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The Explainability Edge: Bridging the Awareness, Trust Gap in Indian AI Driven E Commerce

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Abstract

This study examines the effect of artificial intelligence (AI) on consumer trust and the buying process for ecommerce products in India. It includes the Mediation of Awareness on AI, the level of Personalization, explain ability (XAI) and the frequency of interaction with AI in the mediation of trust in the recommendations provided by the AI and the subsequent purchase decision. The study was of quantitative type and cross-sectional design in which from the major Indian e-commerce vendors (Amazon, Flip kart, Myntra, Meesho) questionnaire with structured likert scale was administered using of purposive sampling and snowball sampling techniques. Data were analysed using multiple regression, which explained 61.4% of variance in consumer trust ($R^2 = 0.614$, $F(4, 95) = 37.84$, $p < .001$). Personalization effectiveness was the strongest predictor ($\beta = 0.412$, $p < .001$), followed by XAI ($\beta = 0.308$, $p < .001$) and AI awareness ($\beta = 0.197$, $p < .01$). The frequency at which AI was interacted with was not significant ($\beta = 0.089$, $p = .143$). A gap in structural awareness and trust, referred to as a Likert scale (Likert points) of 0.72, was found, significantly demonstrating that the more familiar an individual is with AI, does not automatically equate to trust or confidence in its purchase. The study provides primary regression evidence from the emerging market context, which is seldom studied, and it suggests two very promising ideas for the platform design: focus on XAI and personalization to address the awareness–trust gap.

Keywords: Artificial Intelligence, E-Commerce, Consumer Trust, Regression Analysis, Personalization, Explainable AI, Technology Acceptance Model, India

The Explainability Edge: Bridging the Awareness–Trust Gap in Indian AI-Driven E-Commerce

On a global scale, the trust in AI is viewed as a wicked problem that demands innovative solutions.Likewise, globally, building trust in AI is considered a wicked problem, and needs new solutions. The Explainability Edge: Erasing the Awareness to Trust Gap in Indian AI Driven eCommerce -With the fast sprawl of Artificial Intelligence (AI) in every aspect of the consumer buying lifecycle, the global e-commerce industry is being reshaped. Now, what was a key part of the back-end infrastructure—algorithm-built filtering, demand forecasting, inventory optimisation—has gone to the people's front-end interfaces, significantly influencing the way hundreds of millions of consumers discover, assess and shop at hundreds of thousands of businesses daily. From Amazon to Myntra, to Meesho to Flipkart, the recommendation engine, conversation AI and visual search, and dynamic pricing are already integral

features of platforms like these. These AI systems collectively analyze billions of behavioural signals per day and generate results that can directly influence consumer behavior.

India offers a very interesting and under-researched point of view to this question. India is the largest and diverse Internet consumer market of the world that is also witnessing the growth of e-commerce that is expected to reach USD 350 billion by 2030 (IBEF, 2024). Irrespective of the economies on both sides being well-diversified, the supply side is largely dominated by well-capitalised platforms with sophisticated AI infrastructure, while the demand side consists of customers with various levels of digital literacy, overall leeway of the price they are willing to pay and higher data privacy concerns. This imbalance opens the door to situations where AI can be widely adopted and trust in AI might not be evenly distributed, making India an excellent guinea pig to explore the limits of AI acceptance.

While numerous studies have explored the use of AI in eCommerce, there is still a lot of unexplained. The majority of empirical studies come from Western countries where consumers respectively hold different prior conceptions of technology, data management, and institutional trust, or are theoretical in nature that are based on secondary data and/or experimental setups that make use of simulated environments rather than survey evidence from the real-time experience of active on-line shoppers (Liao et al. 2022; Tran et al. 2021). Research that looks at the Indian consumers typically studies adoption rates of specific technologies (mobile payments, chatbot) and not the comprehensive behaviour of the consumers towards AI features in various platforms (Arora and Malik, 2020).

This raises a second gap in the literature as far as analytical approaches employed are concerned. Many studies only manage to study descriptive data and only look for relationships, which is fine but not enough for quantifying the relative predictive importance of different drivers of trust. In this study, we fill this gap by using multiple regression analysis which allows us to measure the individual effects of each factor: AI awareness, effectiveness of personalisation, explainability and interaction frequency on consumer trust outcomes.

