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AI-Driven Personalization and Consumer Trust in E-Commerce: A Synthesis of Contemporary Evidence

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Abstract:
AI now runs most of the personalization machinery in e-commerce — the recommendation systems, the chatbots, the interfaces that affects consumer product identification, evaluation and purchase. But the research findings on the relationship between trust and personalisation remains contradictory. Some studies found that it boosts purchase intention and loyalty by a wide margin. Others find the opposite of it that people get suspicious and worry about privacy they trust the platform less once personalization starts feeling intrusive or hard to explain. This paper pulls together 24 recent studies, including empirical work, conceptual papers, and one bibliometric review, on AI personalization, recommendation systems, and consumer trust. Instead of going study by study, it synthesises them to see where they actually agree and where they don't. The pattern that emerges is that transparency, accuracy, and perceived value tend to build trust whereas Privacy worries, over-personalization, and cultural or religious mismatch tend to break it down. And on one specific point, whether transparency helps or hurts persuasion, the studies contradict each other outright. The paper ends by looking at fairness, accountability, and governance questions in AI-driven personalization, and also suggest future research directions.

Keywords: Artificial Intelligence, Personalization, Consumer Trust, Recommendation Systems, E-commerce, Privacy Paradox.

Introduction

Artificial intelligence has developed from a marginal analytical tool to the core system that e-commerce platforms use to facilitate interactions between consumers and products. Recommendation systems, AI chatbots and algorithmically customized interfaces are increasingly shaping what consumers see, in what order they see it and how it is presented, thus transferring part of consumer decision-making to automated agents (Pal et al., 2023) [12]. This delegation poses a question to a large body of scholarship on marketing and information systems that when do consumers trust AI and act on its recommendations, and when does personalization leads to skepticism, resistance, or disengagement?

The 24 studies we review in this paper collectively suggest that relationship between trust and personalisation is not so simple. A large body of research on e-commerce recommendation systems (Kim et al., 2021) [10], AI-based shopping assistants (Yin & Qiu, 2021) [22], functional food marketplaces (Wang et al., 2025) [20] and tourism-related e-commerce (Duan et al., 2026) [3] showed that effective personalization continue to improve purchase intention, satisfaction and customer loyalty. At the same time, a some researches identifies a “personalization paradox” which means that the same features that make AI recommendations useful also threaten them, as users experience psychological reactance (Duan et al., 2026) [3], privacy concerns (Amil, 2024 [2]; Erlei et al., 2026 [4]), and discomfort about algorithmic transparency (Li et al., 2024) [11]. The third category of research view trust not only as an outcome, but as a mediating or moderating variable, explaining why personalization sometimes succeeds and sometimes don’t (Hassan et al., 2025 [8]; Rivaldiansyah & Supriyanto, 2026 [14]; Teodorescu et al., 2023 [18]).

In this analysis, these three categories are combined with studies on anthropomorphism (Wang et al., 2025) [21], algorithmic transparency (Li et al., 2024 [11]; Teodorescu et al., 2023 [18]), demographic and cultural moderators (Guerra-Tamez et al., 2024 [6]; Hussain, 2025 [9]), and a bibliometric assessment of the discipline’s progression (Gombar et al., 2026) [5]. The document is organized thematically to explore the extent to which different theoretical frameworks converge on similar mechanisms (e.g. trust, transparency, perceived value) and diverge on their directional and interaction effects, rather than treating each paper as a single piece of information that stands alone. This paper is addressed to an academic audience and seeks to add on to the literature on AI, personalization and consumer trust.

Methodology

This analysis consolidates 24 studies extracted from an extensive collection of around 40 articles identified via focused searches in academic databases (including journals indexed in Scopus and Web of Science, such as Sustainability, Journal of Theoretical and Applied Electronic Commerce Research, and Foods, as well as recent conference proceedings from CHI, SIGIR, and ASIS&T) utilizing various combinations of the keywords "AI personalization," "recommendation systems," "consumer trust," "e-commerce," and "privacy. Research was included if it empirically, conceptually, or bibliometrically analyzed the connection between AI-based personalization or recommendation systems and consumer trust, attitudes, or purchase-related results in a commercial or e-commerce-related setting, and was published from 2019 to 2026. The final analysis excluded studies on AI personalization that were not related to a consumer-oriented commercial context or did not propose a separate framework of trust, transparency or purchase intention. The resultant set includes quantitative surveys, structural equation models, qualitative interviews, controlled experiments, and a bibliometric mapping study. These are used to inform the thematic organization detailed below, rather than a chronological or study-by-study approach.

