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PERSONALIZATION, PRIVACY AND TRUST IN AI-ASSISTED ONLINE SHOPPING: A CONCEPTUAL FRAMEWORK DISTINGUISHING TRUST IN THE ASSISTANT FROM TRUST IN THE RETAILER IN THE INDIAN CONTEXT

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ABSTRACT
AI-enabled shopping assistants now help consumers discover products, compare options and ask questions during online purchases. Whether shoppers act on that help depends on how relevant and how personal the advice feels, how well the assistant performs, and what shoppers believe is happening to their data. This conceptual paper develops a stimulus–organism–response framework for AI-assisted online shopping in India. It links two dimensions of perceived personalization (relevance and specificity) and chatbot quality to privacy concerns and trust, and through them to purchase intention. The paper makes three contributions. First, it separates trust in the assistant from trust in the retailer that deploys it. Second, it treats chatbot quality as a construct distinct from personalization and grounds it in research on AI chatbot service quality. Third, it brings together two roles of trust that earlier studies have specified separately, trust as a mediator and trust as a buffer against privacy concerns, in one model with a stated causal order and a route to testing. The framework draws on the technology acceptance model, trust research, privacy-calculus and privacy-boundary reasoning, and the computers-are-social-actors paradigm, and it is positioned against recent peer-reviewed studies of chatbots and shopping assistants, including studies of Indian shoppers. Eight propositions, boundary conditions, measurement guidance and an analytic strategy are offered for empirical work. India, where the Digital Personal Data Protection Rules, 2025 are phasing in notice-and-consent duties, is a timely setting in which to test them.

Keywords: AI shopping assistants; perceived personalization; chatbot quality; privacy concerns; consumer trust; purchase intention; personalization–privacy paradox; India

1. INTRODUCTION
Online retailers increasingly place AI-driven assistants at the point where shoppers make decisions. A shopper can describe a need in ordinary language, receive suggestions, ask about product details and move toward checkout without leaving the conversation. Such assistants promise less search effort and more relevant information. A promise of help, however, is not the same as acceptance of help. Shoppers may doubt the answers they receive, may feel uneasy about how the assistant seems to know their preferences, or may simply decide to buy somewhere else.

Three questions follow. First, does a recommendation that feels tailored build confidence, or does it make shoppers wonder how much the system knows about them? Second, does the quality of the conversation itself, apart from personalization, shape that confidence? Third, when confidence exists, does it carry shoppers toward buying, or does it mainly soften the effect of privacy worries? The first question belongs to the personalization–privacy tradition (Awad & Krishnan, 2006; Bleier & Eisenbeiss, 2015). The second belongs to research on the service quality of conversational agents (Chen et al., 2022; Gnewuch et al., 2017). The third belongs to trust and privacy-calculus research (Dinev & Hart, 2006; Gefen et al., 2003).

These strands are seldom combined. Studies of chatbots in online shopping, including those of Indian shoppers, mostly examine acceptance, satisfaction, loyalty or continued use (Butt & Ahmad, 2023; Kasilingam, 2020; Shahzad et al., 2024), and one Indian study names trust and perceived risk as omissions to be addressed in future work (Butt & Ahmad, 2023). Work on personalization and privacy in e-commerce, in turn, has largely not modelled chatbot quality. A recent survey of Turkish e-commerce customers examines personalization, privacy concerns and brand trust together, but its outcome is consumer well-being rather than purchase intention, and it does not include chatbot quality (Aydin, 2026). A systematic review of conversational AI finds that privacy, security and trust perceptions overlap and are rarely studied jointly (Leschanowsky et al., 2024).

The Indian setting adds a practical reason to study these questions now. India's Digital Personal Data Protection Act, 2023 (Government of India, 2023) was given operational detail by the Digital Personal Data Protection Rules, notified on 14 November 2025, with a phased compliance period of eighteen months (Press Information

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Bureau, 2025). The rules place notice and consent at the centre of how firms may use personal data. Shoppers' reactions to personalized assistants are therefore forming while data practices are being redefined, which makes the market a timely place to test how personalization, privacy and trust interact. Section 3 describes this context.

The paper follows the model-building template for conceptual articles, which draws on theory synthesis and requires that the choice of theories and their roles be stated and justified (Jaakkola, 2020). Section 2 sets out the theories and the role each plays. Section 3 describes the Indian context. Section 4 reviews the closest studies, compares them with the proposed framework and states four gaps. Section 5 presents the framework, its eight propositions and its boundary conditions. Sections 6 to 8 discuss contributions and implications, Section 9 sets out the research agenda, and Section 10 states limitations. The propositions are theoretical expectations to be tested, not findings.