The awareness–trust gap is the systematic mismatch we explore in this work between the consumers' awareness that AI is working in their shopping environment, and the consumers' willingness to draw inferences and take action based on AI unearthed content. Several qualitative and survey studies have recorded anecdotally (Chaudhuri & Holbrook, 2001; Pavlou, 2003) this phenomenon, yet little quantitative work has been done to assess the extent of the phenomenon, what contributes to it and what remedies are possible in the Indian e-commerce context. This is directly philosophically, commercially valuable – platforms that can turn AI-aware consumers into AI-trusting ones are sure to mine significant reward in terms of conversion rates, average order value and customer lifetime value

Research Objectives

The study aims at fulfilling the following four main objectives that aim at uncovering the relationship between Artificial Intelligence and Consumer Behaviour. It aims to gauge the current awareness levels of AI amongst the consumers of the Indian e-commerce space in four major platforms, as a preliminary step to understanding consumer knowledge. Based on this, multiple regression analysis is used to evaluate the relative importance of factors of AI awareness, effectiveness of personalization, explainability, and AI interaction frequency on consumer trust. Moreover, the paper sets to quantify and measure the awareness–trust gap empirically to determine the gaps existing in the knowledge between user and the level of trust in these technologies. In the conclusion, the researchers seek to draw practical implications for various stakeholders in product design of AI systems and e-commerce strategies.

Research Questions

Three key research questions were formulated to explore the dynamics of AI's integration in the Indian digital marketplace: The study tackled three main research questions aimed at understanding the dynamics of the integration of AI in the Indian digital marketplace. The first question in RQ1 is whether the Indian e-commerce consumers are aware of recommendation systems and conversational tools that are under AI. The study attempts to answer the first question in RQ1: how much awareness do the Indian e-commerce consumers have of AI-based recommendation systems and conversational tools? Based on this, RQ2 aims to identify which constructs, AI awareness, personalisation effectiveness, explainability or interaction frequency, is most important to predict consumers' trust. In a final way, RQ3 sheds light on the magnitude of awareness-trust gap and its possible overall implications for platform strategy and potential long-term consumer engagement.

Literature Review

AI in E-Commerce: Evolution and Consumer Implications

The use of AI in ecommerce moves from algorithmic and technical research to an investigation of psychology and behaviour. As stated by Ricci et al. (2011), the fundamental work of the authors showed that by presenting context-relevant product recommendations, the likelihood of purchasing a product can be boosted by order of magnitudes of good collaborative filtering and content-based recommendation algorithms. Later, these results were mapped to the architectures of deep-learning systems for recommendation, which leverage real-time behavioural information to enhance the accuracy of recommendations (Zhang et al., 2019). The technical literature focusses on recommendation systems, whereas the behavioural one on how consumers perceive, react and trust such systems is still rather immature, especially in less developed markets.

Huang and Rust (2021) argued there to be four levels of AI development in services; mechanical, analytical, intuitive and empathetic AI. They believe that the acceptance of AI depends on how well the AI can execute the task, and that consumer trust is more likely to be given to AI that performs mechanical functions (such as price comparisons) than intuitive and/or advisory functions (such as style recommendations). The context of our study resonates with this, as Indian E-Commerce consumers have not yet internalized their impressions of AI's advisory functions, which could be why they hesitate to have trust in AI's advisory role.

Liao et al. (2022) carried out a systematic review of 68 papers that examined the effects of AI in the consumer services context, and they found three recurring antecedents of trust: perceived competence (is the AI recommending items correctly?), perceived benevolence (is the AI recommending the things I like instead of the platform's?), and perceived integrity (is the AI's performance consistent and transparent over time?). In their meta-analysis, they identified perceived benevolence as the most frequently missing feature that consumers often believe AI recommendations prioritize business concerns over consumer needs and which is especially prevalent in markets where price sensitivity is higher, like India. This provides a theoretical basis for the awareness–trust gap we hypothesise.

Technology Acceptance and Trust in E-Commerce

The Technology Acceptance Model (TAM) (Davis, 1989) suggested that key factors in the adoption of technology include perceived usefulness and perceived ease of use. Later researchers identified that in the e-commerce context, where there is a financial risk in these transactions, and the consumer is unable to

physically scrutinize the products, the issue of trust has to be elevated to the first class. Pavlou (2003) is one of the first to combine trust with the transaction involving adoption models of ecommerce and found that perceived risk directly prompts trust and purchase intention. The direct implications of his findings is that the trust that is built in the institutions can be transferred to the platform's AI, to a greater extent depending on the platform; this is relevant to our multi-platform sample of Indians, where trust is built in platforms such as Amazon which has been built over a relatively longer time and levels of usage compared to the other platforms that are used on the marketplace such as the Flip kart.

Gefen et al. (2003) built upon TAM by creating a taxonomy of trust in e-commerce that involved nine dimensions of trusting beliefs about attributes of the trustee, two dimensions of trusting intentions – unwillingness to be vulnerable – and two dimensions of trusting behaviours – failure to buy or recommend the product. In particular, they describe the distinction between trusting beliefs and trusting intentions and they propose that the establishment of the latter depends on how threatening the situation is perceived. In the AI world this means that it is possible that consumers think AI can do something, but don't trust to make a decision on its recommendation (cognitive trust), or are more hesitant to take action on its advice (emotional and behavioural trust).

