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# The Impact of Generative AI on Customer Trust and Purchase Intention in E-Commerce Platforms: The Mediating Role of Brand Authenticity

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## Abstract

Generative artificial intelligence (GenAI) is becoming embedded in e-commerce through conversational assistants, personalized product recommendations, automated product descriptions, synthetic imagery, review summaries, and post-purchase support. These applications can reduce search costs and improve relevance, yet they also raise questions about authorship, reliability, manipulation, privacy, and the credibility of brand communication. This article examines how GenAI-enabled customer experiences shape customer trust and purchase intention, with perceived brand authenticity positioned as the central mediating mechanism. An integrative review of 26 peer-reviewed studies published between 2023 and October 2026 was conducted using a structured search and thematic synthesis of research on GenAI marketing, AI-mediated e-commerce, brand authenticity, chatbot trust, AI disclosure, and online purchase behavior. The synthesis identifies six recurring patterns. First, functional quality, informativeness, responsiveness, and task fit can strengthen trust and decision confidence. Second, perceived brand authenticity explains why the same AI capability may produce favorable or unfavorable brand responses. Third, full automation of emotionally expressive brand communication is more likely to trigger authenticity concerns than human-supervised augmentation. Fourth, disclosure is not uniformly beneficial or harmful; its effects depend on message type, product category, consumer expectations, and the perceived credibility of the disclosure. Fifth, personalization creates value when it is relevant and controllable but can undermine trust when it signals surveillance or opaque data use. Sixth, trust is a proximal predictor of purchase intention, although product risk, brand familiarity, and consumer AI literacy shape the strength of this relationship. On this basis, the article proposes a moderated serial-mediation framework in which GenAI touchpoint design affects purchase intention through brand authenticity and customer trust. Nine testable propositions and a research agenda are developed. The article contributes by distinguishing system trust from brand trust, specifying authenticity as a mechanism rather than a general outcome, and translating mixed findings into a contingent model for e-commerce research and practice.

Keywords: generative artificial intelligence, e-commerce, customer trust, brand authenticity, purchase intention, AI disclosure

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## 1. Introduction

Generative artificial intelligence (GenAI) has moved rapidly from experimental software to a customer-facing layer of digital commerce. Large language models can answer product questions, compare alternatives, summarize customer reviews, draft product descriptions, and support conversational search. Image and video generation systems can produce campaign assets, virtual product scenes, and synthetic models. In parallel, recommender systems increasingly use generative interfaces to explain why an item may fit a shopper's preferences. These applications alter not only the efficiency of online retail operations but also the way customers encounter, interpret, and evaluate brands (Chan & Choi, 2025; Prasanna & Kushwaha, 2026).

From the platform's perspective, GenAI offers an attractive combination of scale, speed, and contextual adaptation. A single system can generate thousands of product descriptions, respond to questions at any hour, and tailor explanations to a customer's stated needs. In principle, this can reduce information asymmetry and the cognitive effort associated with online shopping. Recent e-commerce studies show that chatbot interaction, perceived usefulness, recommendation quality, and review synthesis can contribute to customer engagement and decision processes (Chakraborty et al., 2024; Chang & Park, 2024; Lei & Liu, 2025; Taheri et al., 2024).

Yet the same capabilities create a strategic tension. Consumers may value a fast, relevant answer while questioning whether the answer is accurate, whether the brand is being candid about AI involvement, whether a product image depicts a real item, or whether an apparently personal recommendation is based on excessive data collection. GenAI can make communication more fluent without making it more truthful. It can also reproduce a brand's visual style while weakening the sense that the brand speaks with a distinctive human voice. This distinction is important because trust in a platform's technical performance is not identical to trust in the brand's intentions, values, or promises.

Brand authenticity is therefore a potentially decisive mechanism. In digital markets, customers cannot always inspect products before purchase and often depend on platform-provided information, reviews, images, recommendations, and service interactions. Perceived authenticity helps customers judge whether brand communication is sincere, credible, consistent with the brand's identity, and grounded in genuine commitments. Recent experiments indicate that GenAI-generated brand content can reduce perceived authenticity when consumers interpret automation as replacing human authorship, while human assistance and careful integration can attenuate this effect (Brüns & Meißner, 2024; Kirk & Givi, 2025). Other studies, however, show that AI-disclosed brand voice need not damage authenticity and that AI-generated brand personalities can influence preference and purchase intention under suitable conditions (Kirkby, 2023; Park & Ahn, 2024).

The evidence is consequently mixed rather than uniformly positive or negative. Chatbot studies emphasize interactivity, perceived humanness, service quality, and trust; advertising studies emphasize source credibility, disclosure, novelty, and authenticity; review studies focus on information usefulness and source genuineness; and personalization studies highlight the trade-off between relevance and privacy. These streams are often examined separately. A platform may improve the quality of an AI chatbot while simultaneously damaging brand authenticity through synthetic testimonials or misleading imagery. A single overall measure of "AI adoption" cannot adequately represent these different experiences.

This article addresses that fragmentation by examining the relationship among GenAI-enabled e-commerce touchpoints, perceived brand authenticity, customer trust, and purchase intention. The central research question is: How and under what conditions does GenAI use on e-commerce platforms influence customer trust and purchase intention through perceived brand authenticity? Four subsidiary questions guide the review: (1) Which GenAI-enabled touchpoint characteristics create or erode

customer value? (2) How does brand authenticity translate those experiences into trust? (3) Under what conditions does transparency strengthen or weaken authenticity and trust? and (4) Which contextual factors shape the path from trust to purchase intention?

The article makes three contributions. First, it treats brand authenticity as a mediating psychological mechanism connecting the design of GenAI-enabled touchpoints with trust and purchase intention. Second, it distinguishes functional trust in an AI system from relational trust in the e-commerce platform or brand. Third, it reconciles apparently conflicting findings by identifying implementation configuration, content type, product category, privacy expectations, and consumer characteristics as boundary conditions. The resulting framework is intended to guide empirical testing and managerial decisions rather than to claim that a single average effect applies across all GenAI applications.

The remainder of the article is organized as follows. Section 2 defines the focal constructs and theoretical foundations. Section 3 describes the review method. Section 4 reports the thematic results. Section 5 develops the conceptual model and propositions. Section 6 discusses theoretical implications, Section 7 outlines managerial implications, Section 8 identifies limitations and future research, and Section 9 concludes.

## 2. Conceptual Background and Theoretical Foundations

### 2.1. Generative AI in e-commerce: from content automation to customer-facing interaction

GenAI refers here to machine-learning systems capable of generating or transforming text, images, audio, video, or other content in response to prompts, contextual inputs, or retrieved information. In e-commerce, the relevant unit of analysis is not the model in isolation but the customer-facing touchpoint through which the model shapes information, interaction, or choice. Examples include conversational shopping assistants, generative search, personalized product explanations, automated product copy, image generation, review summarization, virtual try-on descriptions, and post-purchase service communication (Chan & Choi, 2025; Lopez-Lopez & Bara Iniesta, 2025).

These touchpoints differ in their proximity to the transaction and in the type of promise they make. A chatbot that explains delivery options is primarily a service interface. A product description makes factual claims about attributes. A generated lifestyle image makes a visual representation claim. A review summary synthesizes other customers' experiences and may be interpreted as social proof. A personalized recommendation implies that the platform has inferred a customer's preferences. Because these touchpoints carry different credibility expectations, the consequences of GenAI should be assessed at the application level rather than through a binary AI-versus-human distinction.

An important analytical distinction is between augmentation and substitution. In augmentation, AI supports human employees or creators by drafting, summarizing, translating, or generating alternatives that are reviewed before publication. In substitution, AI replaces human authorship or judgment with little meaningful oversight. Brüns and Meißner (2024) find that negative authenticity reactions are attenuated when GenAI assists human content creation rather than fully automating it. Kirk and Givi (2025) similarly show that the AI-authorship effect is sensitive to the emotional character of a message and to whether AI creates the communication or merely edits it. The distinction suggests that the degree of automation is a meaningful predictor, not simply the presence of AI.

GenAI must also be distinguished from conventional predictive AI. Predictive recommenders estimate preferences or rank products; GenAI can generate natural-language explanations, synthetic product content, or conversational answers. In practice, systems may combine retrieval, ranking, and generation. A generated answer may therefore contain retrieved facts, inferred preferences, and model-generated language. This hybrid architecture can improve usability but makes provenance, factual grounding, and accountability more important.