2. THEORETICAL FOUNDATIONS

2.1 The organizing logic: stimulus, organism, response

The framework is organized by the stimulus–organism–response logic (Mehrabian & Russell, 1974), which has been applied to chatbot service quality, trust and loyalty (Shahzad et al., 2024). Features of the assistant act as stimuli. They produce internal states in the shopper, here privacy concerns and trust. Those states in turn shape a behavioural response, here purchase intention. This logic fixes the causal order of the model, which was left open in earlier treatments of trust as either a mediator or a moderator. The three theories below supply the reasons for each link.

2.2 Technology acceptance: the benefit side

Davis (1989) proposed that perceived usefulness and perceived ease of use are the central determinants of whether people accept an information technology. For a shopping assistant, usefulness corresponds to the help it gives in finding suitable products, and ease of use corresponds to how little effort the conversation demands. In this paper, perceived relevance is the content side of usefulness, and chatbot quality is the interaction side of both usefulness and ease of use. Acceptance reasoning explains why shoppers might try an assistant, but not why a useful assistant may still be distrusted. Evidence from shopping chatbots fits this limit: in one TAM-based study, intention to use was directly influenced only by trust, personal innovativeness and attitude, not by usefulness or ease of use alone (Kasilingam, 2020).

2.3 Trust and social responses to conversational machines

Trust is commonly defined as a willingness to be vulnerable to another party based on expectations about that party's ability, benevolence and integrity (Mayer et al., 1995). In electronic commerce, McKnight et al. (2002) distinguished trusting beliefs (competence, benevolence and integrity) from trusting intentions. Gefen et al. (2003) integrated trust with technology acceptance in a study of experienced repeat online shoppers. They found that trust in the e-vendor mattered as much as usefulness and ease of use in explaining intended behaviour.

The object of trust in that work was the vendor. An AI assistant introduces a second object. The computers-are-social-actors paradigm holds that people apply social rules and expectations to computers that interact with them in human-like ways (Nass & Moon, 2000). If so, shoppers can form trusting beliefs about the assistant as an interacting party, and those beliefs need not coincide with their beliefs about the retailer. In this paper, trust in the assistant means a shopper's willingness to rely on its advice, based on perceived ability, benevolence and integrity. Trust in the retailer means the same willingness directed at the firm that deploys the assistant.

2.4 Privacy calculus and privacy boundaries

Early work measured individuals' concerns about organizational information practices (Smith et al., 1996), and later work conceptualised Internet users' information privacy concerns in terms of collection, control and awareness (Malhotra et al., 2004). Culnan and Armstrong (1999) showed that perceived procedural fairness and impersonal trust shape willingness to accept information use. Dinev and Hart (2006) tested an extended privacy-calculus model on 369 respondents. Privacy concerns inhibited the willingness to provide personal information needed for online transactions, but Internet trust and personal Internet interest could outweigh perceived privacy risk. Privacy concern is treated here as a perception that shoppers weigh against benefits. It is not a measure of how secure a system actually is.

Communication privacy management theory adds a reason why specificity, in particular, should raise concern. It holds that people treat private information as something they own and whose boundaries they manage (Petronio, 2002). A suggestion that reveals detailed knowledge of the shopper signals that a boundary has been crossed, whereas a suggestion that simply answers what the shopper has said does not.

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2.5 How the theories fit together

Technology acceptance describes the perceived benefit of assistance, trust research and the social-actor paradigm describe the willingness to rely on a party under uncertainty, and privacy calculus and boundary theory describe the weighing of benefits against information-related costs. The stimulus–organism–response logic arranges them into one causal sequence. Table 3 states the mechanism behind each path.

3. THE INDIAN CONTEXT: AI-ASSISTED SHOPPING AND DATA PROTECTION

Regulation. The Digital Personal Data Protection Act, 2023 (Government of India, 2023) was followed by the Digital Personal Data Protection Rules, notified on 14 November 2025, which introduce an eighteen-month period for phased compliance and require a clear, easily understood consent notice (Press Information Bureau, 2025). The substantive notice-and-consent duties of firms therefore take effect during 2027. Until then, retailers are redesigning how they explain and obtain consent for data use, and shoppers meet personalized assistants against a background of changing disclosure practices. This is the condition that makes perceived transparency and control, treated in Section 5 as a boundary condition, practically relevant.

Existing evidence on Indian shoppers. Research on Indian shoppers and AI-based assistants has so far concentrated on acceptance and satisfaction. A survey of 554 Indian online shoppers who had used a leading retailer's chatbot examined information quality, service quality, usefulness, enjoyment and engagement as drivers of satisfaction, continued use and electronic word of mouth (Butt & Ahmad, 2023). Information quality and service quality both had positive effects on satisfaction, but the effects were small, and trust and perceived risk were left to future research. Other work has examined Indian shoppers' motivation to use AI (Chopra, 2019) and the acceptance of online shopping assistants with trust as a mediator and gender and education as moderators (Singh et al., 2024). None of these studies models personalization specificity, privacy concerns, chatbot quality and two objects of trust together.