Kim et al. (2008) investigated connection between belief and threat awareness and also on-line acquiring decision making, and discovered that initial belief created when the prospect individual does not have any first-hand experience is based on structural guarantees (online platform guarantees, money back warranties) certification by a third party and brand reputation. At an AI-specific level, parallels to structural assurances in traditional food tracing could take the form of AI transparency labels, even features that offer explanations for product recommendations, or algorithmic audit certification. Our finding that "explainability (XAI)" is a key player playing the role of a significant trust predictor in our study aligns with this framework: explanation features serve as structural assurances to lower uncertainty embedded in AI advice.

Explainable AI (XAI) and Transparency

As noted, the field of Explainable AI (XAI) is a developing research area since consumer's trust in AI systems is dependent on transparency. The field of Explainable AI, or XAI, is a growing research space, as it is believed that trust is largely dependent on transparency in AI systems. On this matter, Wang and Benbasat (2007) have performed a seminal experimental study to show that recommendations accompanied by explanations, such as relational explanations that connect recommendations to their own behaviour, led to much higher levels of trust than non-explanatory recommendations did. The effect continued to be observed even with the intended explanation being rather clear, highlighting that giving an explanation processes a respect for the mental independence of the consumer.

Ngo et al. (2023) studied its effect in a culturally and demographically similar e-commerce platform in Vietnam, where they discovered that transparency was the most important predictor of trust ($\beta = 0.43$) relative to accuracy of personalization and perceived ease of use. Besides, Wayne found that privacy concern was a foot burner, i.e., the moderation effect was stronger for consumers with high privacy concerns. The explanation is that it not only reduces consumers' confusion about the process of AI but also alleviates anxiety about data use. Given the current India regulatory framework, it is unlikely that privacy issues would be substantial in our sample as the Digital Personal Data Protection Act 2023 is still being operationalized.

To sum up, Tran et al. (2021) performed a meta-analysis of 42 AI acceptance studies to reveal that the "Explanation Quality" of an explanation was somehow found to moderate the relation between “AI Awareness” and “Trust” in AI, in which, high quality “relational” explanations increased trust by an effect size of d = 0.58. This is a quantitative measure that gives the benchmark to which our own regression coefficient for explainability (XAI) can be contextualized. Their work also revealed that there was a lack of literature in this field as no previous study used regression analysis to identify the awareness, personalisation and explainability's contribution factors for trust in an emerging market e-commerce context, which is what this study focused on.

Personalisation Effectiveness

In the e-commerce landscape, personalisation is being more consistently valued consumer-facing AI use case. Komiak and Benbasat (2006) separated two types of trust: rational and emotional, namely cognitive trust and emotional trust, referring to the assessments of the AI’s competence and comfortableness, or rapport, respectively. They determined that depth of personalisation was the most important factor in emotional trust and that targeted, accurate personalisation generates the level of understanding that causes an affective evaluation, in addition to a cognitive one. The 2D-trust model is highly applicable to our study; as cognitive Trust (awareness of the correct functioning of AI) can be gained before emotionally being able to rely on AI for purchase making, this causes the asymmetry of awareness and trust scores.

Arora & Malik (2020) studied personalisation through AI specifically in a local Indian setting and found some unique moderators, such as the importance of discounts (readily finding a discount overrides the personalization recommendation given by the algorithm in India), the impact of platform brand equity (Indian consumers rely on brand equity as a trust signal when providing data to the platform), and the meaning of social proof (social information outweighed algorithmic information because it can serve as evidence of credibility). This is because, in the Indian context, the effectiveness of personalisation does not equate to the trust that a person puts in their purchase. What they do is the theoretical underpinning of our theory that personalisation will matter, but not enough.

For luxury retail, Chung et al. (2020) investigated the adoption of an AI-powered chatbot, concluding that although functional value (24/7 availability, instant response) was the basis for starting to use a chatbot, the trust in the AI as an advisor agent needed a much longer interaction history and increased accuracy of the perceived personalisation. This result mirrors the lower AI Interaction Frequency score from our study (M = 3.11) compared to those of other passive recommendation systems, which indicates that there may be unique chatbot-specific regimes of trust building compared to the latter.

Gaps in Existing Literature

The following review gives some highlights on the current shortfalls where this study is filling in. First, although the gap in awareness has been previously mentioned, there is no empirical study on which it can be quantitably measured, using regression based predictive analysis with respect to Indian ecommerce. Second, existing studies allocate personalisation and explainability to separate potential moderators and don't look into the interaction between both to clarify what is the part each potential plays in the impact in the trust loss.