Table 1: Summary of Reviewed Studies

Author(s) & Year	Context / Sample	Theoretical Lens	Key Finding
1. Adawiyah et al. (2024)	Cosmetics recommendations, Shopee	TAM-style constructs	Ease of use, usefulness, and trust jointly explain intention to use AI+AR recommendations.
2. Amil (2024)	453 Amazon customers	Privacy calculus	Perceived benefits reduce privacy concern; perceived

			risk (breach, consent) increases it; anonymity has no effect.
3. Duan et al. (2026)	AI tourism e-commerce, Gen Y/Z	SOR; Psychological Reactance Theory	Personalization raises usage intention but also reactance; privacy concern amplifies the reactance pathway.
4. Erlei et al. (2026)	Experimental (CHI '26)	Privacy / economic risk	Ambiguous (unranged) risk reduces adoption; quantifiable risk does not, even for anonymized data.
5. Gombar et al. (2026)	Bibliometric mapping, 163 pubs (2012-2025)	Acceptance Triangle (proposed)	Field shifting from usability to governance; proposes trust, exposure fairness, and accountability as nested layers.
6. Guerra-Tamez et al. (2024)	Gen Z, fashion/tech/beauty/education	Brand trust	AI meaningfully shapes brand trust and purchasing behavior specifically for Gen Z.
7. Gupta & Bansal (2019)	1,500 consumers	Behavioral/conversion metrics	Personalization boosts CTR and conversion; over-personalization risks choice overload; Millennials most receptive.
8. Hassan et al. (2025)	AI-driven e-commerce	Trust-satisfaction-loyalty chain	Trust drives satisfaction and loyalty; personalized recommendations strengthen this chain.
9. Hussain (2025)	211 Pakistani consumers, modest fashion	Consumer Trust Theory; Regulatory Focus Theory	Sharia compliance moderates the personalization-purchase intention relationship.
10. Kim et al. (2021)	Recommender-system design	Accuracy/diversity metrics	Accuracy and diversity both raise satisfaction with deep-learning recommenders; only accuracy matters for traditional systems.
11. Li et al. (2024)	E-commerce recommendation systems	Three-layered trust model	Transparency raises trust via perceived effectiveness

			(+) and discomfort (-); net effect positive but double-edged.
12. Pal et al. (2023)	Stock-market AI recommendations	Trust/acceptance model	Attitude and perceived accuracy build trust; AI anxiety erodes it; trust predicts acceptance.
13. Raza et al. (2025)	Critical review	Economic/demand framing	AI reshapes demand via pattern recognition; the same capacity enables demand manipulation.
14. Rivaldiansyah & Supriyanto (2026)	Shopee users, Indonesia	AI technology trust	Reliability and accuracy drive adoption directly and via trust (partial mediation).
15. Rolando (2025)	E-commerce purchase decisions	Multi-factor purchase model	Accuracy, personalization, interface quality, trust, and value jointly shape purchase decisions.
16. Saxborn et al. (2024)	Fashion e-commerce, qualitative	Trust Building Model	Competence belief outweighs structural assurance in shaping behavioral intention.
17. Sharma et al. (2025)	Consumer perspective survey	Cognitive/affective response	Personalization shapes the cognitive and affective reactions underlying trust and value.
18. Teodorescu et al. (2023)	Romanian university students	Trust in AI algorithms	Transparency, familiarity, and perceived usefulness positively associated with trust.
19. Vafaei-Zadeh et al. (2024)	AI customer service, Malaysia	SOR + Task-Technology Fit	AI readiness moderates task-fit to adoption; initial trust is not a significant moderator.
20. Wang, Chen & Kuang (2025)	Functional food purchases	Perceived value mediation	Personalization and transparency affect purchase intention mainly indirectly, via perceived value/packaging.
21. Wang, Sauka & Situmeang (2025)	Generative AI marketing communication	Anthropomorphism / social presence	AI-disclosure transparency undercuts

			anthropomorphism's effect on social presence, trust, and purchase intention.
22. Yin & Qiu (2021)	Online shopping platforms	SOR	Accuracy, insight, and interaction quality raise utility and hedonic value; purchase intention (hedonic stronger).
23. Yoon & Lee (2021)	AI vs. human-expert recommendation	Empathy / need for cognition	Tech quality to personalization quality to intention via empathy; moderated by need for cognition.
24. Zhang et al. (2024)	AI chatbot recommendations	Elaboration Likelihood Model	Reliability, accuracy, and trust drive adoption; perceived self-threat undermines it.