Heterogeneity. Indian online shoppers differ widely in language, device, city tier and digital experience. The framework does not assume that Indian shoppers respond differently from shoppers elsewhere. It treats India as a setting in which regulation is changing, in which the shopper base is highly varied, and in which the relationships can therefore be tested across meaningful sub-groups. Language of interaction, city tier and digital experience are carried into the framework as boundary conditions (Section 5.5).

4. LITERATURE REVIEW AND POSITIONING AGAINST THE CLOSEST STUDIES

4.1 Personalization and privacy

Awad and Krishnan (2006) surveyed more than 400 online consumers and found a central paradox for firms that rely on personalization: consumers who value information transparency are less willing to be profiled for personalization. Firms need customer data to personalize, yet the shoppers who most want to know how data are used are the least willing to take part. Xu et al. (2011) examined how consumers decide under the same tension in location-aware mobile marketing, which shows that the paradox extends beyond web-based profiling.

Bleier and Eisenbeiss (2015) used field data and laboratory experiments to show that responses to personalized online advertising depend on trust in the advertiser. Personalization is therefore not uniformly beneficial. Privacy concerns and perceived intrusiveness drive negative reactions, and these reactions are strongest toward retailers that have not earned trust. In their design, trust works as a condition that shapes the effect of personalization.

Aydin (2026) studied 400 e-commerce customers in Türkiye with partial least squares structural equation modelling. Personalization was split into perceived relevance and perceived specificity. Both raised privacy concerns, but specificity did so much more strongly ($\beta = 0.445$ against 0.117 for relevance). Privacy concerns reduced psychological well-being, and brand trust weakened that harmful effect. The study shows that treating personalization as a single, uniformly positive construct is no longer defensible, and the present framework adopts its relevance–specificity distinction. Its outcome, however, is well-being, and it has no chatbot-quality construct.

4.2 Chatbot service quality and its outcomes

Research on information systems success treats information quality and service quality as determinants of user satisfaction (DeLone & McLean, 2003), and research on electronic service quality offers multi-item scales for web-based service (Parasuraman et al., 2005). Early design work on conversational agents for customer service noted that such agents promise a fast, convenient and low-cost channel but often fail to meet expectations (Gnewuch et al., 2017). Chen et al. (2022) then developed dimensions and scales specific to AI chatbots. Using interviews with 55 organizations in 17 countries and 47 customers, they identified seven second-order and

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eighteen first-order dimensions of AI chatbot service quality and showed that it positively influences satisfaction, perceived value and intention to continue using chatbots. This work gives chatbot quality an established measurement basis that is separate from personalization.

Studies of chatbots in retail and brand settings link service quality and related chatbot features to satisfaction and loyalty. Chung et al. (2020) examined chatbot e-service and customer satisfaction for luxury brands. Ashfaq et al. (2020) modelled the determinants of satisfaction and continuance intention for AI-powered service agents. Shahzad et al. (2024), working within the stimulus–organism–response logic with 301 Chinese consumers of luxury fashion brands, found that chatbot service quality influenced e-brand loyalty and that chatbot user trust, experience and electronic word of mouth mediated the relationship. In the Indian survey described in Section 3, information quality and service quality had small but significant effects on satisfaction (Butt & Ahmad, 2023). Across these studies the outcomes are satisfaction, loyalty and continued use. Purchase intention after an interaction, privacy concerns and personalization are not part of the models.

In this paper chatbot quality means a shopper's evaluation of how well the assistant carries out the conversation: the accuracy and sufficiency of its information, the clarity and consistency of its answers, its responsiveness, and its handling of errors. Chatbot quality is separate from perceived relevance. Relevance is a property of the recommendation, namely how well it fits what the shopper has asked for. Quality is a property of the exchange. An assistant can make a highly relevant suggestion through a confusing, slow or inconsistent dialogue, and it can conduct a smooth dialogue while suggesting poorly matched products. For this reason 'relevance' is not part of the chatbot-quality definition used here.

4.3 Trust in chatbots and shopping assistants

Evidence on how trust works in chatbot shopping is mixed. In a TAM-based study of smartphone chatbots for shopping, intention to use was directly influenced only by trust, personal innovativeness and attitude (Kasilingam, 2020). A study of online shopping assistants examined acceptance from functional, social, relational and security perspectives, with trust as a mediator and gender and education as moderators (Singh et al., 2024). Work on service failures examines how consumer trust in AI chatbots can be sustained, drawing on attribution and computers-are-social-actors theories (Gu et al., 2024). Yet in a study of 385 customers who had used AI-driven chatbots on e-commerce platforms in Sri Lanka, chatbot affordances affected purchase intention mainly indirectly through satisfaction and trust, and trust did not directly influence purchase intention (Yatawara et al., 2025). In earlier e-commerce research, trust was found to be an important determinant of intended behaviour (Gefen et al., 2003) and to outweigh privacy risk perceptions in some circumstances (Dinev & Hart, 2006).