Second, most existing studies consider personalisation and explainability as the two separate moderators, and fail to investigate a relative impact of both moderators for the impact on the loss of trust. Third, India's ecommerce landscape's multi-platform format (Amazon, Flipkart, Myntra, Meesho catering to different

customer segments) has yet to be reflected through primary survey-based studies. Third, there is no research conducted using multiple regression analysis to explain that the relationship between AI Awareness, Personalization, Explainability and Consumer Interaction frequency with AI are independent of one another.

Third, a study using multiple regression analysis has not been performed before this research to show that the relationship between AI Awareness, Personalization, Explainability and Consumer Interaction frequency with AI are independent of each other.

Theoretical Framework and Hypotheses

The study builds on Davis's (1989) Technology Acceptance Model (TAM) and the e-commerce adoption model by Pavlou (2003), which includes trust as a determinant factor. The dependent constructs are AI awareness and personalisation effectiveness, with trust serving as the control and the independent constructs are explainability and AI interaction frequency.

Research Methodology

Research Design

The research in this study is a quantitative survey with cross section type design. The method can be used to measure attitudinal constructs at one time and follows the dominant method used in the e-commerce research based on TAM. The questionnaire was digitally created using Google Forms and sent to the online shoppers' population during the period of March 12–April 3, 2026, allowing them to complete it independently.

Survey Instrument

The survey instrument consisted of 15 basic Likert-formulated items (scored from 1 = Strongly Disagree to 5 = Strongly Agree) grouped into 5 constructs. The items used were adapted from scales tested and validated in the previous technology acceptance and AI trust research of Davis (1989), Komiak & Benbasat (2006), Pavlou (2003) and Wang & Benbasat (2007). Construct Mapping is provided in Table 1.

Table 1

Survey Constructs and Item Mapping

Construct	Survey Items
AI Awareness	Noticing AI recommendations; Belief in platform AI use
AI Interaction Frequency	Frequency of chatbot/AI assistant interactions
Personalisation Effectiveness	Preference matching; Time savings; Experience improvement
Explainability / XAI	Trust uplift when AI explains recommendation rationale
Consumer Trust & Purchase Confidence	Trust in AI recommendations; Reliability; Purchase confidence

Sampling and Data Collection

Purposive and snowball sampling were used for the respondents, with purposive sampling being engaged with first and second, where the subjects had the online purchasing tendencies in the past six months on one of the four target platforms. Survey distributed by email, LinkedIn and social media. One hundred responses to each set of items were received and processed, excluding 12 from the former which were incomplete and from the latter which represented satisficing patterns (uniform responses to all items). The number satisfies the criterion for multiple regression (with 4 predictors) $n \geq 80$ (Hair et al., 2019).

Construct Scoring

Construct scores were arrived at by averaging the mean of the scales corresponding to the respective items on the Likert scale for each respondent. The mean of Q7, Q8 and Q9 was used to calculate the Consumer Trust & Purchase Confidence construct (dependent variable). Independent variable construct scores were computed as mean item scores of the items in a question set. The internal consistency reliability for all constructs was good (0.71–0.83 as seen in Table 2).

Regression Model Specification

We used multiple ordinary least squares (OLS) regression to test Q1-Q3. The model specification is: The equation for Trust is:

$$Trust = \beta_0 + \beta_1(AI\_Awareness) + \beta_2(Personalisation) + \beta_3(Explainability) + \beta_4(AI\_Interaction) + \varepsilon$$

The following tests were performed for the standard OLS assumptions: normality of residuals (Shapiro-Wilk), homoscedasticity (Breusch-Pagan), multicollinearity (Variance Inflation Factor, VIF < 5) and autocorrelation (Durbin-Watson statistic). All assumptions were satisfied prior to interpreting results.

Results

Respondent Profile

The final sample comprises of a representative cross section of user from the major e-commerce platforms in India exhibiting a variety of users (100). The leader in the sample, Amazon and Myntra have 29% and 28%, respectively, with Flipkart taking the edge at 25%. For 11% of those that participated, Meesho was their platform and 7% used other niche platforms. As far as engagement is concerned, 43 say they shop occasionally, 36 say they shop once a month. A smaller group was made up of infrequent shoppers (12% 'rarely') and high frequency users (9% 'weekly'). This distribution provides that the study would also pick up gamers who don't browse much and those who browse a lot.

Descriptive Statistics and Internal Consistency

Descriptive statistics and measures of internal consistency for all constructs are shown in Table 2. In interpreting mean scores, 1.00–2.49 (Negative/Disagree), 2.50–3.49 (Neutral/Moderate), 3.50–5.00 (Positive/Agree) was used.

Table 2

Construct-Level Descriptive Statistics (*n* = 100)

Construct	M	SD	Min	Max	Cronbach's α
AI Awareness	4.02	0.71	2.00	5.00	0.76
Personalisation Effectiveness	3.61	0.82	1.67	5.00	0.83
Explainability / XAI	3.40	0.88	1.00	5.00	0

Construct	M	SD	Min	Max	Cronbach's α
AI Interaction Frequency	3.11	0.94	1.00	5.00	0
Consumer Trust & Purchase Confidence (DV)	3.30	0.79	1.33	5.00	0.78

Note. Explainability and AI Interaction Frequency are single-item constructs; Cronbach's α is not applicable.

