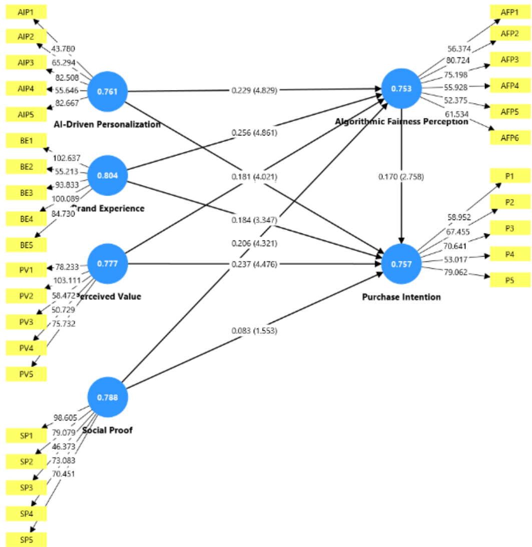

Fig. 2. Bootstrapping Results of the PLS-SEM Model

This study offers several theoretical contributions to digital marketing, AI-mediated consumer behavior, and algorithmic platform research. First, it extends the literature on AI-driven personalization by shifting the focus from effectiveness to fairness-based algorithmic evaluation. Previous discussions have often emphasized relevance and convenience, while this study demonstrates that consumers also assess whether the algorithmic processes behind personalization are fair and transparent. Second, the research positions algorithmic fairness perception as a key mediating mechanism between AI-driven marketing stimuli and purchase intention (Bader & Kaiser, 2019). The findings reveal that AI-driven personalization, brand experience, perceived value, and social proof influence purchase intention both directly and indirectly through consumers' evaluations of fairness. Third, this study enhances the understanding of social proof by illustrating that it does not directly influence purchase intention in algorithmically curated environments. Instead, its impact hinges on whether consumers perceive the display of reviews and ratings as fair (Gong *et al.,* 2026). This suggests a need to reevaluate social proof in algorithmic platforms, where visibility and ranking are influenced by opaque recommendation systems.

The research also provides practical implications for digital marketplace managers and AI-based platform designers. First, platform managers should view AI personalization as more than just a technical recommendation tool. Personalized recommendations must be designed to appear fair and consumer-oriented. Aggressive or biased recommendations may undermine consumers' perceptions of fairness. Second, enhancing brand experience is vital, as it significantly impacts algorithmic fairness perception. A seamless interface, consistent recommendation quality, transparent product information, and reliable transaction processes can strengthen consumers' belief in the fairness of the platform's algorithm. Thus, integrating algorithmic design into brand experience management is essential. Third, platforms should focus on increasing perceived value by ensuring that algorithmic recommendations help consumers save time, reduce search effort, compare alternatives, and make informed decisions. Consumers are more likely to develop purchase intentions when they recognize meaningful benefits relative to the data and attention they provide. Lastly, social proof should be managed transparently. Since it does not directly influence purchase intention, platforms should ensure that reviews, ratings, and popularity indicators appear credible and fairly displayed. Implementing clearer review sorting options, transparent rating systems, and visible disclosures of sponsored products can enhance perceptions of fairness.

5 | CONCLUSIONS AND FUTURE WORK

This study demonstrates that AI-driven personalization, brand experience, perceived value, and social proof significantly influence consumers' perceptions of algorithmic fairness. Additionally, AI-driven personalization, brand experience, perceived value, and algorithmic fairness perception positively affect purchase intention. Although social proof does not directly impact purchase intention, it exerts a significant indirect influence through algorithmic fairness perception. This indicates that consumers evaluate not only marketing stimuli but also the fairness of the algorithmic processes shaping their digital experiences. The findings underscore algorithmic fairness perception as a crucial psychological mechanism linking AI-enabled marketing practices with consumer purchase intention. This research extends the AI marketing literature by showing that the effectiveness of personalization relies not only on recommendation relevance but also on consumers' perceptions of transparency, objectivity, and fairness. Therefore, algorithmic fairness should be viewed as both an ethical principle and a strategic capability for enhancing consumer trust and fostering sustainable customer relationships in AI-driven digital commerce.

From a practical standpoint, digital platforms should focus on more than just improving recommendation accuracy; they must prioritize the development of transparent, explainable, and consumer-oriented AI systems. Enhancing brand experience, increasing perceived value, and ensuring the fair presentation of recommendations, reviews, and ratings can bolster consumers' confidence in AI-enabled platforms and ultimately improve purchase intention. These findings offer valuable guidance for managers aiming to balance technological innovation with responsible AI governance. Future research should consider employing longitudinal or experimental designs to establish stronger causal relationships and explore how consumers' perceptions of algorithmic fairness evolve over time. Comparative studies across different digital platforms and cultural contexts are also recommended to enhance the generalizability of the findings. Furthermore, future models could incorporate additional variables such as algorithmic transparency, explainability, privacy concerns, consumer trust, AI literacy, and perceived manipulation to provide a more nuanced understanding of consumer behavior in increasingly AI-driven digital marketplaces.

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