Literature Review

The Consistent Case: Personalization Increases Purchase Intention and Satisfaction

Large-scale quantitative studies agree that AI-driven personalization significantly improves important e-commerce outcomes. Gupta and Bansal (2019) [7] conducted a survey and behavioural analysis of data from 1,500 consumers and found that AI personalization resulted in substantially higher click-through rates, site visits, add-to-cart rates, and order completions than non-personalized approaches. Web sites employing full AI personalization experienced about twice the year-over-year conversion growth as sites with limited personalization. Similarly, Yin and Qiu (2021) [22] adopted Stimulus-Organism-Response (SOR) framework in the context of online shopping platforms and found that the precision, perceptiveness and quality of interaction delivered by AI technology significantly improved the utility and hedonic values of consumers, which affected their purchase intentions, with hedonic value as the stronger motivator. Rolando (2025) [15] also identified accuracy of recommendations, personalization, interface quality, trust and perceived value together affected purchasing decisions of e-commerce consumers. Sharma et al. (2025) [17] found that AI-driven personalization affected not only behavioural intentions, but also cognitive and emotional responses which are the basis of consumer trust and perceived value.

In some product classifications you can see this trend. In their study on functional food purchases, Wang et al. (2025) [20] found that individualization of AI recommendations had a significant positive influence on purchase intention directly and indirectly through perceived packaging and perceived value. In contrast, Adawiyah et al. (2024) [1] showed that perceived ease of use, usefulness, and trust explained together consumers' willingness to use personalized recommendation features in their study on AI-and-AR-embedded cosmetics recommendations on Shopee. Kim et al. (2021) [10] found that for a deep learning-based recommender system both precision and variety of recommendations increase customer satisfaction, but for a traditional non-deep learning recommender system only precision was significant. Their study implies that the benefits of personalization depend on sophistication of the underlying algorithm, not on personalization as a general idea.

Trust as the Pivotal Mediating Mechanism

Later, a set of studies re-conceptualizes personalization as not a direct driver of purchasing behavior but a factor that primarily affects trust and then influences later-outcomes. In the study by Hassan et al. (2025) [8], trust was shown to be a significant predictor of satisfaction and loyalty in AI-based e-commerce. The trust-satisfaction-loyalty nexus was moderated by personalized recommendations, which increased the explanatory power of the model. A similar finding was observed in the study of Shopee users in Indonesia by Rivaldiansyah and Supriyanto (2026) [14] stating that reliability and accuracy of recommendations have positive effect on adoption intention both directly and indirectly through trust in AI technology where trust is a partial mediator and not only a correlate of personalization quality. Pal et al. (2023) [12] applied this logic to a more sensitive domain, stock market investment advice, and found that attitude towards AI and perceived AI precision positively predicted trust in AI, while AI anxiety negatively predicted trust in AI. Trust then predicted willingness to accept AI recommendations. Saxborn et al. (2024) [16], using qualitative Trust Building Model methodology in fashion e-commerce, found that belief in competence had the strongest effect on behavioral intention among traditional trust antecedents. This result, according to the authors, is the opposite of the conclusions of the Trust Building Model, where structural assurance or site quality is usually the most important factor.

Zhang et al. (2024) [24] approached trust through the Elaboration Likelihood Model (ELM), and found that the reliability and accuracy of AI chatbot recommendations, together with users' trust in the AI technology, were most important factors in shaping adoption intention, and that perceived self-threat, the sense that the AI recommendation intrudes personal autonomy, worked against adoption. This finding anticipates a theme that becomes more important in the "paradox" literature below. that trust in AI recommendations is not simply a function of how good the recommendation is, but of how the interaction is perceived to affect the user's sense of control.

Transparency: A Contested Lever

Transparency is often suggested as a way to improve consumer trust in AI, but the studies we reviewed showed a lot of variability in the overall effect. In Li et al. (2024) [11], it was shown how the use of a three-tier trust model in e-commerce recommendation systems increased consumers' trust in recommendation systems (CTRS) through two opposing mediators, i.e., the increase of perceived effectiveness (which increases trust) and the increase of discomfort (which decreases trust), so it had a net positive effect, but with a truly dual-faceted mechanism. The positive role of transparency was interpreted very positively by Teodorescu et al. (2023) [18], who found that confidence in AI algorithms used in e-commerce was strongly and positively correlated with transparency, familiarity with other AI technologies and perceived utility when examining Romanian university students. On the other hand, Wang et al. (2025) [21] examined generative AI (GAI) in marketing communication. They found that transparency, which is defined as disclosing that the content was generated by AI, reduces the positive effect of anthropomorphism on perceived social presence, and therefore reduces the subsequent effect of anthropomorphism on trust and purchase intention with the increase of disclosure. "By telling consumers 'this was produced by AI' you remove the anthropomorphic cues that initially made the AI appealing."

This is in contrast with the common belief that transparency necessarily builds trust, e.g., Li et al. (2024) [11], Teodorescu et al. (2023) [18]. In their research on functional food recommendations, Wang, Chen, and Kuang (2025) [20] clarify that the transparency of AI recommendations affects purchase intention indirectly via perceived value, rather than directly. This finding implies that the relationship of transparency and behaviour is more complex and mediated than the simple assertion that "transparency builds trust". Taken together, these findings suggest that transparency is not an explicitly positive mechanism, and that its effects depend on the type of disclosure, the audience, and the psychological route taken (effectiveness vs. discomfort, social presence vs. perceived value).