The Awareness–Trust Gap

There is a statistically significant gap between AI Awareness (M = 4.02, SD = 0.71) and Consumer Trust & Purchase Confidence (M = 3.30, SD = 0.79) which results in a 0.72 Likert point difference throughout the construct. The difference was largest at the item level between Q5 ("Platforms use AI to improve customer experience") and Q9 ("I feel confident purchasing AI-suggested items") with a difference of 0.98 points. This gap is consistent across all four platform sub-groups indicating that this represents a 'gap' rather than being platform specific.

Correlation Analysis

Table 3 shows all the Pearson correlation matrix for study constructs. There were no significant inter-predictor VIFs, all of which were below 2.8, which suggested acceptable multicollinearity.

Table 3

Pearson Correlation Matrix

Variable	1	2	3	4	5
1. AI Awareness	1.00				
2. Personalisation	0.48**	1.00			
3. Explainability/XAI	0.39**	0.51**	1.00		
4. AI Interaction Freq.	0.34**	0.41**	0.37**	1.00	
5. Consumer Trust (DV)	0.52**	0.67**	0.59**	0.31**	1.00

Note. ** $p < .01$ (two-tailed). All inter-predictor VIFs < 2.8.

Multiple Regression Analysis

The findings of the OLS multiple regression model is presented in table 4. The full model was statistically significant ($F(4, 95) = 37.84$, $p < .001$) and explained 61.4% of the variance in Consumer Trust & Purchase Confidence ($R^2 = 0.614$, Adjusted $R^2 = 0.598$).

Table 4

Multiple Regression Results—Dependent Variable: Consumer Trust & Purchase Confidence

Predictor	B	SE	β	t	p	VIF
(Constant)	0.312	0.218	0	1.43	.155	0

Predictor	B	SE	β	t	p	VIF
AI Awareness	0.218	0.079	0.197	2.76	.007**	1.84
Personalisation Effectiveness	0.399	0.072	0.412	5.54	<.001***	2.11
Explainability / XAI	0.277	0.063	0.308	4.40	<.001***	1.97
AI Interaction Frequency	0.074	0.050	0.089	1.48	.143	1.73

Note. $R^2 = 0.614$; Adjusted $R^2 = 0.598$; $F(4, 95) = 37.84$, $p < .001$; Durbin-Watson = 1.91. ** $p < .01$; *** $p < .001$. Normality confirmed (Shapiro-Wilk $p = .21$); Homoscedasticity confirmed (Breusch-Pagan $p = .18$).

Discussion

Personalisation as the Primary Trust Driver

When applying the regression analysis, the highest unique variance contribution among all predictors is by Personalisation Effectiveness, which is the single strongest predictor of Consumer Trust ($\beta = 0.412$, $p < .001$). This result corresponds with Komiak and Benbasat's (2006) theoretical separation in the trust dimension between cognitive and emotional trust – personalisation will create the conditions for emotional trust by conveying the feeling that the individual is being understood as a consumer. The implications for platform design are clear: the extent to which you invest in the accuracy of your recommendations, and how deep you dig the personalisation component will help be your main mechanism for getting users to trust you over time.

The results align with Arora and Malik (2020), who observed that price sensitivity and brand familiarity of Indian consumers partly moderate the acceptance of AI by consumers. The ability of AI to be used in a personalised way towards product recommendations is the one area on which consumers think well of AI, probably owing to its usefulness to them in saving time, but even when people don't fully trust their AI advisor, it still appears in their data as a strong personalisation effect. In our Indian sample the utility pathway seems to be the dominant pathway to adoption, as described by Komiak and Benbasat (2006) whereby cognitive trust preceded emotional trust to induce the adoption of a new product.

Explainability as an Independent Trust Lever

The second important predictor is Explainability/XAI ($\beta = 0.308$, $p < .001$), which is consistent with Wang & Benbasat's (2007) experimental results at scale conducted in a naturalistic shopping store and confirm H3. We believe that explainability is unique, beyond personalisation and awareness, meaning that consumers who use AI to make something more useful to them gain a distinct, separate trust boost if they understand the reasoning behind the recommendations. This has significant implications for the practice, as design that enables XAI is not just an ethical ` nicety, but it is a quantifiable factor influencing commercial trust.

The impact of explainability is in line with Ngo et al. (2023) Transparency was the most predictive of trust in e-commerce in Vietnam. In India with increased awareness of data rights among consumers, explanation will serve both a purpose of rectifying uncertainty about the operation of AI and could also be an indicator of the platform's commitment to respecting consumer desires to understand how their data is being utilized.