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### 2.2. Customer trust: trust in the system, the platform, and the brand

Trust is a willingness to rely on another party under conditions of uncertainty and vulnerability. In e-commerce, uncertainty concerns product quality, seller reliability, payment security, delivery, returns, data handling, and the accuracy of product information. Trust can be directed toward at least three objects: (a) the AI system, including its competence and reliability; (b) the platform, including its security, governance, and service processes; and (c) the brand, including its integrity, benevolence, and consistency. These objects are related but not interchangeable.

Trust in an AI assistant is often grounded in perceived competence: does the system understand the request, provide relevant information, acknowledge uncertainty, and avoid fabricating details? Platform trust additionally depends on privacy protection, secure transactions, clear policies, and effective remedies. Brand trust depends on whether the company appears honest, responsible, and consistent with its stated values. A shopper may find a chatbot useful but still distrust the brand if the chatbot conceals sponsorship or invents product attributes. Conversely, a familiar brand may lend initial credibility to a new AI interface, creating a trust-transfer effect (Chang & Park, 2024).

Recent reviews of chatbot research show that trust is multidimensional and shaped by user characteristics, machine attributes, interaction quality, social context, and situational risk. The evidence base remains heterogeneous, with many studies relying on cross-sectional self-reports and inconsistent definitions of trust (Fares & Lee, 2026; Ng & Zhang, 2025). This article therefore uses customer trust as a higher-order relational evaluation of the platform or brand, while recognizing that trust in the AI system can be an antecedent or component of that evaluation.

Trust is expected to support purchase intention because it reduces perceived vulnerability and the need for costly verification. A meta-analysis of e-commerce research identifies trust, perceived risk, security, and electronic word-of-mouth as significant correlates of purchase decisions, while also showing that perceived risk changes the strength of the trust–decision relationship (Handoyo, 2024). Thus, trust should not be treated as a guarantee of purchase. Customers may trust a retailer but defer a high-cost purchase because of price, product fit, or external constraints.

### 2.3. Perceived brand authenticity

Perceived brand authenticity is the customer's judgment that a brand is genuine, sincere, credible, and faithful to a recognizable identity. It is not equivalent to the technical originality of an image or the literal absence of automation. A brand may use AI extensively and still be perceived as authentic if its communication remains accurate, consistent with its commitments, and accountable. Conversely, a human-written message can be inauthentic if it is deceptive, exaggerated, or inconsistent with the brand's conduct.

For this review, authenticity is conceptualized through four connected dimensions. Continuity refers to consistency between current communication and the brand's established identity and history. Credibility refers to the believability and factual integrity of claims. Integrity refers to alignment between stated values and actual conduct, including responsible disclosure and data practices. Symbolism refers to the capacity of the brand to express meanings and identities that customers regard as distinctive and personally relevant. These dimensions help explain why a realistic AI image or fluent chatbot response may still feel inauthentic if it conflicts with the brand's voice or appears to simulate experiences that never occurred.

Recent empirical findings place authenticity close to the center of consumer responses to GenAI. Brüns and Meißner (2024) report that perceived brand authenticity mediates negative effects of GenAI content automation on brand-related outcomes. Kirk and Givi (2025) identify authenticity as a mechanism through which AI authorship can reduce favorable responses to emotional marketing

communications. Eze (2025), studying AI-generated customer reviews in an e-commerce setting, reports lower perceived genuineness for AI-authored reviews and a strong association between authenticity and purchase intent. By contrast, Kirkby (2023) finds that disclosed AI use in brand voice does not necessarily lower perceived authenticity or brand attitude. Taken together, the evidence indicates that authenticity depends on the perceived purpose, execution, and honesty of AI use rather than on disclosure alone.

Authenticity should also be distinguished from anthropomorphism. Anthropomorphism is the degree to which a system is perceived as human-like; authenticity concerns whether the brand or communication seems genuine. A chatbot may use natural language and display social presence without being perceived as sincere. Indeed, excessive human-likeness can produce eeriness or reactance in some contexts, while autonomy, social support, and user control may be more consequential for trust than human-like appearance (Hameed et al., 2026; Fares & Lee, 2026).

### 2.4. Purchase intention in digital commerce

Purchase intention refers to a consumer's stated likelihood or willingness to buy a product or service from a particular seller or platform within a specified context. It is a proximal behavioral outcome, not a direct measure of completed transactions. Actual purchases are additionally affected by price, inventory, delivery time, payment options, competing offers, habit, and situational constraints. This distinction matters because many GenAI studies use intention, adoption, or willingness-to-use measures rather than observed conversion data.

In this article, purchase intention is modeled as the outcome of a customer's evaluation of the brand and its offer after exposure to GenAI-enabled information or interaction. The construct may be measured at the product level (intention to buy the recommended item), platform level (intention to purchase through the platform), or brand level (intention to choose the brand). Researchers should specify the target of the intention measure and avoid treating these levels as interchangeable. A platform may improve the likelihood that a shopper considers a product without necessarily increasing trust in the brand.

### 2.5. Theoretical integration: stimulus–organism–response and signaling perspectives

The stimulus–organism–response (S–O–R) perspective provides a useful organizing logic. GenAI touchpoint features constitute stimuli; perceived authenticity and trust represent internal cognitive and relational states; and purchase intention represents a behavioral response. This approach is consistent with recent e-commerce work linking website characteristics, engagement, and trust to downstream loyalty and satisfaction (Taheri et al., 2024). It also accommodates both positive and negative effects: the same stimulus can generate perceived usefulness for one consumer and perceived manipulation for another.

Signaling theory explains why disclosure, provenance, verification, and human oversight matter. Online shoppers cannot directly observe the internal process used to produce a recommendation, image, or product description. A clear statement about AI involvement, a traceable source, a verified product specification, or access to a human representative can reduce information asymmetry. However, a signal is credible only when it is specific and consistent with observable practice. A generic AI label may reveal authorship without establishing factual accuracy, while a detailed explanation of which elements were generated and which were verified can communicate stronger accountability.

The elaboration likelihood perspective adds a distinction between central and peripheral evaluation. For high-involvement or high-risk purchases, shoppers may scrutinize factual accuracy, evidence, source provenance, and privacy practices. For lower-involvement decisions, convenience, visual appeal, novelty, and conversational fluency may play a larger role. Jiang et al. (2025) show that relevant

and divergent AI-generated advertisements can activate different cognitive routes through usefulness and entertainment, with product involvement shaping the effects. The framework proposed here combines these lenses: S–O–R organizes the pathway, signaling explains credibility cues, and elaboration likelihood explains why product involvement and information quality matter.

## 3. Methodology

This study uses an integrative literature review with a structured search and thematic synthesis. The purpose is theory development across adjacent research streams rather than statistical aggregation of a homogeneous set of effect sizes. The review is therefore not presented as a PRISMA-compliant systematic review, nor does it claim exhaustive coverage of every publication on artificial intelligence and online shopping. This distinction is important because the focal topic is recent, terminology is unstable, and relevant studies appear across marketing, information systems, psychology, retailing, and electronic commerce.

The search was conducted on 30 October 2026. Search activity covered publisher and scholarly-index pages and accessible institutional repositories associated with major scholarly outlets, including Elsevier/ScienceDirect, Springer Nature, Emerald, SAGE, Wiley, PubMed/PMC, and university research repositories. Search strings combined terms from four groups: (1) technology: “generative AI,” “GenAI,” “AIGC,” “ChatGPT,” “conversational AI,” and “AI chatbot”; (2) context: “e-commerce,” “online shopping,” “digital marketing,” “online reviews,” and “product recommendation”; (3) relational constructs: “trust,” “brand authenticity,” “transparency,” “privacy,” and “credibility”; and (4) behavioral outcomes: “purchase intention,” “purchase decision,” “consumer response,” and “adoption.” Search terms were used in multiple combinations, and reference lists of directly relevant studies were checked to identify additional recent work.

The inclusion criteria were: (a) publication between 2023 and 30 October 2026; (b) publication as a peer-reviewed journal article or a clearly identified scholarly review; (c) direct relevance to GenAI, AI-mediated marketing, e-commerce interaction, consumer trust, authenticity, disclosure, personalization, online reviews, or purchase-related outcomes; and (d) sufficient bibliographic and abstract-level information to identify the research context and its main contribution. Studies focusing exclusively on technical model performance without consumer or brand implications were excluded. Non-scholarly commentary and undated marketing claims were also excluded from the core synthesis.