Two features of this literature motivate the framework. First, trust is specified in different roles: as a mediator in the trust-and-acceptance tradition (Gefen et al., 2003; Shahzad et al., 2024), as a moderating condition in Bleier and Eisenbeiss (2015) and Aydin (2026), and as a factor that can outweigh privacy risk in Dinev and Hart (2006). Second, the object of trust varies across studies (vendor, brand, advertiser, chatbot user trust) and is rarely stated. Leschanowsky et al. (2024) add that privacy, security and trust perceptions overlap in their sub-constructs and that scale reliability and validity deserve attention. Privacy concerns and the two forms of trust therefore have to be measured with clearly separable items.

4.4 Anthropomorphism and disclosure

Research on conversational agents has also examined how anthropomorphic design cues shape perceptions of the agent and the company (Araujo, 2018) and how disclosing that a conversational agent is a chatbot affects customer purchases (Luo et al., 2019). These factors are not placed on the main causal path in the present framework, because they are properties of how the assistant is presented rather than of what the assistant does. They are treated as boundary conditions in Section 5.5.

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4.5 Comparison with the closest studies

Table 1. Closest studies and what they leave open

Study	Context and method	Constructs and role of trust	What it leaves open for this paper
Aydin (2026)	Türkiye; survey of 400 e-commerce customers; PLS-SEM	Relevance and specificity, privacy concerns, well-being; brand trust as moderator	Outcome is well-being, not purchase intention; no chatbot quality; no separation of assistant and retailer trust
Bleier & Eisenbeiss (2015)	Field data and laboratory experiments; personalized banner advertising	Personalization, privacy concerns, intrusiveness; trust in the advertiser as a condition	Advertising rather than a conversational assistant; no chatbot quality
Dinev & Hart (2006)	Survey of 369 respondents; SEM	Privacy concerns, Internet trust, personal interest; disclosure intention	General Internet transactions; predates AI assistants; no personalization or quality constructs
Gefen et al. (2003)	Experienced repeat online shoppers; integrated model	Usefulness, ease of use, trust in the e-vendor; intended behaviour	Vendor trust only; no privacy or personalization constructs
Awad & Krishnan (2006)	Survey of more than 400 online consumers	Information transparency, willingness to be profiled	No trust or purchase intention; no conversational setting
Chen et al. (2022)	Interviews (55 organizations, 47 customers) and scale development; AI chatbots in frontline service	AI chatbot service quality (7 second-order, 18 first-order dimensions); satisfaction, perceived value, continued use	Frontline service rather than shopping; personalization, privacy concerns and trust are not part of the reported nomological test
Shahzad et al. (2024)	301 Chinese luxury-fashion consumers; PLS-SEM; stimulus–organism–response	Chatbot service quality and awareness; trust (organism) with experience and eWOM; e-brand loyalty	Loyalty outcome; no personalization or privacy constructs; one object of trust
Butt & Ahmad (2023)	554 Indian online shoppers who used a retailer's chatbot; PLS-SEM; IS success and TAM	Information quality, service quality, usefulness, enjoyment, engagement; satisfaction, continued use, eWOM; trust not modelled	Trust and perceived risk named for future work; no privacy or personalization constructs; outcome is not purchase intention
Kasilingam (2020)	Smartphone chatbots for shopping; TAM and diffusion of innovations	Usefulness, ease of use, enjoyment, price consciousness, perceived risk, trust, innovativeness; attitude and intention; trust directly influenced intention	Intention to use the chatbot rather than purchase after interaction; no personalization or chatbot quality; one object of trust

Study	Context and method	Constructs and role of trust	What it leaves open for this paper
Singh et al. (2024)	Online shopping assistants; 272 online shoppers in an Indian context; PLS-SEM; extended TAM with functional, social, relational and privacy factors	Usefulness, ease of use, anthropomorphism, privacy risk and trust; trust as mediator; gender and education as moderators; outcome is acceptance	Acceptance rather than purchase intention; no personalization or chatbot-quality constructs; one object of trust (the assistant)
Yatawara et al. (2025)	Sri Lanka; 385 customers who had used AI-driven chatbots; quantitative survey	Chatbot affordances, satisfaction, trust, engagement; trust did not directly influence purchase intention	Affordances rather than privacy or personalization; single object of trust; not an Indian sample
Leschanowsky et al. (2024)	Systematic review of conversational AI	Privacy, security and trust perceptions	Review of constructs and scales; no model of purchase intention

Note. Entries summarise the sources as described in their abstracts and, for Aydin (2026), Butt and Ahmad (2023) and Singh et al. (2024), the full text. Entries state what each source does not address; they do not claim that no study in the wider literature does.