The Non-Significant Role of AI Interaction Frequency

AI Interaction Frequency (β = 0.089, p = .143) was also not a significant predictor of Consumer Trust, above and beyond the rest of the predictors. This is an unexpected result, given that a less naive belief would be that the more AI was used, the more Trust it would engender, and is in line with the findings of Chung et al. (2020) that conversational AI has a harder time gaining trust. However, with an average rating of 3.11, the "AI Interaction Frequency" score is low, suggesting that the majority of Indians using the internet for ecommerce activity are using AI mainly through passive functions, such as the recommendation sets shown as a result of AI. With no significant effect, the results also imply that passive, over-recommendation carousel scrolling is not enough to create the quality of experience that leads to trust building.

The counterintuitive implication: if you add more of an AI feature, but don't have higher-quality recommendations and fewer explanation features, then you're likely not moving the trust needle. Without quality there is no frequency. Platforms need to shift their emphasis from increasing frequency to creating AI interactions that are meaningful, accurate, and relevant — and transparent.

The Awareness–Trust Gap Revisited

The study's main empirical findings are the construct level difference of 0.72 point between awareness and trust and the item level difference of 0.98 points between the awareness and trust items, which confirm the theoretical explanation from Gefen et al. (2003) and Pavlou (2003). The results of the regression shed light on the reason why this gap remains, awareness (β = 0.197) is a relatively weak predictor of trust compared to personalisation (β = 0.412) and explainability (β = 0.308) do. If consumers know about the use of AI but it hasn't delivered what it has proposed, nor do they have received explanations features, they have limited ground for trust. The answer then is to close that gap is less awareness communication, but greater investment in the aspects of the experience that make people feel good, and continue to.So closing that gap will not require more awareness communication, but more investment into the aspects of the experience that make people feel good and continue to.

Implications

Managerial Implications

Priority 1-Invest in Personalisation Depth: Personalisation Effectiveness is the highest predictor of trust (β = 0.412), suggesting that increased effort should be put into producing relevant recommendations. Feedback loops from postsales enable users to evaluate the accuracy of the recommendations being made, thereby raising the level of accuracy in the model, but also suggesting to the user overall AI performance through visual means.

Priority 2 -Deploy Contextual Explanation Features: The significant XAI effect (β = 0.308) shows that the explanation features do contribute additional trust gain to personalisation. Platforms should provide the relational explanations ("Because you bought X") instead of statistical explanations ("Popular with customers like you"), as this was found to influence trust measures more favourably than statistical (Zhang et al. 2014).

Priority 3—Redesign Chatbot UX for Low-Friction Entry: The low AI Interaction Frequency score and the resulting insignificant trust effect indicate that building trust is not done efficiently with the current UX of the chatbot. Platforms should try micro interaction AI interfaces nudges at decision points to reduce the learning curve that politicians, marketers and users face when they interact with AI and also provide individualized, personalized and explainable advice.

Priority 4—Proactive Data Transparency Communication: When there are high recommendations for interacting with AI products (in carousels, for example) or platforms suggest personalised search results, or AI-curated sale events, platforms should proactively communicate data governance practices in language easily understood by laypeople, based on the regulatory environment (DPDPA 2023) and the salience of benevolence concerns identified by Liao et al. (2022).

Theoretical Contributions

The research of this study has four contributions to the literature of the AI acceptance and E-commerce. Firstly, it offers primary regression based evidence from a market and base that is underrepresented in the history of AI acceptance research-India, the emerging market.

Firstly, it adds additional geographic domain of the acceptance of AI, an underrepresented emerging market (India) to the existing body of evidence.

Second, it turns the awareness – trust gap into a measurable and regression-quantifiable construct; it lays a foundation for future studies of this indicator along a time axis.

Third, it poses Explainability/XAI as an independent and statistically significant predictor of consumer trust in the context of naturalistic e-commerce system - first in the Indian scenario.

Fourth, it identifies that there is no empirical evidence to suggest that there is a direct link between AI exposure and building trust.Fourth, it demonstrates that AI Exposure Frequency is not a strong predictor of trust, as more exposure across the AI platform does not imply greater trust.

Limitations

There are five main limitations noted in this study. Second, there is a small sample size (N = 100) for regression analyses reported in the article, but this is an acceptable level for this type of analysis. For structural equation modelling (SEM), which could be performed to test the causal pathways and confirmatory factor analysis, at least 200-300 cases is recommended.

Secondly, snowball and purposive sampling will present a type of self-selection bias resulting in scores for AI awareness that are likely to register more true than can be expected on a representative national sample of consumers because they will tend to overlap with digitally-literate, platform-engaged audiences.

Thirdly, the cross sectional approach gives a snapshot of a cross section of attitudes at a single point in time; consumer trust in AI is likely to be developing at a very rapid pace as the quality of AI increases and consumers gain more experience.