After relevance screening and removal of overlapping records, 26 recent peer-reviewed studies were retained as the core evidence set. The studies included experiments, surveys, structural equation models, meta-analyses, systematic reviews, and conceptual or integrative analyses. The synthesis did not weight studies by sample size or combine their coefficients because the independent variables, contexts, outcomes, and measurement approaches were not sufficiently comparable. Instead, findings were coded thematically around six categories: (1) functional value and information quality; (2) trust formation in conversational and recommendation interfaces; (3) brand authenticity and AI authorship; (4) disclosure and transparency; (5) personalization, privacy, and governance; and (6) contextual moderators such as product type, involvement, brand familiarity, and consumer AI orientation.

To reduce interpretive overreach, the review distinguishes direct empirical evidence from conceptual inference. For example, a study showing that authenticity mediates responses to AI-generated social content is treated as evidence about the authenticity mechanism, but it is not assumed to establish the same coefficient for every e-commerce interface. Likewise, evidence from hospitality or luxury advertising is used to identify plausible boundary conditions, not as a direct estimate of effects in all retail categories. When a study’s full text was not accessible, bibliographic information and available abstracts were used conservatively; no unreported sample statistics or effect sizes were reconstructed.

The review is limited by its focused search strategy, English-language emphasis, and reliance on a fast-developing literature in which publication status and terminology can change quickly. The resulting synthesis should be interpreted as a transparent, theory-building map of recent evidence rather than a definitive census of the field.

**Table 1. Review scope and synthesis procedure**

| Element | Operational approach |
|---|---|
| Review design | Integrative literature review; structured search; thematic synthesis; no meta-analysis. |
| Search cut-off | 30 October 2026; eligible publication window: 2023–30 October 2026. |
| Search locations | Publisher platforms and scholarly repositories, including Elsevier, Springer Nature, Emerald, SAGE, Wiley, PubMed/PMC, and university repositories. |
| Core search concepts | Generative AI / GenAI / AIGC / ChatGPT; e-commerce / online shopping; trust / authenticity / transparency / privacy; purchase intention / decision. |
| Inclusion | Recent peer-reviewed research or scholarly reviews with consumer, brand, marketing, or e-commerce relevance. |
| Exclusion | Purely technical AI papers without consumer implications; non-scholarly commentary; records without usable bibliographic information. |
| Synthesis | Six thematic categories; findings interpreted by context and method; no pooled effect sizes. |
| Core evidence set | 26 recent peer-reviewed studies; evidence strength and transferability assessed qualitatively. |

## 4. Results: Thematic Synthesis of Recent Evidence

### 4.1. GenAI creates functional value when information is useful, accurate, and task-aligned

A consistent positive theme is the potential of GenAI to reduce search effort and make product information more accessible. In online grocery shopping, a generative chatbot framework grounded in interviews and survey evidence identifies factors that shape trust in the platform and the AI-supported shopping experience (Chakraborty et al., 2024). Research on AI-generated reviews similarly indicates that review quality, emotional resonance, length, and credibility can influence purchase decisions through perceived usefulness (Lei & Liu, 2025). These findings suggest that consumers do not necessarily reject generated information; they evaluate whether it helps them solve a shopping problem.

Recommendation systems can also affect the composition of the consumer's consideration set. Chang and Park (2024) compare ChatGPT-style recommendations with conventional AI recommenders and find that both can influence the purchase journey through trust in the recommender and trust in recommended products. Their findings also indicate that brand awareness changes the trust-transfer process. This is important for e-commerce platforms that recommend unfamiliar brands: an AI assistant may help consumers consider options, but the platform must still provide reliable product evidence and clear commercial context.

Functional value is not equivalent to trustworthiness. A fluent answer can be useful while still containing an error. In product categories where safety, fit, durability, or compatibility matters, factual precision and the ability to verify claims are essential. The value of GenAI therefore depends on retrieval quality, source grounding, recency, and the system's willingness to signal uncertainty. The review supports a conditional proposition: functional quality can strengthen trust when it is visible to customers and supported by verifiable product information.

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### 4.2. Interaction quality and social presence support trust, but human-likeness is not sufficient

Research on e-commerce chatbots emphasizes interactivity, perceived humanness, responsiveness, and social presence. Ding and Najaf (2024), using a time-lagged design with e-commerce customers, report that interactivity and perceived humanness are associated with trust toward chatbots and intention to adopt them. Wang et al. (2025) examine generative AI marketing communication and find that anthropomorphism can influence purchase intention through social presence and trust, while disclosure changes the strength of some pathways. In the grocery context, Chakraborty et al. (2024) also identify interaction quality and perceived anthropomorphism as relevant to attitude and trust.

However, human-like design should not be treated as a universal trust-building solution. The 2026 meta-analysis by Fares and Lee finds that anthropomorphic features can enhance enjoyment without necessarily increasing trust. Hameed et al. (2026) report that autonomy and social-role features can strengthen chatbot trust, whereas greater human-likeness may increase eeriness and reduce trust in some circumstances. The implication is that customers may prefer an assistant that is helpful, predictable, and respectful of user control over one that imitates human emotion too aggressively.

Trust-building interaction therefore requires functional competence and relational appropriateness. The chatbot should identify its role, respond consistently, avoid pretending to have personal experiences, and provide an easy route to human assistance. A conversational interface can support a brand relationship, but it should not manufacture intimacy or conceal that the customer is interacting with an automated system.

### 4.3. Brand authenticity is a central mechanism connecting GenAI use to brand responses

The strongest direct evidence for the proposed mediating role of authenticity comes from studies of AI-generated brand communication. Brüns and Meißner (2024) conduct three experiments and show that GenAI adoption in social-media content creation can reduce perceived brand authenticity and downstream brand-related responses. Their findings also show that negative reactions are attenuated when GenAI assists human creators rather than replacing them. Kirk and Givi (2025), using seven preregistered experiments, find that AI authorship can reduce positive word-of-mouth and loyalty for emotional communications, with perceived authenticity and moral disgust explaining important parts of the effect. The effect is weaker for factual communication and when AI is used for editing rather than original authorship.

These studies imply that customers may interpret creative authorship as a signal of a brand's sincerity and investment in the relationship. When an emotional message appears to be fully automated, the perceived effort or personal commitment behind it may decline. This is not necessarily a judgment about the technical quality of the text; it is a judgment about what the brand's use of AI means. The effect may be particularly relevant when the message claims empathy, personal appreciation, social responsibility, or a distinctive brand story.

Yet disclosure and AI authorship do not always produce negative authenticity judgments. Kirkby (2023) reports that disclosing AI-generated brand voice in product descriptions or chatbot text did not necessarily reduce perceived authenticity or brand attitude. Park and Ahn (2024) show that AI-generated brand personalities can align with consumer perceptions and influence brand preference and purchase intention through self-brand connection in luxury fashion contexts. Jung et al. (2025) find that perceived artificial creativity can improve trust in AI and perceived humanness, which then influence advertising attributes and purchase intention. These positive findings suggest that customers may accept AI-generated brand expressions when they are informative, distinctive, aligned with brand identity, and appropriate to the product context.

Evidence from other service settings reinforces the importance of context. Ali et al. (2025) examine GenAI and brand authenticity in the restaurant industry and show that the effect of AI-generated content depends on brand perceptions and self-brand congruity. Grigsby et al. (2025) find that AI disclosure in service advertising can lower trust and ad attitudes in some contexts, partly because service advertising often communicates intangible promises. These findings should not be generalized mechanically to physical products, but they demonstrate why authenticity needs to be assessed in relation to the promise being made.

Overall, authenticity is best understood as a mechanism through which consumers interpret the meaning of GenAI use. It can transmit both positive and negative effects. GenAI that makes product information more coherent, accessible, and brand-consistent may strengthen authenticity. GenAI that simulates human experience, invents testimonials, or produces exaggerated claims may undermine it.