4.6 Literature identification and research gaps

Studies were identified through keyword searches that combined AI shopping assistant and chatbot terms with personalization, privacy concern, trust, service quality, purchase intention, e-commerce and India. The searches covered publisher pages, institutional repositories and indexing services, and they were supplemented by backward citation tracing from the closest studies. Peer-reviewed journal articles and conference proceedings were admitted when their bibliographic details and abstract could be confirmed on a publisher, repository or indexing page. Preprints, theses, press items and unrefereed uploads were excluded. Foundational theoretical and methodological works were cited as standard references and were not part of the search. Indian studies were included where they met these criteria.

Against the studies in Table 1, four gaps are stated. Each applies to the studies reviewed and is not a claim about the whole literature.

- *Gap 1: joint modelling.* Studies of chatbots in online shopping examine acceptance, satisfaction, loyalty or continued use, while studies of personalization and privacy do not include chatbot quality. No reviewed study models relevance, specificity, chatbot quality, privacy concerns and trust together in a purchase-intention model.
- *Gap 2: the role of trust.* Trust is specified one way at a time: as a mediator (Gefen et al., 2003; Shahzad et al., 2024), as a moderating condition (Bleier & Eisenbeiss, 2015; Aydin, 2026), and as a factor that can outweigh privacy risk (Dinev & Hart, 2006). The reviewed studies do not place these roles in one model with a stated causal order.
- *Gap 3: the object of trust.* Trust is directed at the vendor, the brand, the advertiser or the chatbot user relationship, and trust in an AI assistant is not separated from trust in the retailer that deploys it.
- *Gap 4: evidence from conversational shopping in India.* Findings on personalization specificity and privacy concerns come from advertising and general e-commerce settings, and the Indian chatbot studies reviewed concentrate on acceptance, satisfaction and continued use. Whether these relationships hold in conversational shopping among Indian shoppers is untested.

5. PROPOSED CONCEPTUAL FRAMEWORK

5.1 Constructs and causal order

The framework contains seven constructs arranged by the stimulus–organism–response logic. The stimuli are perceived relevance and perceived specificity (the two dimensions of perceived personalization) and chatbot

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quality. The organism consists of privacy concerns, trust in the assistant and trust in the retailer. The response is purchase intention. Perceived transparency and control is added as a boundary condition drawn from Awad and Krishnan (2006) and Bleier and Eisenbeiss (2015). Working definitions are given in Table 2, and the framework is shown in Figure 1.

Table 2. Working definitions of the constructs

Construct	Working definition	Main conceptual basis
Perceived relevance	The extent to which a shopper judges the assistant's suggestions to match the needs and interests the shopper has expressed	Aydin (2026)
Perceived specificity	The extent to which a shopper judges the assistant's suggestions to reflect detailed knowledge of the shopper's personal characteristics or past behaviour	Aydin (2026); Bleier & Eisenbeiss (2015)
Chatbot quality	A shopper's evaluation of how well the assistant carries out the conversation: the accuracy and sufficiency of its information, the clarity and consistency of its answers, its responsiveness, and its handling of errors	Chen et al. (2022); DeLone & McLean (2003); Parasuraman et al. (2005)
Privacy concerns	A shopper's worry about how personal information is collected, used and shared when using the assistant	Smith et al. (1996); Malhotra et al. (2004); Dinev & Hart (2006)
Trust in the assistant	Willingness to rely on the assistant's advice, based on perceived ability, benevolence and integrity	Mayer et al. (1995); McKnight et al. (2002); Nass & Moon (2000)
Trust in the retailer	Willingness to rely on the retailer that deploys the assistant, based on the same three beliefs	Gefen et al. (2003); Mayer et al. (1995)
Perceived transparency and control	A shopper's perception of being informed about, and able to influence, how personal data are used	Awad & Krishnan (2006)
Purchase intention	A shopper's stated likelihood of buying from the retailer after interacting with its assistant	Gefen et al. (2003)

5.2 Two roles of trust in one model

Earlier studies specify trust either as a mediator or as a moderator. The framework includes both roles, each with a stated place in the causal order. In the mediating pathway (Model A), trust in the assistant carries the effects of relevance and chatbot quality to purchase intention (P5). In the buffering pathway (Model B), trust in the retailer changes how strongly privacy concerns reduce purchase intention (P7). Trust in the retailer is also an antecedent of trust in the assistant (P6), because a shopper who already trusts a retailer is likely to extend part of that trust to the assistant it deploys. The two pathways do not exclude each other. When both hold, the result is a moderated-mediation structure, and nested model comparison is the proposed way to decide how much each contributes.