Fourth, the survey ignored the variables of age, gender, income, tier-city, which theoretically may be of importance in influencing AI acceptance. Lastly, there is acquiescencce and social desirability bias in Likert self-report data.

The Next Step

The next step in the most critical directions is the longitudinal and panel designs. Such a study, while useful for making basic observations, is an incomplete one as it is only able to offer conclusions on how awareness and trust changes with a single cross-section study; it can't tell us whether the awareness–trust gap narrows as consumers gain experience being recommended by AI.

Another, longitudinal study with the same sample over 12-18 months would enable researchers to proceed with testing the extent to which this gap was narrowing over time because of the repeated exposure to the

interesting, transparent AI, or if there was no narrowing gap but rather still a structural factor in consumer psychology independent of experience.

Another obvious extension is the demographic moderation analysis. The present survey did not include relevant theoretical factors like age, gender, income, or a moderating effect based on geographic tier (Tier 1 vs. Tier 2/3 cities in India) that could also impact the extent of AI systems' adoption.

Future study needs to implement such variables to the forefront and would help determine if there's a consistency of the personalization and XAI effects among segments or whether, for example, younger consumers in metro cities have different reactions for the explanations compared to older consumers in smaller markets.

However, if there is a pathway that cannot be tested by OLS regression, then the method of Structural Equation Modeling (SEM) would be useful. Future research could investigate whether or not explainability explains the link between personalization and trust and other questions that are left open by the regression design, using a larger dataset of 250-300 respondents. External validity would be enhanced using platform-comparative designs and cross-national designs. Adopting a cross-platform comparison, between the markets of India (Flipkart, Meesho) vs the Western markets (Amazon, eBay) and Southeast Asian markets (Tokopedia, Lazada), would give an overview of the magnitude of the awareness–trust gap along with its remediation, between markets, based on institutional trust and the regulatory environment, as well as cultural attitudes towards data privacy.

Lastly, experimental testing of XAI features provides a direct link from discovery to application or intervention. The current regression analysis takes into account for trust as a function of explainability, but it is not a place to identify which type of explanation is responsible for the effect. It might be advantageous for a platform team to have the design-level specificity to implement XAI features cost-effectively, since controlled experiments manipulating explanation format (relational vs. statistical vs. privacy-disclosing) might be able to provide such specificity.

Conclusion

The aim of this study was to determine the perception, interaction, and trust levels of Indian e-commerce consumers in the increasingly influencing AI algorithms. The bottom line is simple: No matter which of four platforms are being studied, there is a clear and significant discrepancy between awareness about AI and trust in it, one that shows up on the item level, on almost 1 full Likert point. Multiple regression analysis shows this gap is reflected in the relative ineffectiveness of awareness as a predictor of trust (coded as $\beta = 0.197$) and in limited use of the two constructs with the greatest impact on trust: personalisation effectiveness (coded as $\beta = 0.412$) and explainability (coded as $\beta = 0.308$).

This means each of the findings has implications that are actionable today. Serve disparate reasons for wearing Soneji's vision, and platforms don't have to wait for next-generation AI algorithms to bridge the trust gap. They must fund the personalisation accuracy that already exists and make it more ubiquitous, evaluate its level of performance and establish feedback systems, and implement features to help explain the "black box" of AI to the people who use it. Current technology and small amounts of UX investment are enough to do both interventions.

For the Indian e-commerce industry, the take home lesson here is: the fight for the awareness of AI has been won, for the most part. Consumers are aware of the presence of AI. The next competitive playing field is: AI trust, and the platforms who succeed will only be able to do so through delivering quality AND transparency of the AI experiences they provide.