### 4.4. AI disclosure produces a context-dependent transparency paradox

Disclosure is often presented as a simple ethical requirement, but consumer-response evidence shows a more complex pattern. A disclosure label can increase perceived novelty or signal honesty, while simultaneously making AI authorship salient and reducing perceived human involvement. Shi and Jiang (2026), across three online experiments, identify this dual pathway: AI labels can improve advertising and purchase responses through perceived novelty while weakening them through reduced authenticity. The balance varies by regulatory focus and product type. Kirkby (2023), in contrast, finds no general authenticity penalty from disclosure of AI-assisted brand voice. These results are not necessarily contradictory: the studies examine different message forms, products, and disclosure contexts.

Wang et al. (2025) show that transparency can weaken the influence of anthropomorphism on social presence, although the overall pathway from anthropomorphism through social presence and trust to purchase intention remains. Grigsby et al. (2025) report lower trust and less positive attitudes when AI involvement is disclosed in service advertisements. Together, these findings suggest that disclosure is not merely an information variable; it changes how consumers interpret the source, intent, and credibility of the communication.

The relevant managerial distinction is between disclosure as a bare label and transparency as an accountable explanation. A bare label tells the customer that AI was involved. A more complete explanation can clarify what the system did, what information was used, which claims were verified, whether a human reviewed the output, and how the customer can challenge or correct it. The latter is more likely to function as a meaningful signal of integrity. The evidence does not justify hiding AI involvement to protect short-term conversion. Rather, it supports designing disclosures that are proportionate, understandable, and connected to real governance practices.

### 4.5. Personalization improves relevance but can activate privacy and surveillance concerns

GenAI can make personalization more conversational and context-sensitive. Instead of merely ranking products, a system can explain why an item matches stated preferences, ask clarifying questions, or generate a comparison based on user constraints. However, personalization depends on data. If customers do not understand what is collected, how long it is retained, or whether it is shared, personalization can be interpreted as surveillance. Shithii et al. (2026) identify privacy concerns and perceived risk as relevant to trust in AI-driven e-commerce. The broader e-commerce meta-analysis by Handoyo (2024) also shows that risk changes how trust relates to purchase decisions.

Recent research on AI-generated word-of-mouth further shows that product type and privacy concerns can shape whether customers adopt different forms of AI-mediated recommendation. Ma et al. (2026) find that one-way AI word-of-mouth may fit utilitarian products, while interactive formats may better

suit hedonic products; functional and human-like trust mediate these matching effects, and privacy concern moderates adoption. This suggests that personalization should be calibrated to both product purpose and consumer expectations.

Trustworthy personalization requires data minimization, understandable consent, preference controls, clear explanations of why an item is recommended, and a practical way to opt out. The customer should be able to benefit from relevance without feeling that the platform has inferred intimate information or manipulated choice. In this respect, privacy governance is not a technical back-office issue; it is part of the brand's authenticity and integrity.

### 4.6. Product type, involvement, brand familiarity, and AI orientation shape the effects

The literature indicates that GenAI effects vary with the type of product and the decision context. For utilitarian purchases, customers may prioritize accuracy, comparability, and time savings. For hedonic purchases, they may place greater weight on imagination, emotional resonance, aesthetics, and identity expression. Jiang et al. (2025) show that relevant AI advertisements can support perceived usefulness and purchase intention, whereas divergent advertisements can enhance entertainment and advertising attitudes; product involvement changes the strength of these routes. Ma et al. (2026) similarly identify different effective formats of AI word-of-mouth for utilitarian and hedonic products.

Brand familiarity can influence the way consumers transfer trust from the platform or recommender to the recommended brand. Chang and Park (2024) show that brand awareness changes the trust transfer effect. In high-awareness situations, existing brand knowledge may dominate; in low-awareness situations, the recommender's credibility may become more influential. Park and Ahn (2024) further suggest that AI-generated brand personality can create self-brand connection, particularly in a luxury fashion context. These findings indicate that brand authenticity is partly relational: it is judged against what consumers already know and expect from the brand.

Consumer AI literacy and prior experience may also matter. A customer who understands how generative systems work may distinguish between AI-assisted drafting and fully synthetic claims. Another customer may treat all AI-generated content as equally unreliable or, conversely, may overestimate the system's capabilities. The literature increasingly identifies AI familiarity, privacy concern, and individual trust propensity as important boundary conditions (Fares & Lee, 2026; Lei & Liu, 2025; Shi & Jiang, 2026). These variables should be measured rather than assumed.

**Table 2. Selected empirical and review evidence informing the synthesis**

| Study | Context and method (as reported) | Relevant finding for the present framework |
|---|---|---|
| Kirkby (2023) | 3 × 3 experiment; 624 participants; AI vs. human vs. undisclosed brand voice. | AI disclosure did not automatically reduce brand-voice authenticity or brand attitude. |
| Brüns & Meißner (2024) | Three experiments on GenAI social-media content. | Automation can reduce perceived brand authenticity; human assistance attenuates negative reactions. |
| Chakraborty et al. (2024) | Interviews plus survey of 372 online grocery shoppers; SEM and fsQCA. | Interaction quality, credibility, and anthropomorphism are relevant to trust in GenAI-enabled shopping. |
| Chang & Park (2024) | Within-subject study; 443 responses; ChatGPT-style vs. conventional AI recommendations. | Recommendation trust transfers to product consideration; brand awareness shapes the pathway. |
| Ding & Najaf (2024) | Time-lagged survey; 343 e-commerce customers. | Interactivity and perceived humanness are associated with chatbot trust and adoption intention. |
| Taheri et al. (2024) | Survey of 819 users of an Iranian e-commerce platform. | Website experience and engagement factors are related to trust and loyalty. |
| Handoyo (2024) | Meta-analysis of e-commerce trust, risk, security, and e-WOM research. | Trust, risk, security, and e-WOM are important correlates of e-commerce purchase decisions. |

| Study | Context and method (as reported) | Relevant finding for the present framework |
|---|---|---|
| Kirk & Givi (2025) | Seven preregistered experiments on AI-authored marketing communication. | Authenticity helps explain negative reactions to AI-authored emotional messages. |
| Wang et al. (2025) | Survey/experimental marketing scenarios; 444 participants. | Anthropomorphism affects purchase intention through social presence and trust; transparency changes pathway strength. |
| Grigsby et al. (2025) | Three experiments on GenAI service advertising. | AI disclosure can reduce trust and ad attitudes in some intangible service contexts. |
| Jung et al. (2025) | Study of 461 respondents with prior GenAI experience; luxury advertising. | Artificial creativity can increase trust in AI and perceived humanness; informativeness and novelty matter for purchase intention. |
| Lei & Liu (2025) | Questionnaire study of generative AI reviews. | Review quality and credibility affect purchase decisions through perceived usefulness. |
| Eze (2025) | Survey experiment with 300 Nigerian e-commerce users. | AI-generated reviews were judged less genuine; perceived authenticity predicted purchase intent. |
| Jiang et al. (2025) | Eye-tracking and questionnaire experiments; 240 participants. | Relevant and divergent AIGC ads operate through usefulness and entertainment routes. |
| Ali et al. (2025) | Scenario-based experiment in restaurant branding. | GenAI content effects on authenticity and behavioral intentions depend on brand perceptions and self-brand congruity. |
| Ng & Zhang (2025) | Systematic review of 40 chatbot-trust articles. | Trust antecedents span user, machine, interaction, social, and context-related factors. |
| Ma et al. (2026) | Four studies on AI word-of-mouth and product type. | Product type shapes the fit of one-way versus interactive AI WOM; trust and privacy are mechanisms. |
| Shi & Jiang (2026) | Three online experiments on AI disclosure labels. | Disclosure can increase novelty while reducing authenticity; product type and regulatory focus moderate effects. |
| Fares & Lee (2026) | Systematic review and meta-analysis; 34,302 respondents across 48 quantitative studies. | Usefulness, ease of use, trust, and satisfaction support bot acceptance; anthropomorphism does not necessarily build trust. |
| Hameed et al. (2026) | PLS-SEM study of 429 AI-enabled shopping chatbot users. | Autonomy and social role support trust; excessive human-likeness can create eeriness. |
| Shithii et al. (2026) | Hybrid SEM–ANN study of 250 e-commerce users. | Privacy concern and perceived risk are central to trust in AI-driven e-commerce. |

### 4.7. Summary of the thematic results

The evidence supports neither a blanket pro-AI nor a blanket anti-AI conclusion. GenAI can improve the usefulness and accessibility of shopping information, but its effects on trust depend on whether the system is reliable, transparent, and appropriately governed. Brand authenticity provides a plausible explanatory bridge between the way AI is used and the way customers interpret the brand. Human supervision, accurate product grounding, clear provenance, and customer control are recurring conditions that help align efficiency with credibility.