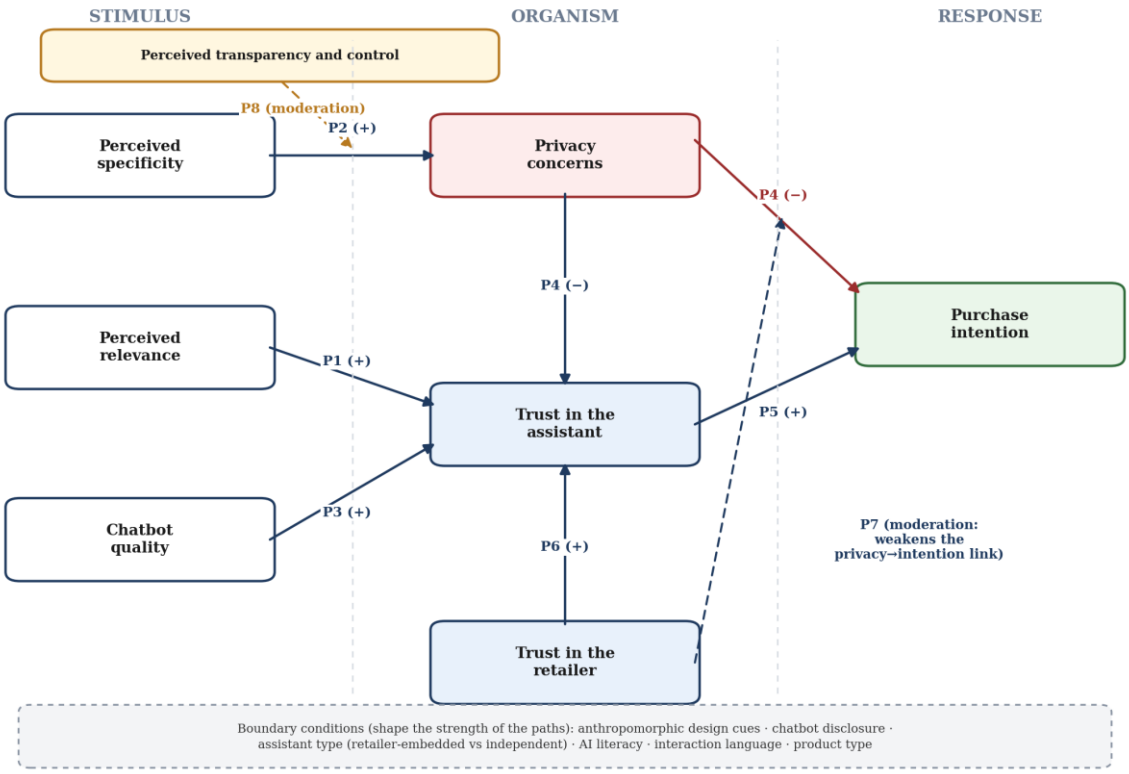
Reversing the roles, with trust in the retailer as mediator and trust in the assistant as moderator, is held as a robustness check for empirical work and is not part of the primary model, because P6 already places trust in the retailer ahead of trust in the assistant. The reversal is still informative. If it fits as well as the primary model, the roles of the two objects of trust cannot be told apart in the data.

5.3 When the two objects of trust differ

Trust in the assistant and trust in the retailer are expected to diverge most when the assistant is clearly distinguishable from the retailer: when it is a general-purpose or third-party AI model rather than the retailer's own tool, when its machine identity is disclosed, and when its answers draw on sources beyond the retailer's catalogue. For an assistant that is presented as the retailer's own, the two forms of trust may overlap heavily. Whether they do is an empirical question, and it is the reason the framework requires evidence of discriminant validity between them (Section 9). Retailer-embedded versus independent assistants is therefore treated as a boundary condition.

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Figure 1. Proposed conceptual framework (P1–P8 refer to the propositions in Table 3). Solid arrows are direct paths; dashed arrows are moderation. Trust in the assistant mediates the effects of relevance and chatbot quality on purchase intention (P5).