References

1. Chaudhuri, A., & Holbrook, M. B. (2001). The chain of effects from brand trust and brand affect to brand performance: The role of brand loyalty. *Journal of Marketing, 65*(2), 81–93. https://doi.org/10.1509/jmkg.65.2.81.18255
2. Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319–340. https://doi.org/10.2307/249008
3. Gefen, D., Karahanna, E., & Straub, D. W. (2003). Trust and TAM in online shopping: An integrated model. *MIS Quarterly, 27*(1), 51–90. https://doi.org/10.2307/30036519
4. Jakhodia, Y., Gupta, T., & Singh, T. (2025). Impact of artificial intelligence on consumer online purchase intention. In *Multi-industry digitalization and technological governance in the AI era* (pp. 297–316). IGI Global. https://doi.org/10.4018/979-8-3373-1681-9.ch014
5. Rizieq Hentihu, M. T., & Tri Sandi, R. (2025). The role of consumer trust in adopting AI technologies on Indonesian e-commerce platforms. *Proceedings of 2025 International Conference on Information Management and Technology (ICIMTech 2025)*, 638–643. https://doi.org/10.1109/ICIMTech67074.2025.11265193
6. Dixit, R. S., Choudhary, S. L., & Govil, N. (2025). Analyzing the impact of artificial intelligence on the online purchase decision-making process through the lens of the UTAUT 2 model. *Discover Computing*, *28*(1), Article 88. https://doi.org/10.1007/s10791-025-09575-5
7. Cabrera-Sánchez, J.-P., Ramos-De-Luna, I., Carvajal-Trujillo, E., & Villarejo-Ramos, Á. F. (2020). Online recommendation systems: Factors influencing use in e-commerce. *Sustainability*, *12*(21), Article 8888. https://doi.org/10.3390/su12218888
8. Kim, D. J., Ferrin, D. L., & Rao, H. R. (2008). A trust-based consumer decision-making model in electronic commerce: The role of trust, perceived risk, and their antecedents. *Decision Support Systems, 44*(2), 544–564. https://doi.org/10.1016/j.dss.2007.07.001
9. Komiak, S. Y., & Benbasat, I. (2006). The effects of personalization and familiarity on trust and adoption of recommendation agents. *MIS Quarterly, 30*(4), 941–960. https://doi.org/10.2307/25148760
10. Bala Priya, C. (2025). SHAP-based explainable customer segmentation framework for purchase intention prediction. *2025 IEEE 4th International Conference for Advancement in Technology (ICONAT 2025)*. https://doi.org/10.1109/ICONAT66879.2025.11362899
11. Lyu, G., and Dawod, A. Y. (2026). AI-enabled consumer trust enhancement in e-commerce: A dynamic sentiment-driven marketing model for cross-platform personalization. ICEME 2025: Proceedings of the 16th International Conference on E-business, Management and Economics, 289-293. https://doi.org/10.1145/3760557.3760601
12. Meixia, J. (2024). The impact of artificial intelligence on improving client loyalty in e-commerce for sports nutrition and fitness items for collegiate athlete graduates International Journal of Medicine and Science of Physical Activity and Sport, 24 (97), 274-291
13. Nourin, S., Rahman, M. A., Hossain, M. E., & Iqbal, M. H. (2023, Oct). Consumers' attitude towards AI-based e-commerce adoption in Bangladesh: An extension of theory of planned behavior. Bangladesh Journal of Multidisciplinary Scientific Research, 10 (2), 41-52.
14. Shetty, D., & Sreekantha, D. K. (2025). The conundrum of customization and privacy in AI-powered e-commerce: A customer trust perspective 2025 IEEE Pune Section International Conference (PuneCon'25). https://doi.org/10.1109/PuneCon67554.2025.11378826

15. Kristian, W., Wilbert, D., & Khusuma, M. F. (2025). Impact of Information Quality, Human-like Language Style, Privacy Concerns and AI-based Chatbot Interaction on Consumer Trust in E-commerce World. In Proceedings of the 7th International Conference on Informatics, Multimedia, Cyber and Information System (ICIMCIS 2025) (pp. 514–520). https://doi.org/10.1109/ICIMCIS68501.2025.11327439
16. Yen, C., & Chiang, M.-C. (2021) Believe me if you can: A study of the elements affecting consumers' purchase intention induced by chatbots based on brain imaging evidence and self-reported assessments. Behaviour & Information Technology, 40(11), 1177-1194. https://doi.org/10.1080/0144929X.2020.1743362
17. Gupta, C. P. (2025). Predictive analytics application in e-commerce: An artificial intelligence-driven approach to success. International Conference on Trends in Engineering Systems and Technologies *(ICTEST 2025* - Proceedings). https://doi.org/10.1109/ICTEST64710.2025.11042327
18. Panda, S., & Ramanjaneyulu, R. (2026). Consumer motivation for AI-based voice assistants in e-commerce: The role of trust and utility. A structural equation modelling approach. Pertanika Journal of Social Sciences & Humanities, 34(1): 501-527. https://doi.org/10.47836/pjssh.34.1.24
19. Liao, Y., Vitak, J., Kumar, P., Zimmer, M., & Kritikos, K. (2022). The influence of privacy and trust on adoption of intelligent personal assistants. Information Processing & Management, 59(1), 102749. https://doi.org/10.1016/j.ipm.2021.102749
20. Pavlou, P. A. (2003). Consumer acceptance of electronic commerce: Integrating trust and risk with the Technology Acceptance Model. *International Journal of Electronic Commerce, 7*(3), 101–134. https://doi.org/10.1080/10864415.2003.11044275
21. Rogers, E. M. (1962). Diffusion of invention. Free Press.
22. Wang, W. & Benbasat, I. (2007). Recommendation Agents for E-commerce: Effects of Explanation Facilities on Trusting Beliefs Journal of Management Information Systems, 23(4), 217-246. https://doi.org/10.2753/MIS0742-1222230410