The personalization paradox Privacy, reactance and over-personalization

A unique series of studies shows a "personalization paradox" in which the same processes that increases the value of AI recommendations also trigger resistance. Duan et al. (2026) [3] investigated AI-enhanced tourism e-commerce for Generation Y and Z consumers. They proposed a Threat-Substitution Mechanism based on the SOR/Psychological Reactance Theory framework. They found that AI-driven personalization increased usage intention, and also increased psychological reactance. The psychological reactance played a mediating role, and reduced the positive relationship between personalization and usage intention. Importantly, privacy concerns strengthened this negative trend, suggesting that privacy-sensitive individuals responded to personalization with great threat perception rather than ongoing resistance, thus redefining the paradox as contextual rather than universal.

Erlei et al. (2026) [4] experimentally isolated the dimension of privacy and found that when there is a measurable risk (known probability of data leakage), privacy threats did not reduce AI adoption compared to the neutral scenario. However, in uncertain situations (variable probability of leakage), privacy threats reduced significantly the adoption, even for anonymized information. Theoretically, this means that consumer resistance to personalized AI is driven more by uncertainty about privacy risks, rather than the risks themselves, and that people are willing to pay a premium for clarity on how their data will be used. Amil (2024) [2], in a master's thesis focusing on AI-powered personalization tools, identifies privacy concerns as a threat to consumer trust in e-commerce and claims that effective privacy management is a prerequisite for successful personalization. Gupta and Bansal (2019) [7] observe a relevant mechanical risk that exists even without privacy issues that excessive personalization can lead to information/choice overload, adversely affecting the shopping experience, suggesting that the paradox encompasses not just data ethics but also cognitive load.

Anthropomorphism, Cultural Moderators, and Demographic Boundary Conditions

In addition to trust and transparency, many studies provide particular boundary conditions that influence the effectiveness of personalization. Wang et al. (2025) [21] found that anthropomorphism or human-likeness of an AI agent positively influences purchase intention directly and indirectly through perceived social presence and trust, and that this effect is stronger in chatbot interactions compared to static AI-generated advertisements, indicating that interactivity enhances the persuasive power of human-like AI. Yoon and Lee (2021) [23] found a different but similar process in which AI recommendation service increased perceived technology quality relative to a human expert recommendation, which increased personalization quality, which increased behavioral intention mediated by perceived empathy, and the mediation was moderated by users' need for cognition such that the empathy effect was exacerbated in users with low need for cognition as technology quality increased. The cultural and religious context further modulates the effects of personalization in ways that are not accounted for in general models. Hussain (2025) [9] investigated modest fashion e-commerce among 211 Pakistani consumers and found that Sharia compliance mediates the relationship between AI-driven personalization and purchase intention. AI recommendations that are consistent with Islamic ethical and modesty standards significantly enhance trust and purchase intention compared to those that are religiously misaligned, extending Consumer Trust Theory and Regulatory Focus Theory into a new domain. Guerra-Tamez et al. (2024) [6] studied Generation Z in fashion, technology, beauty, and education. They found that AI has a powerful impact on brand trust and purchasing decisions for this demographic. Gupta and Bansal (2019) [7] found that Millennials were more receptive to AI personalization than other demographics and the conversion effect was larger in travel and subscription industries, especially among consumers with high baseline site trust. Vafaei-Zadeh et al. (2024) [19] studied the adoption of AI customer service in Malaysia, applying an integrated SOR and Task-Technology Fit (TTF) framework. Their results showed that AI readiness positively affected the association between task-technology fit and adoption intention. Initial trust, however, did not have a significant moderating effect on the relationship for this sample, contrary to the trust-centric results shown elsewhere in this review, and indicating that the moderating effect of trust may be context-specific, whether national or platform.