Three distinctions emerge as particularly important. First, augmentation differs from substitution: AI assistance under meaningful human review is less likely to threaten authenticity than unreviewed replacement of human authorship. Second, disclosure differs from transparency: a label may reveal AI involvement, while transparency also explains the scope, source, and accountability of that involvement. Third, system trust differs from brand trust: a useful chatbot does not automatically make the company appear honest. These distinctions inform the conceptual model developed in the next section.

## 5. Proposed Conceptual Model and Research Propositions

The proposed framework treats GenAI implementation as a configuration of customer-visible features rather than a binary adoption variable. Five dimensions are especially relevant: functional quality (accuracy, relevance, informativeness, and responsiveness); personalization quality (fit with expressed needs and the perceived appropriateness of data use); interaction quality (clarity, user control, and ease of escalation); transparency (disclosure of AI involvement, data sources, and verification); and human oversight (meaningful review, correction, and accountability). These dimensions may operate independently or interact.

Perceived brand authenticity is positioned as the primary mediator. Customers infer whether the brand is genuine from the consistency between the brand's identity and the experience delivered through AI. If a system offers useful and accurate assistance in a way that reflects the brand's promises, authenticity may increase. If it fabricates claims, simulates customer testimonials, or uses emotional language without accountability, authenticity may decrease. Customer trust is then expected to develop from this authenticity judgment, together with direct evaluations of platform competence and security. Trust is positioned as a proximal predictor of purchase intention.

The model also allows for a direct path from GenAI touchpoint quality to purchase intention. Some customers may act on a relevant recommendation because it reduces search costs even before forming a strong brand judgment. The indirect pathway through authenticity and trust is nevertheless expected to explain a meaningful portion of the relationship, especially for purchases involving uncertainty, brand claims, or relational communication.

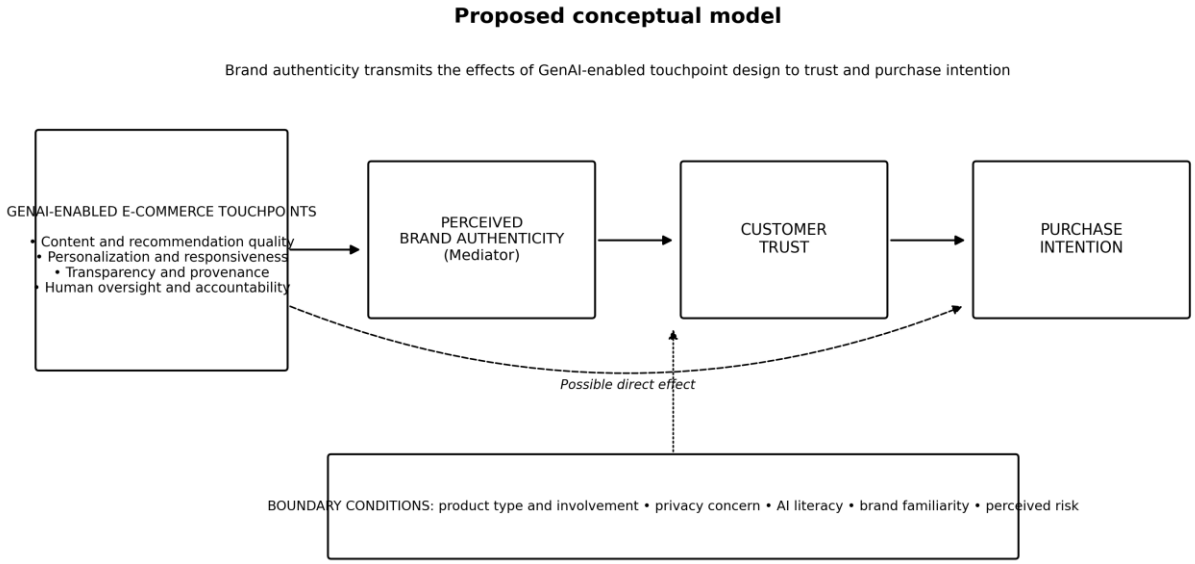



*Figure 1. Proposed moderated serial-mediation model linking GenAI-enabled e-commerce touchpoints to purchase intention through perceived brand authenticity and customer trust.*

### 5.1. Core propositions

Proposition 1 (functional quality and authenticity). The perceived accuracy, relevance, informativeness, and responsiveness of GenAI-enabled e-commerce touchpoints are positively

associated with perceived brand authenticity when generated outputs are consistent with verified product information and the brand's established identity.

Proposition 2 (automation intensity and authenticity). Perceived full automation of brand communication is negatively associated with perceived brand authenticity compared with human-supervised GenAI augmentation, particularly for emotional, identity-expressive, or relationship-oriented messages.

Proposition 3 (transparency and authenticity). Specific, understandable, and actionable transparency about AI involvement, source provenance, and human verification is positively associated with perceived brand authenticity. The effect of a simple AI label is contingent on message type, product category, and consumer expectations.

Proposition 4 (authenticity and trust). Perceived brand authenticity is positively associated with customer trust in the e-commerce platform or brand because authenticity signals credibility, integrity, and consistency.

Proposition 5 (trust and purchase intention). Customer trust is positively associated with purchase intention, with a stronger relationship when perceived product risk and information asymmetry are high and when the purchase is made through an unfamiliar seller or platform.

Proposition 6 (mediation by authenticity). Perceived brand authenticity mediates the relationship between GenAI touchpoint configuration and customer trust. Better-designed GenAI touchpoints increase trust partly by strengthening authenticity; opaque or deceptive implementations reduce trust partly by weakening authenticity.

Proposition 7 (serial mediation). Perceived brand authenticity and customer trust serially mediate the relationship between GenAI touchpoint configuration and purchase intention. The expected indirect pathway is GenAI touchpoint quality → brand authenticity → customer trust → purchase intention.

Proposition 8 (privacy boundary condition). Privacy concern weakens the positive association between AI-enabled personalization and customer trust when personalization is perceived as intrusive, insufficiently explained, or based on data beyond the customer's reasonable expectations.

Proposition 9 (product and consumer boundary conditions). Product type, product involvement, brand familiarity, and consumer AI literacy moderate the effects of GenAI disclosure and content design on perceived authenticity. In particular, utilitarian and high-involvement decisions may place greater weight on verifiable information, whereas hedonic decisions may place greater weight on emotional congruence and symbolic meaning.

**Table 3. Proposed hypotheses for empirical testing**

| Hypothesis | Proposed relationship | Expected direction |
|---|---|---|
| H1 | GenAI functional quality → perceived brand authenticity | Positive |
| H2 | Full automation (vs. human-supervised augmentation) → perceived brand authenticity | Negative |
| H3 | Specific transparency and provenance → perceived brand authenticity | Positive, conditional |
| H4 | Perceived brand authenticity → customer trust | Positive |
| H5 | Customer trust → purchase intention | Positive |
| H6 | Brand authenticity mediates GenAI configuration → customer trust | Indirect effect |
| H7 | Authenticity and trust serially mediate GenAI configuration → purchase intention | Positive or negative, depending on configuration |

| Hypothesis | Proposed relationship | Expected direction |
|---|---|---|
| H8 | Privacy concern moderates personalization → customer trust | Negative moderation |
| H9 | Product type, involvement, brand familiarity, and AI literacy moderate disclosure/authenticity effects | Context-dependent |

### 5.2. Construct definitions and measurement guidance

The proposed model is suitable for survey-based structural equation modeling, scenario experiments, or longitudinal field studies. Measurement should preserve the distinction between the AI system, the platform, and the brand. The following constructs and candidate indicators are offered as a starting point for scale adaptation. They are not presented as a newly validated instrument; researchers should conduct expert review, cognitive interviews, pilot testing, and confirmatory factor analysis before using them in a substantive study.