5.4 Propositions

Table 3. Propositions, mechanisms and basis

No.	Proposition	Mechanism	Main basis
P1	Perceived relevance is positively associated with trust in the assistant.	When suggestions match what the shopper has said, the assistant shows competence and attention (the usefulness logic of technology acceptance), which supports trusting beliefs about ability and benevolence.	Davis (1989); Mayer et al. (1995); Gefen et al. (2003); Aydin (2026)
P2	Perceived specificity is positively associated with privacy concerns, and more strongly than perceived relevance is.	Suggestions that reveal detailed knowledge of the shopper signal that an information boundary has been crossed, which prompts concern about collection and use.	Petronio (2002); Aydin (2026); Bleier & Eisenbeiss (2015)
P3	Chatbot quality is positively associated with trust in the assistant, over and above personalization.	People apply social expectations to conversational computers, so accurate, clear, consistent and responsive conduct signals ability and integrity.	Nass & Moon (2000); Chen et al. (2022); Shahzad et al. (2024)
P4	Privacy concerns are negatively associated with trust in the assistant and with purchase intention.	Shoppers weigh information-related costs against benefits. Concern lowers both the willingness to rely on the assistant's advice and the willingness to buy.	Dinev & Hart (2006); Culnan & Armstrong (1999); Aydin (2026)

No.	Proposition	Mechanism	Main basis
P5 (Model A)	Trust in the assistant is positively associated with purchase intention and mediates the effects of perceived relevance and chatbot quality on purchase intention.	Willingness to rely on the assistant's advice is the step that turns favourable perceptions into willingness to buy.	Gefen et al. (2003); Shahzad et al. (2024), loyalty outcome; contrary evidence in Yatawara et al. (2025)
P6	Trust in the retailer is positively associated with trust in the assistant.	A shopper who trusts the retailer is likely to extend part of that trust to the assistant it deploys, especially when the assistant is presented as the retailer's own.	Conceptual expectation; no reviewed study tests it directly
P7 (Model B)	Trust in the retailer moderates the relationship between privacy concerns and purchase intention, which is weaker when trust in the retailer is high.	A retailer believed to use data legitimately gives shoppers a reason to give privacy concerns less weight in the buying decision.	Bleier & Eisenbeiss (2015); Aydin (2026); Dinev & Hart (2006)
P8	Perceived transparency and control weaken the association between perceived specificity and privacy concerns.	Knowing how data are used, and being able to influence that use, restores a sense of control over information boundaries.	Awad & Krishnan (2006); Bleier & Eisenbeiss (2015); Petronio (2002)

Note. Taken with P2 and P4, specificity is expected to have a negative indirect effect on trust in the assistant through privacy concerns.

The propositions are theoretical expectations. P2 and P7 rest on evidence from Türkiye and from advertising settings, respectively, and are carried to conversational shopping among Indian shoppers as hypotheses to be tested. P5 is stated with the contrary evidence of Yatawara et al. (2025) in view: if trust does not act directly on purchase intention in some settings, the mediation in Model A will be partial or conditional, and the empirical test is designed to show which. P6 has no direct empirical support in the sources reviewed and is offered as a conceptual expectation.

5.5 Boundary conditions

Several factors are expected to shape the strength of the paths without adding new causal routes. Keeping them outside the core model preserves parsimony, and Table 4 states what each is expected to do.

Table 4. Boundary conditions

Condition	Expected influence	Basis
Anthropomorphic design cues	May strengthen the assistant's social presence and so the effect of chatbot quality on trust in the assistant	Araujo (2018); Nass & Moon (2000)
Disclosure of machine identity	May change how shoppers interpret the assistant's advice and how far trust in the assistant differs from trust in the retailer	Luo et al. (2019)
Assistant type: retailer-embedded or independent	Determines how far the two objects of trust overlap (Section 5.3)	Conceptual
AI literacy and digital experience	May shape how shoppers read specificity and judge chatbot quality	Conceptual; see Butt & Ahmad (2023) for experience-based samples
Interaction language and city tier	Indian shoppers differ widely in language and digital access, so path strengths may differ across sub-groups	Section 3

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Condition	Expected influence	Basis
Product type and involvement	Price, availability, delivery terms and brand reputation also shape buying, and their weight differs across product types	Section 10

6. DISCUSSION

The framework treats AI assistance as a bundle of benefits and costs that shoppers weigh together. Personalization is a conditional benefit. Relevance is likely to build reliance, while specificity can signal how much the system knows and may trigger concern (Aydin, 2026). Chatbot quality is a separate route to reliance, one that does not depend on knowing the shopper, and it has an established measurement basis in research on AI chatbot service quality (Chen et al., 2022).

Privacy concerns may operate independently of how well the assistant performs. A shopper may admire an assistant's answers and still decline to buy because of how information seems to be used. Trust may reduce this effect, as Dinev and Hart (2006) suggest, but the evidence is mixed on whether its role is to carry effects forward or to condition them. By giving trust a stated place in each role, the model lets a single data set show how much of the effect runs through trust in the assistant and how much through a buffering effect of trust in the retailer.