Theoretical Framework and Discussion

The studies reviewed here draw on a heterogeneous set of theoretical frameworks, SOR (Duan et al., 2026 [3]; Vafaei-Zadeh et al., 2024 [19]; Wang et al., 2025 [21]; Yin & Qiu, 2021 [22]), ELM (Zhang et al., 2024 [24]), the Trust Building Model (Saxborn et al., 2024 [16]), Consumer Trust Theory and Regulatory Focus Theory (Hussain, 2025 [9]), Psychological Reactance Theory (Duan et al., 2026 [3]), and Task-Technology Fit (Vafaei-Zadeh et al., 2024 [19]), yet they converge on a small set of shared constructs: perceived accuracy, perceived value, trust, and perceived control or autonomy. Together, these frameworks suggest a layered model of how AI personalization operates. At the base layer, technical performance (accuracy, reliability, diversity of recommendations) shapes perceived value and perceived effectiveness (Kim et al., 2021 [10]; Li et al., 2024 [11]; Zhang et al., 2024 [24]). At a second layer, this perceived value and effectiveness leads to trust, which functions as the central mediating variable connecting AI system quality to behavioral outcomes such as adoption, purchase intention, and loyalty (Hassan et al., 2025 [8]; Pal et al., 2023 [12]; Rivaldiansyah & Supriyanto, 2026 [14]). At a third layer, moderating variables, need for cognition (Yoon & Lee, 2021 [23]), domain knowledge (Li et al., 2024 [11]), privacy sensitivity (Duan et al., 2026 [3]; Erlei et al., 2026 [4]), cultural/religious alignment (Hussain, 2025 [9]), and demographic cohort (Guerra-Tamez et al., 2024 [6]; Gupta & Bansal, 2019 [7]), determine how strongly the trust and outcome relationship holds for a given consumer.

An integrative structure for this complex model is provided by the Acceptance Triangle framework of Gombar et al. (2026) [5], which is derived from a bibliometric analysis of 163 publications from 2012 to 2025. The authors argued that the field has shifted from usability to governance, such that algorithmic acceptability in recommender systems is mediated through three interconnected levels that are trust calibration at the interface, exposure fairness at the platform, and accountability mechanisms at the institutional level. This model is important because it solves an obvious disagreement in the literature. Studies that treat trust simply as an interface-level, individual-psychological phenomenon (e.g., Yoon & Lee, 2021 [23]; Pal et al., 2023 [12]) are not wrong, but only the innermost layer of a layered system, with outer layers about fairness in information dissemination and accountability in algorithm governance being examined by a different and more institutionally oriented research stream (Gombar et al., 2026 [5]; Raza et al., 2025 [13]).

This layered reading helps explain the contradictions identified in the literature review. The disagreement between Li et al. (2024) [11] and Teodorescu et al. (2023) [18], who found transparency as directly trust-enhancing, and Wang et al. (2025) [21], who find that AI-disclosure transparency cuts thee anthropomorphism's persuasive effect, can be reconciled by distinguishing transparency about system logic (which reduces discomfort and increases perceived effectiveness) from transparency about content provenance (which can puncture the social illusion that makes anthropomorphized AI persuasive). Similarly, the contradiction between studies that find personalization uniformly beneficial (Gupta & Bansal, 2019 [7]; Rolando, 2025 [15]; Sharma et al., 2025 [17]) and those that find it can trigger reactance (Duan et al., 2026 [3]) is resolved by recognizing that the former studies largely measure average effects across a general population, while the latter isolates the subgroup of privacy-sensitive or autonomy-sensitive consumers for whom the same personalization mechanism is perceived as a threat rather than a service. Delegation of decision-making to AI, in other words, is not experienced uniformly: some consumers experience delegation as a convenience that increases perceived empathy and technology quality (Yoon & Lee, 2021 [23]), while others experience the same delegation as a loss of control that must be actively defended against (Pal et al., 2023 [12]; Zhang et al., 2024 [24]).

Although they operationalized the "organism" phase in different ways (perceived value, task-technology fit, psychological reactance, and social presence, respectively), it is remarkable that the SOR framework appears in various product categories, such as online shopping platforms (Yin & Qiu, 2021 [22]), AI customer service (Vafaei-Zadeh et al., 2024 [19]), tourism (Duan et al., 2026 [3]), and generative AI marketing communication (Wang et al., 2025 [21]). This convergence suggests that the SOR stimulus-organism-response framework is generally appropriate for modeling AI personalization; nevertheless, the discipline has not yet established a common set of organism-stage constructs, which complicates cross-study comparisons of effect sizes even though a common theoretical basis exists. A similar observation belongs to the trust-focused research: Hassan et al. (2025) [8], Pal et al. (2023) [12], Rivaldiansyah and Supriyanto (2026) [14], and Saxborn et al. (2024) [16] all consider trust as essential, yet they employ distinct methodologies for its measurement and situate it variably within the causal framework, occasionally as a mediator, at times as a moderator, and sometimes as an ultimate outcome variable. This variability in measurement is a key finding. It suggests that "trust in AI" is an umbrella term that may include several conceptual constructs (e.g., competence trust, benevolence trust, and system trust) that have not yet been disentangled in the literature.