| Construct | Working definition | Illustrative measurement indicators |
|---|---|---|
| GenAI functional quality | Customer evaluation of the accuracy, relevance, completeness, and timeliness of AI-generated assistance. | The response is accurate; the recommendation fits my stated needs; the explanation is useful; the system acknowledges uncertainty. |
| Human oversight | Perceived presence of meaningful human review, correction, and accountability. | Important claims are checked; a human can review or correct the response; responsibility for errors is clear. |
| Transparency / provenance | Clarity about AI involvement, information sources, data use, and verification. | The platform explains when AI is used; sources are traceable; I understand what information informed the output. |
| Perceived brand authenticity | Perceived genuineness, consistency, credibility, and integrity of the brand. | The brand communicates sincerely; its messages fit its identity; its claims are credible; it acts consistently with its stated values. |
| Customer trust | Willingness to rely on the platform or brand under uncertainty. | The brand is reliable; it keeps its promises; it acts in customers' interests; I feel safe relying on it. |
| Privacy concern | Concern about collection, inference, retention, and secondary use of personal data. | The personalization uses more data than necessary; data use is unclear; I feel monitored; I can control my data. |
| Purchase intention | Stated likelihood of purchasing from the brand or platform in the focal scenario. | I would consider buying; I intend to purchase; I would choose this seller over comparable alternatives. |

### 5.3. Alternative model specifications

Researchers should test whether authenticity is a first-order mediator, a higher-order construct, or one dimension within a broader brand-credibility construct. A competing model could position trust as the only mediator and authenticity as an antecedent. Another could test parallel mediation through perceived usefulness and authenticity. Such comparisons are important because AI-generated product recommendations may influence choice through usefulness even when brand authenticity remains unchanged (Lei & Liu, 2025).

A further possibility is that the relationship is reciprocal over time. A successful AI-supported purchase may increase trust in the platform and make subsequent AI recommendations feel more authentic. Conversely, a single fabricated claim or privacy incident may reduce trust and cause customers to reinterpret previous AI interactions as manipulative. Cross-sectional designs cannot fully capture these learning effects. Longitudinal and event-based designs are therefore needed.

### 5.4. Operationalizing GenAI implementation as a configuration

A central measurement challenge is that "GenAI use" is not a single observable treatment. A platform may use a language model only to rephrase a verified product description, or it may allow a model to create the description from sparse prompts. It may use an image model to create a decorative background while retaining authentic product photography, or it may display a fully synthetic product image. It may summarize verified customer reviews, or it may generate review-like text without traceable source material. These implementations differ in both objective risk and the meaning customers attach to them. Empirical studies should therefore measure the type, intensity, and governance of GenAI use separately.

A practical operationalization can distinguish five exposure dimensions. The first is content-generation scope: editing, drafting, summarizing, recommending, or creating original claims and creative assets. The second is automation intensity: human-led, human-assisted, jointly generated, or AI-led with limited review. The third is customer visibility: invisible back-end use, disclosed assistance, clearly labeled AI generation, or interactive AI-mediated service. The fourth is evidence grounding: outputs based on verified catalog data and retrieved sources versus outputs based mainly on model-generated inference. The fifth is accountability: the availability of human review, correction, complaint handling, and responsibility for errors. These dimensions can be measured as reflective perceptions, formative indices, or experimentally manipulated conditions, depending on the research question.

A formative specification may be preferable for the overall implementation construct because the dimensions need not covary. A retailer could have high transparency but weak human oversight, or strong source grounding but poor privacy controls. Treating these elements as interchangeable reflective indicators could conceal important implementation differences. Researchers should justify the measurement model theoretically, report indicator weights and collinearity diagnostics for formative constructs, and test whether results are robust to alternative specifications.

The customer's perceived implementation may also differ from the platform's actual implementation. Customers infer AI use from labels, interface cues, response style, or external information. Researchers should distinguish objective system configuration from perceived AI involvement. A useful design would collect both: technical or managerial documentation of how the touchpoint operates and consumer measures of what the customer believes occurred. The difference between actual and perceived use may itself influence authenticity, especially when customers discover undisclosed automation after an interaction.

### 5.5. Distinguishing mediation, moderation, and direct utility effects

The proposed model contains both mediating and moderating mechanisms, and these should not be conflated. Mediation concerns the process through which GenAI implementation affects an outcome. In the focal model, brand authenticity explains part of the relationship between touchpoint configuration and customer trust, while trust carries part of the relationship onward to purchase intention. Moderation concerns the conditions under which a path is stronger or weaker. Privacy concern may weaken the personalization-to-trust relationship; product type may change the effect of disclosure on authenticity; and human oversight may strengthen the effect of functional quality on authenticity.

A direct utility pathway should also be estimated. A customer may purchase because an AI-generated comparison makes the product easier to evaluate, even if brand authenticity does not change. If researchers force all effects through authenticity, they may overstate the mediator's explanatory role. A competing partial-mediation model should therefore include direct paths from functional quality and perceived usefulness to purchase intention, alongside indirect paths through authenticity and trust.

Parallel mediation through perceived usefulness and authenticity may be particularly relevant for AI-generated review summaries and recommendation explanations.

For experimental work, a factorial design could manipulate three factors: AI role (human-assisted versus AI-automated), disclosure (specific disclosure versus no disclosure), and verification (verified versus unverified product claims). Participants would evaluate the same product, brand, and message content across conditions. The design would allow researchers to estimate main effects and interactions while testing authenticity as a mediator. Manipulation checks should establish that participants noticed the AI role, understood the disclosure, and perceived the verification cue. Researchers should avoid confounding disclosure with message quality or visual attractiveness.

For survey-based work, a two-wave or three-wave design is preferable to a single cross-sectional questionnaire. GenAI touchpoint perceptions can be measured after exposure, authenticity and trust at a later point, and purchase intention or observed behavior subsequently. This reduces common-method concerns and improves temporal ordering, although it does not by itself establish causality. Bootstrapped confidence intervals should be reported for indirect effects, and measurement invariance should be assessed before comparing consumer groups or countries.

## 6. Discussion

### 6.1. Explaining mixed findings through implementation configuration

The first contribution of the synthesis is to explain why recent findings on GenAI and consumer response appear inconsistent. Some studies identify lower authenticity or trust when AI authorship is disclosed; others find neutral or positive effects. The evidence becomes more coherent when AI use is decomposed into the task performed, degree of automation, message type, disclosure design, and governance. A factual product specification generated from verified attributes is not psychologically equivalent to an emotional apology written in the brand's voice. A review summary grounded in real customer reviews is not equivalent to a synthetic testimonial presented as a real customer experience.

GenAI should therefore be evaluated as a socio-technical arrangement. Model capability matters, but so do the organizational processes that select data, approve content, verify claims, handle complaints, and assign responsibility. The customer experiences the entire arrangement through the output. A technically strong model can still create a poor brand experience if the platform does not establish boundaries for its use. Conversely, human oversight can make an imperfect generation process more trustworthy by ensuring that uncertain claims are corrected before publication.

### 6.2. Why authenticity should mediate rather than simply accompany trust

Authenticity and trust are related but conceptually distinct. Trust concerns whether a customer is willing to rely on a brand or platform. Authenticity concerns whether the brand appears genuine and faithful to its identity. A customer may regard a platform as technically reliable while considering its marketing communication inauthentic. For example, the customer may believe that an AI chatbot can correctly identify a product size but dislike the brand's use of synthetic customer stories. Conversely, a brand may appear authentic because its communication is consistent and transparent, while the customer remains uncertain about payment security or delivery reliability.

Positioning authenticity as a mediator captures the interpretive step between exposure to AI and a relational judgment about the brand. It also explains why AI can have different effects on trust depending on whether it supports or undermines the brand's perceived sincerity. The serial pathway from authenticity to trust to purchase intention is particularly relevant for purchases involving brand promises, product uncertainty, or emotional significance. It is less likely to be the only pathway for low-cost, routine purchases where usefulness and convenience may dominate.

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### 6.3. Transparency is a governance signal, not a universal persuasion tactic

The review suggests that transparency should not be optimized as if more disclosure always increases conversion. Disclosure may trigger an authenticity penalty when customers infer that a brand has delegated a human or creative responsibility to a machine. Yet concealing AI involvement creates a risk of perceived deception when the customer later discovers the source. The appropriate goal is not to maximize or minimize disclosure but to make the disclosure informative, proportionate, and connected to accountability.