Separating trust in the assistant from trust in the retailer sharpens the question. A shopper may trust a familiar retailer and doubt its chatbot, or value the chatbot while mistrusting the retailer's data practices. If both forms of trust can be measured, the framework can show which one matters for which part of the process, and managers can see which of the two a failing experience is damaging.

7. THEORETICAL CONTRIBUTIONS

The paper makes three contributions, each stated against the closest studies.

- It places two roles of trust, as mediator and as buffer, in one stimulus–organism–response model with a stated causal order, where earlier work specifies one role at a time, and it provides a route to deciding between them through nested model comparison and a role-reversal check.
- It separates trust in the assistant from trust in the retailer, an object-of-trust distinction that the vendor-, brand-, advertiser- and chatbot-focused studies reviewed here do not draw, and it states the conditions under which the two should diverge.
- It positions chatbot quality, grounded in AI chatbot service-quality research, as a construct separate from personalization and places it alongside privacy concerns and trust in a purchase-intention model, extending the relevance–specificity distinction of Aydin (2026) to a conversational shopping setting.

8. MANAGERIAL IMPLICATIONS

- *Personalize for relevance before specificity.* Recommendations that answer what the shopper has said are less likely to raise privacy concerns than recommendations that reveal deep knowledge of the shopper.
- *Treat conversation quality as its own target.* Accurate, clear and consistent answers, with an easy route to a human, may build reliance even when little personal data are used.
- *Explain data use at the moment of personalization.* Transparency and control are plausible levers for weakening the link between specificity and privacy concern. Where notice and consent are required under India's data protection rules, designing them so that shoppers can understand them may serve trust as well as compliance.
- *Measure trust in the assistant and trust in the retailer separately,* and measure privacy concerns separately from both. A single satisfaction score can hide which one is failing.

9. FUTURE RESEARCH AGENDA

The empirical agenda has four parts.

- *Survey test.* Sample Indian online shoppers who have actually used an AI shopping assistant, stratified by language of interaction and city tier where possible, and estimate the model with structural equation modelling. Compare Models A and B through nested models, add the role-reversal check described in Section 5.2, and test conditional indirect effects with a conditional-process approach (Hayes, 2022). Show discriminant validity among privacy concerns, trust in the assistant and trust in the retailer, using the Fornell–Larcker criterion (Fornell & Larcker, 1981) and the heterotrait–monotrait ratio (Henseler et al.,

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2015), as the review by Leschanowsky et al. (2024) makes advisable. Because all constructs would be self-reported, design the survey to limit common method bias and test for it (Podsakoff et al., 2003).

- *Measurement.* Adapt validated scales. Privacy concerns can draw on Smith et al. (1996) and Malhotra et al. (2004), and trust on the trusting-belief items of McKnight et al. (2002). Chatbot quality can be measured by adapting the dimensions and scales developed for AI chatbot service quality (Chen et al., 2022), with a validation step for shopping assistants. Aydin (2026) adapted relevance, specificity, privacy concern and trusting-belief items from earlier work, including Bleier and Eisenbeiss (2015) for specificity, and these provide a starting point.
- *Experiments.* Manipulate personalization depth and the transparency of data explanations to test P2 and P8, and manipulate whether the assistant is presented as the retailer's own or as independent to test when the two objects of trust diverge (Section 5.3).
- *Boundary conditions and behaviour*. Compare product categories, retailer familiarity, digital experience, anthropomorphic cues, disclosure of machine identity and language of interaction, and, where data allow, replace stated intention with observed purchases.

A broader systematic review of recent Indian and international studies, following a documented search protocol, would also allow the gaps stated there to be re-examined as the literature grows.

10. LIMITATIONS

The paper is conceptual and reports no primary data, so the propositions remain to be tested. The literature comparison draws on studies whose bibliographic details could be confirmed, and it is not a systematic review. Two propositions borrow evidence from other settings (P2 and P7), and one (P6) has no direct empirical support in the sources reviewed. The model omits price, availability, delivery terms and brand reputation, which affect purchase intention, and it uses stated intention rather than observed purchase. The paper also does not establish that any relationship is specific to Indian consumers. India is the setting in which the framework is to be tested, and comparative work would be needed to show distinctiveness.

11. CONCLUSION

AI shopping assistants may widen what shoppers discover, but shoppers act on that help only when they find it reliable and acceptable in its use of their information. This paper offers a framework that puts relevance, specificity and chatbot quality ahead of privacy concerns and trust, and through them purchase intention, in one stimulus–organism–response model. Its contribution is threefold. It gives trust two stated roles in one causal order, it separates trust in the assistant from trust in the retailer, and it treats chatbot quality as a construct distinct from personalization. The eight propositions, boundary conditions and measurement guidance give empirical work in India a structured set of tests at a time when data protection rules are redefining how personalized assistants may use shoppers' information.

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