Challenges and Fairness Considerations

The literature we have studied here suggests several different challenges for AI powered personalization in e-commerce. Initially, the trade-off between privacy and personalization is not merely characterized by "increased data leads to heightened risk and diminished trust"; Erlei et al. (2026) [4] demonstrate that uncertainty related to risk, rather than the risk itself, undermines adoption, suggesting that platforms that want to maintain trust must focus on conveying clear and defined risks instead of merely reducing data accumulation. Sharma et al. (2025) [17] describe this problem as a holistic transparency and data-ethics problem which means that while satisfaction on platforms is reported to be high, users often do not understand how algorithms shape their viewing experiences, leading to what the authors call a personalization-privacy paradox, where consumers want personalized experiences but at the same time are worried about data misuse.

Amil's (2024) [2] study of 453 Amazon consumers provides a useful addition to the risk and ambiguity distinction outlined by Erlei et al. (2026) [4]. The results showed that higher levels of perceived benefits of personalization reduced users privacy concerns, while higher levels of perceived risks, especially data-breach and consent risks, increased them. The perceived anonymity of the internet did not have a significant effect on privacy concerns. As per the research of Erlei et al. (2026) [4], suggests that consumers consider personalization choices along at least two separate axes: perceived advantage and perceived danger, rather than simply a privacy and personalization dichotomy, indicating the possibility that attempts to reduce perceived risk alone without simultaneously communicating tangible benefits may not be enough. Raza et al. (2025) [13], in a comprehensive analysis of AI's influence on e-commerce consumer demand, contextualize this conflict within a wider economic perspective, asserting that AI-enhanced demand-shaping instruments, such as recommendation systems, predictive analytics, and dynamic pricing, are transforming entire economic structures by facilitating quick recognition of extensive behavioural trends, yet they warn that the same pattern-recognition abilities that allow for beneficial personalization also permit demand manipulation that current consumer protection regulations are unable to handle.

Second, fairness and exposure equity are emerging as governance concerns distinct from individual-level trust. Gombar et al. (2026) [5] explicitly identify exposure fairness, whether recommendation systems distribute visibility equitably across products, sellers, or demographic groups, as a platform-level concern that usability-focused research has previously neglected, and to address this issue, the authors argue that standard, interface-level trust features must be paired with broader institutional accountability mechanisms.This suggests that fairness in AI-driven personalization cannot be fully addressed by improving individual consumers trust or satisfaction; it also requires structural oversight of how recommendation algorithms distribute visibility and opportunity.

Third, the importance of cultural and religious equity is obvious but has not been sufficiently explored. Hussain (2025) [9] demonstrates that a personalization framework that has been developed in the West, when employed in a religiously sensitive market (Sharia-compliant modest fashion), may evoke doubt unless the AI system's outputs are explicitly aligned with the ethical principles of the target consumer group, raising a fairness question about the normative basis of AI personalization systems and the potential impact of any misalignment. This is exacerbated by the demographic-boundary-condition results mentioned earlier (Guerra-Tamez et al., 2024 [6]; Gupta & Bansal, 2019 [7]), indicating that the identical personalization system does not yield consistent performance across different groups, suggesting that systems that are fine-tuned on collective metrics may neglect consumers whose preferences differ from the predominant trend in the training or assessment data.

Fourth, many studies suggest a trade-off between persuasive effectiveness and consumer independence with important ethical implications. Zhang et al. (2024) [24] found that the perception of self-threat reduces the acceptance of AI chatbot suggestions, suggesting that overly persuasive and anthropomorphized AI (Wang et al., 2025 [21]) may shift from beneficial personalization to manipulation if it fails to preserve a consumer's sense of autonomy. Initial trust did not significantly affect the relationship between technology fit and adoption in the Malaysian sample of Vafaei-Zadeh et al. (2024) [19], challenging the idea that trust is a sufficient safeguard; task-technology fit and AI readiness may operate independently of trust, suggesting that interventions focused only on building trust may not be sufficient for ethical and well-calibrated adoption.