Transparency should answer the questions that matter to the customer: Was AI used to generate or edit the content? Were product facts checked against an authoritative source? Are customer reviews being summarized or synthesized? Is the image a photograph of the actual product or a generated illustration? Does personalization rely on browsing history, purchase history, or information the customer supplied in the current session? Can the customer correct an inference or request human assistance? These questions turn transparency into a usable trust signal.

### 6.4. Implications for theory

First, the framework extends S–O–R applications in e-commerce by treating brand authenticity as a distinct organism-level state between AI touchpoint stimuli and customer trust. Second, it connects signaling theory with the practical design of GenAI systems: provenance, verification, and human review are observable signals that can reduce information asymmetry. Third, it refines technology acceptance perspectives by showing that usefulness and ease of use may not be sufficient for brand-level outcomes. A system can be easy to use and still undermine authenticity if its use conflicts with customer expectations.

Fourth, the framework introduces automation intensity and human oversight as theoretically meaningful dimensions. Rather than comparing “AI” and “human” as fixed categories, researchers can examine whether AI is used to assist, co-create, or replace human judgment. Fifth, it calls for multi-object trust measurement. Studies that ask only whether a chatbot is trustworthy may miss the customer’s separate judgment of the platform or brand. These distinctions can improve construct validity and explain why findings vary across studies.

### 6.5. Boundary conditions and plausible counter-explanations

Authenticity may not mediate every effect of GenAI. In low-involvement purchases, convenience, price, availability, and delivery speed may dominate brand meaning. A customer who buys a low-cost household item may rely on an accurate recommendation without forming a strong authenticity judgment. In these cases, perceived usefulness may be a stronger mediator than authenticity. Similarly, a well-known marketplace may benefit from institutional trust that partly substitutes for brand-specific authenticity judgments, although a major privacy or misinformation incident can weaken that institutional trust.

A second counter-explanation is that customers may evaluate the content rather than the source. If a generated product description is accurate, complete, and useful, some consumers may care little whether a human or AI wrote it. This is consistent with evidence that AI disclosure effects vary by message and product type. The source cue becomes more influential when the content makes emotional, experiential, identity-related, or socially consequential claims. Researchers should therefore test source sensitivity as a function of claim type rather than assume a universal AI penalty.

A third possibility is that familiarity with AI changes the meaning of disclosure. For consumers who routinely use generative systems, an AI label may signal innovation and efficiency. For consumers with lower AI literacy, it may signal uncertainty or loss of human care. A fourth possibility is that the brand’s prior reputation dominates the immediate AI cue. Customers may forgive a familiar brand’s

use of AI when they have accumulated positive experiences, but they may interpret the same practice as opportunistic when the brand is unfamiliar. These counter-explanations do not invalidate the proposed framework; they identify conditions under which the authenticity pathway should be stronger or weaker.

## 7. Managerial Implications for E-Commerce Platforms

1. Match the AI application to the customer task. Use GenAI where it demonstrably improves search, comparison, accessibility, translation, and product understanding. Do not assume that every customer-facing task benefits from a conversational interface. For high-risk product claims, rely on verified product databases and explicit source grounding rather than free-form generation.

2. Preserve human accountability for consequential claims. Product safety, compatibility, warranties, delivery commitments, refund rules, and health-related claims should be checked against authoritative records. Human review should be meaningful rather than symbolic: reviewers need the authority and time to correct, reject, or escalate generated outputs.

3. Use human-in-the-loop design for emotionally expressive communication. Messages of apology, gratitude, sympathy, community commitment, or brand purpose carry relational meaning. AI may help with drafting or translation, but the final communication should reflect a responsible human decision-maker and the brand's actual conduct.

4. Design disclosure around provenance and verification. A short label can be appropriate for generated images or text, but customers should be able to access more detail when the information affects a purchase decision. Distinguish generated creative material from factual product evidence. Never present a synthetic testimonial as a real customer statement.

5. Make personalization legible and controllable. Explain why a product is recommended, allow customers to edit preference assumptions, and provide accessible controls for personalization and data use. Avoid using sensitive or unexpected inferences when they are not necessary for the transaction.

6. Separate AI-system performance monitoring from brand-trust monitoring. Operational dashboards should track factual error rates, hallucination incidents, escalation rates, response latency, and recommendation relevance. Brand dashboards should separately monitor perceived sincerity, authenticity, complaint themes, disclosure comprehension, and trust.

7. Avoid excessive anthropomorphism. Natural language can improve usability, but a system should not imply that it has personal feelings, lived experiences, or independent human judgment. Make the assistant's automated role clear and provide an easy transition to a human agent.

8. Tailor the experience to product involvement and category. For routine utilitarian products, concise comparisons and verified specifications may be most useful. For hedonic or identity-expressive products, preserve distinctive brand storytelling and use AI-generated creative assets carefully. For unfamiliar brands, make evidence and provenance especially visible.

9. Build a correction and remedy process. Customers should be able to flag an inaccurate AI-generated description, recommendation, or answer. The platform should correct the underlying record, not merely apologize in the chat. Repeated errors should trigger model, prompt, retrieval, or governance changes.

10. Treat authenticity as an operating outcome. Authenticity cannot be created solely through a visual style or disclosure badge. It emerges when the brand's communication, product evidence, service behavior, and data practices are consistent. GenAI governance should therefore be linked to brand strategy, customer service, product operations, and privacy management.

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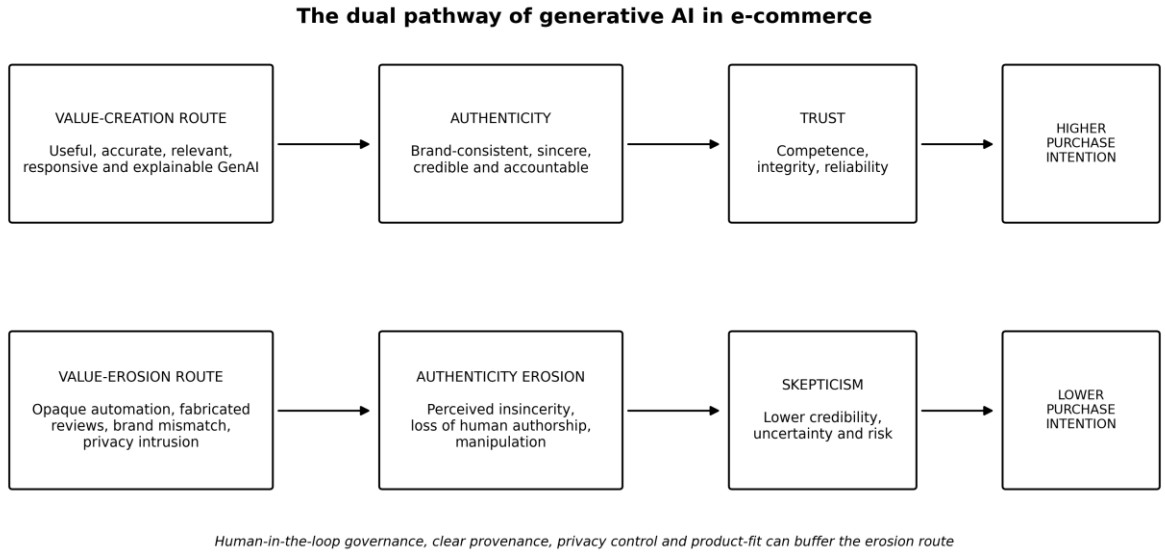



*Figure 2. Dual pathway through which GenAI can create customer value or erode brand authenticity and purchase intention.*

**Table 4. Practical governance controls by GenAI touchpoint**

| Touchpoint | Primary customer risk | Recommended control |
|---|---|---|
| Product descriptions | Hallucinated attributes, exaggerated claims, outdated specifications. | Generate only from verified catalog fields; flag missing data; human approval for consequential claims. |
| Product imagery | Synthetic image mistaken for a photograph of the actual item. | Label illustrative/generated imagery; preserve accurate color, fit, and product details; show real product photos where material. |
| Shopping chatbot | Confidently incorrect advice, false human impression, poor escalation. | Ground answers in current policy/catalog sources; disclose AI role; expose uncertainty; enable human handoff. |
| Recommendations | Opaque ranking, hidden sponsorship, intrusive personalization. | Explain recommendation rationale; distinguish sponsored placements; provide preference and privacy controls. |
| Review summaries | Misrepresentation of customer sentiment or fabricated social proof. | Summarize only authentic source reviews; retain links to original reviews; disclose synthesis; audit for omitted negatives. |
| Marketing messages | Inauthentic emotional tone or brand-identity mismatch. | Use AI for assistance; require human ownership for emotional and purpose-related messages. |
| Post-purchase support | Inconsistent refund/return guidance and accountability gaps. | Connect to authoritative order and policy systems; log decisions; route exceptions to trained staff. |

### 7.1. A staged implementation roadmap

A practical implementation sequence can help e-commerce managers translate the review into governance. Stage 1 is use-case selection: identify customer tasks where GenAI can reduce friction without making unsupported promises. Stage 2 is risk classification: distinguish low-risk drafting and navigation from high-risk claims about product performance, safety, warranties, delivery, or customer rights. Stage 3 is source grounding: connect generation to verified product catalogs, policy databases, and traceable review corpora. Stage 4 is human accountability: assign named organizational responsibility for approval, correction, and escalation. Stage 5 is customer-facing transparency: explain AI involvement and data use at the point where the information matters. Stage 6 is outcome monitoring:

evaluate not only speed and conversion but also accuracy, complaint patterns, perceived authenticity, trust, and repeat behavior.