Conclusion

In the 24 studies analyzed, the positive impact of AI-based personalization on consumer behavior in e-commerce is significant but not always positive. There is a large body of research that repeatedly shows that the accuracy, reliability, and perceived value of recommendations significantly enhance purchase intention, satisfaction, and loyalty (Gupta & Bansal, 2019 [7]; Kim et al., 2021 [10]; Rolando, 2025 [15]; Wang et al., 2025 [20]; Yin & Qiu, 2021 [22]), with trust being the key mechanism mediating and moderating these dynamics (Hassan et al., 2025 [8]; Pal et al., 2023 [12]; Rivaldiansyah & Supriyanto, 2026 [14]; Saxborn et al., 2024 [16]). The literature presents a genuine contrast regarding the overall impact of transparency, which can reduce discomfort and foster trust in certain situations (Li et al., 2024 [11]; Teodorescu et al., 2023 [18]), yet may undermine the anthropomorphic and persuasive efficacy of AI-generated content in other scenarios (Wang et al., 2025 [21]). Additionally, there is debate over whether personalization is perceived as a beneficial service or a menacing threat, with factors such as privacy uncertainty, cultural discord, and a perceived erosion of autonomy contributing to the adverse effects of personalization (Duan et al., 2026 [3]; Erlei et al., 2026 [4]; Hussain, 2025 [9]; Zhang et al., 2024 [24]). The academic discussions is sharply contrasting regarding the implications of transparency, which can reduce discomfort and enhance trust in specific contexts (Li et al., 2024 [11]; Teodorescu et al., 2023 [18]), while simultaneously possessing the potential to diminish the anthropomorphic and persuasive attributes of AI-generated content in alternative contexts (Wang et al., 2025 [21]). Furthermore, there is an ongoing debate about whether personalization is regarded as a service or a threat, with privacy ambiguity, cultural misalignment, and perceived autonomy loss identified as conditions that can lead to the failure of personalization (Duan et al., 2026 [3]; Erlei et al., 2026 [4]; Hussain, 2025 [9]; Zhang et al., 2024 [24]). The Acceptance Triangle framework (Gombar et al., 2026 [5]) frames trust calibration, exposure fairness, and institutional accountability as interconnected components, providing a promising pathway to join these individually credible but seemingly dissimilar findings into a comprehensive governance-oriented model of algorithmic acceptability.

Future Research Gaps

The analyzed literature has many shortcomings. Initially, a limited number of investigations directly compared transparency regarding system logic with transparency concerning content provenance within a singular experimental framework; conducting such comparisons would aid in reconciling the discrepancies highlighted between Li et al. (2024) [11]/Teodorescu et al. (2023) [18] and Wang et al. (2025) [21]. Second, the replication of findings across cultures and religions is infrequent: Hussain (2025)

[9] findings on Sharia compliance and Guerra-Tamez et al. (2024) [6]. The findings about Gen Z are based on individual-context samples. We do not know whether the relationships between personalization and trust may or may not transfer to other religious, generational, or national contexts beyond this collection of 24 studies. Third, none of the studies analyzed longitudinally examine the progression of trust in AI personalization after a privacy breach or a revealed algorithmic mistake, even though Erlei et al. (2026) [4] show that uncertainty about risk (rather than the risk itself) drives resistance, which a single cross-sectional survey cannot capture. Fourth, the issues of fairness and exposure-equity raised by Gombar et al. (2026) [5] are theoretical and bibliometric in nature, without empirical validation regarding individual consumer outcomes; empirical research that directly measures the effect of unequal algorithmic exposure on trust or perceived fairness among marginalized sellers or underrepresented consumer demographics would greatly improve this body of literature. Most of the studies reviewed rely on self-report survey data of trust and intention rather than actual purchasing behavior, which limits causal claims of the impact of trust fueled by personalization on sustained behavioral change rather than fleeting stated intentions.

REFERENCES:

1. Adawiyah, S.R, Purwandari, B, Eitiveni, I. Purwaningsih, E.H, The influence of AI and AR technology in personalized recommendations on customer usage intention: A case study of cosmetic products on Shopee, Applied Sciences, 2024, 14 (13), Article 5786. https://doi.org/10.3390/app14135786
2. Amil, Y, The impact of AI-driven personalization tools on privacy concerns and consumer trust in e-commerce, Master's thesis, HEC Liège - University of Liège, 2024.
3. Duan, H, Dawod, A.Y, Wan, G, The personalization paradox in AI-driven tourism e-commerce: Psychological reactance, threat-substitution, and the moderating role of privacy concerns, Journal of Theoretical and Applied Electronic Commerce Research, 2026, 21 (4), Article 127. https://doi.org/10.3390/jtaer21040127
4. Erlei, A, Abbas, T, Bizer, K, Gadiraju, U, The data-dollars tradeoff: Privacy harms vs. economic risk in personalized AI adoption, Proceedings of the 2026 CHI Conference on Human Factors in Computing Systems (CHI '26), Association for Computing Machinery, 2026. https://doi.org/10.1145/3772318.3791427
5. Gombar, M, Topalović, A, Pejić Bach, M, Trust in algorithms in e-commerce recommender systems: A bibliometric mapping (2012-2025) and a managerial playbook for acceptability, Journal of Theoretical and Applied Electronic Commerce Research, 2026, 21 (6), Article 166. https://doi.org/10.3390/jtaer21060166
6. Guerra-Tamez, C.R, Kraul Flores, K, Serna-Mendiburu, G.M, Chavelas Robles, D, Ibarra Cortés, J, Decoding Gen Z: AI's influence on brand trust and purchasing behavior, Frontiers in Artificial Intelligence, 2024, 7, Article 1323512. https://doi.org/10.3389/frai.2024.1323512
7. Gupta, T., Bansal, S, The AI advantage: Assessing personalization effects on e-commerce shopping behaviors, International Journal of Science and Research, 2019, 8 (8).
8. Hassan, N, Abdelraouf, M, El-Shihy, D, The moderating role of personalized recommendations in the trust-satisfaction-loyalty relationship: An empirical study of AI-driven e-commerce, Future Business Journal, 2025, 11, Article 66. https://doi.org/10.1186/s43093-025-00476-z

9. Hussain, Z, AI-driven personalization and purchase intention in modest fashion: Sharia compliance as moderator, International Journal of Halal Industry, 2025, 1 (1), 33-45. https://doi.org/10.20885/IJHI.vol1.iss1.art3
10. Kim, J, Choi, I, Li, Q, Customer satisfaction of recommender system: Examining accuracy and diversity in several types of recommendation approaches, Sustainability, 2021, 13 (11), Article 6165. https://doi.org/10.3390/su13116165
11. Li, Y, Deng, X, Hu, X, Liu, J, The effects of e-commerce recommendation system transparency on consumer trust: Exploring parallel multiple mediators and a moderator, Journal of Theoretical and Applied Electronic Commerce Research, 2024, 19 (4), 2630-2649. https://doi.org/10.3390/jtaer19040126
12. Pal, A, Chua, A.Y.K, Banerjee, S, Examining trust and willingness to accept AI recommendation systems, Proceedings of the ASIS&T Mid-Year Conference 2023, Association for Information Science and Technology, 2023.
13. Raza, A, Salahuddin, Ali, G, Soomro, M.H, Batool, S, Analyzing the impact of artificial intelligence on shaping consumer demand in e-commerce: A critical review, International Journal of Information Engineering and Electronic Business, 2025, 17 (5), 42-61. https://doi.org/10.5815/ijieeb.2025.05.04
14. Rivaldiansyah, M, Supriyanto, A, Pengaruh recommendation reliability dan recommendation accuracy terhadap adoption intention melalui AI technology trust pada pengguna Shopee, JSMA (Jurnal Sains Manajemen dan Akuntansi), 2026, 18 (1).
15. Rolando, B, The impact of artificial intelligence-based recommendation systems on consumer purchase decisions in e-commerce, AIRA: Artificial Intelligence Research and Applied Learning, 2025, 4 (2).
16. Saxborn, M, Pan, Y, Said, A, Trust through recommendation in e-commerce, Proceedings of the 2024 ACM SIGIR Conference on Human Information Interaction and Retrieval, Association for Computing Machinery, 2024. https://doi.org/10.1145/3627508.3638294
17. Sharma, S.K, Mehta, S, Manu, T.U, Puranik, A.M, Singh, R.K, Sharma, V, The impact of AI-powered recommendations on online purchase decisions: A consumer perspective, Advances in Consumer Research, 2025, 2 (4).
18. Teodorescu, D, Aivaz, K.-A, Vancea, D.P.C, Condrea, E, Dragan, C, Olteanu, A.C, Consumer trust in AI algorithms used in e-commerce: A case study of college students at a Romanian public university, Sustainability, 2023, 15 (15), Article 11925. https://doi.org/10.3390/su151511925
19. Vafaei-Zadeh, A, Nikbin, D, Wong, S.L, Hanifah, H, Investigating factors influencing AI customer service adoption: An integrated model of stimulus-organism-response (SOR) and task-technology fit (TTF) theory, Asia Pacific Journal of Marketing and Logistics, 2024, Advance online publication. https://doi.org/10.1108/APJML-05-2024-0570
20. Wang, W, Chen, Z, Kuang, J, Artificial intelligence-driven recommendations and functional food purchases: Understanding consumer decision-making, Foods, 2025, 14 (6), Article 976. https://doi.org/10.3390/foods14060976
21. Wang, Y, Sauka, K, Situmeang, F.B.I, Anthropomorphism and transparency interplay on consumer behaviour in generative AI-driven marketing communication, Journal of Consumer Marketing, 2025, Advance online publication. https://doi.org/10.1108/JCM-04-2024-6806

22. Yin, J, Qiu, X, AI technology and online purchase intention: Structural equation model based on perceived value, Sustainability, 2021, 13 (10), Article 5671. https://doi.org/10.3390/su13105671
23. Yoon, N, Lee, H.-K, AI recommendation service acceptance: Assessing the effects of perceived empathy and need for cognition, Journal of Theoretical and Applied Electronic Commerce Research, 2021, 16 (5), 1912-1928. https://doi.org/10.3390/jtaer16050107
24. Zhang, X, Chen, A.L, Piao, X, Yu, M, Zhang, Y, Zhang, L, Is AI chatbot recommendation convincing customer? An analytical response based on the elaboration likelihood model, Acta Psychologica, 2024, 250, Article 104501. https://doi.org/10.1016/j.actpsy.2024.104501