The roadmap should include stop rules. A touchpoint should be paused or narrowed when it repeatedly produces fabricated product attributes, misrepresents customer feedback, gives inconsistent policy advice, or uses personal data in ways customers do not reasonably expect. A high conversion rate should not override these warning signals. Short-term conversion gains can be offset by returns, complaints, regulatory exposure, and loss of long-term trust. Governance indicators should therefore be reviewed alongside commercial performance.

Finally, organizations should create a feedback loop between customer service and model governance. Customer complaints can reveal systematic failures in product data, retrieval, prompt design, or policy integration. Correcting the underlying source is more valuable than repeatedly asking an AI assistant to apologize. Where customers report that AI communication feels generic or insincere, the remedy may involve revising the brand voice, limiting automation for emotional messages, or restoring human ownership rather than simply increasing the system's anthropomorphic features.

## 8. Limitations and Future Research Directions

This review has several limitations. First, the evidence base is recent and heterogeneous. GenAI systems and consumer expectations are changing quickly, so findings from early chatbot or image-generation studies may not transfer directly to newer multimodal and agentic systems. Second, the review is focused on English-language scholarly publications and a structured but non-exhaustive search. Relevant studies in other languages, regional journals, or unpublished datasets may have been missed. Third, many studies use self-reported trust, attitudes, or purchase intention rather than observed transactions. Such measures are useful but cannot establish whether stated intention becomes actual purchase behavior.

Fourth, a portion of the evidence comes from adjacent contexts such as social-media marketing, luxury advertising, hospitality, and service communication rather than e-commerce platforms alone. These studies are included because they illuminate authenticity and disclosure mechanisms, but transferability should be tested rather than assumed. Fifth, the current framework is conceptual and has not been empirically estimated as a unified model. The propositions are therefore hypotheses for future research, not confirmed causal relationships.

Future work should prioritize the following directions:

- Longitudinal studies that measure trust and authenticity before and after repeated exposure to GenAI touchpoints, including recovery after an error.
- Field experiments that compare human-only, AI-assisted, and AI-automated content while holding message content and product attributes constant.
- Behavioral outcomes such as click-through, add-to-cart, conversion, return rates, complaint rates, and repeat purchase, linked to survey measures of authenticity and trust.
- Cross-category comparisons involving utilitarian, hedonic, high-risk, high-involvement, and experience goods, with explicit tests of product type as a moderator.
- Cross-cultural replication, especially in markets with different levels of digital trust, privacy regulation, platform maturity, and consumer AI literacy.
- Measurement development that distinguishes brand authenticity, perceived content authenticity, AI-system trust, platform trust, and brand trust rather than combining them into a single scale.
- Studies of provenance design, content credentials, independent verification, and customer-facing explanations to determine which transparency signals are understood and trusted.
- Research on synthetic reviews and review summaries that tests whether AI synthesis preserves the distribution of positive and negative customer experiences.

Research on human-in-the-loop governance that examines the actual authority, training, and accountability of employees who review AI-generated customer-facing outputs.

Analysis of multimodal and agentic commerce, where AI systems can not only recommend products but also negotiate, configure baskets, place orders, or initiate returns.

A particularly valuable design would combine a randomized field experiment with a longitudinal survey. Customers could be randomly exposed to AI-assisted or AI-automated product communication, with disclosure and verification cues varied experimentally. Researchers could then observe actual product-page engagement and conversion while measuring authenticity, trust, perceived risk, and privacy concern over time. Such a design would test both the proposed mediation pathway and the gap between stated intention and behavior.

### 8.1. A recommended empirical validation design

A focused empirical test of the proposed framework could be conducted with active e-commerce customers who have recently used a product recommendation, chatbot, or AI-generated review summary. A two-stage design would be particularly useful. In the first stage, participants would be randomly assigned to a realistic product-page scenario in which the AI role, transparency cue, and human verification are manipulated. The product, price, brand familiarity, product description length, and visual design should be held constant. A manipulation check would assess perceived AI involvement, clarity of disclosure, and perceived verification.

Immediately after exposure, participants would rate functional quality, perceived usefulness, perceived brand authenticity, trust in the AI system, trust in the platform or brand, privacy concern, perceived risk, and purchase intention. The measures should be separated by construct and should avoid wording that embeds the proposed causal relationship. For example, authenticity items should assess sincerity and consistency rather than ask whether the brand is trustworthy. Trust items should assess willingness to rely on the brand, not whether its advertising is attractive. Purchase intention items should refer to the focal product and seller explicitly.

In the second stage, researchers could invite participants to revisit the product page after several days or link the experimental exposure to a simulated or real choice task. Outcomes could include click-through, product comparison, add-to-cart, choice, or request for human assistance. A field partnership with a retailer would allow analysis of actual conversion, cancellation, return, and complaint outcomes. Where a field partnership is unavailable, an incentive-compatible choice task would be preferable to relying exclusively on hypothetical intention.

The analysis could proceed in four steps: validate the measurement model; test the direct and indirect paths; estimate moderation by privacy concern, product type, and AI literacy; and compare alternative models in which usefulness and authenticity operate as parallel mediators. For latent-variable analysis, researchers should report reliability, convergent validity, discriminant validity, and collinearity diagnostics. For experimental mediation, indirect effects should be estimated with bootstrap confidence intervals and interpreted cautiously because mediator-outcome relationships are not automatically randomized. Preregistration, transparent exclusion rules, and data/material sharing would improve credibility.

Sample size should be determined through an a priori power analysis based on the smallest interaction or indirect effect of substantive interest, not by an arbitrary rule of thumb. The sample should include sufficient representation across age, digital experience, product categories, and prior AI use. If the study compares countries or language groups, measurement equivalence should be assessed before interpreting group differences. Such a design would directly test whether authenticity is the central mechanism proposed here or whether usefulness, privacy assurance, and institutional trust explain a larger share of the purchase pathway.

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## 9. Conclusion

GenAI is changing e-commerce not only by automating content production but by reshaping the information and relationship cues through which customers evaluate brands. Recent evidence shows that useful recommendations, responsive chatbots, and well-designed AI-generated reviews can improve decision support and customer experience. The same evidence also shows that opaque automation, synthetic social proof, privacy intrusion, and poorly calibrated emotional communication can weaken authenticity and trust.

This article argues that perceived brand authenticity is a central mechanism linking GenAI-enabled touchpoint design to customer trust and purchase intention. The proposed model suggests that GenAI is most likely to support purchase intention when it delivers accurate and relevant assistance, remains consistent with brand identity, makes its role and sources understandable, protects customer control, and preserves human accountability. Authenticity then supports customer trust, which in turn increases willingness to purchase. The model also recognizes direct usefulness effects and boundary conditions associated with product type, involvement, privacy concern, brand familiarity, and AI literacy.

The practical conclusion is not that e-commerce platforms should avoid GenAI or maximize automation. Rather, they should design GenAI around customer tasks and brand promises, distinguish assistance from substitution, and treat transparency and human oversight as elements of brand governance. The strategic advantage will belong not simply to platforms that generate more content, but to those that use generative systems in ways customers can understand, verify, and trust.

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