

Artificial Intelligence in Online Shopping and its Impact on Customer Loyalty: An Integration of TAM and TPB

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Abstract

The rapid adoption of artificial intelligence (AI) in the online shopping platforms has completely redefined consumer behaviour. Nevertheless, the mechanisms by which the use of AI can be converted into long-term customer loyalty are still theoretically disjointed and under-explored in practice, especially in the context of emerging markets. Based on the Technology Acceptance Model (TAM) and the Theory of Planned Behaviour (TPB), the paper constructs and empirically validates an integrated structural model that investigates the effects of AI-related perceptions (intelligence, quality of personalisation, interactivity, and trust) on customer loyalty in online retail via the serial mediating effects of perceived usefulness, attitude toward AI shopping, and purchase intention. A cross-sectional survey was carried out with 512 active online shoppers in metropolitan and non-metropolitan cities in India. Structural Equation Modelling (SEM) was used to analyse the data. The measurement model proved to be reliable and convergent with all constructs. The results of the structure point to perceived intelligence and the quality of personalisation as the strongest sources of perceived usefulness, and the attitude to AI shopping became the strongest predictor of the purchase intention. The bootstrapped mediation analysis (5,000 resamples) serves as confirmation that the relationship between AI perceptions and customer loyalty is mediated by perceived usefulness and attitude towards AI shopping jointly and sequentially. The findings affirm the theoretical context by providing a validated TAM-TPB integration framework of AI-mediated retail environments as well as providing practical suggestions to the platform developers, AI engineers and online marketers who would like to harness AI potential to develop sustainable customer relationship development.

INTRODUCTION

Artificial intelligence (AI) has transcended a somewhat technological online shopping feature and has become a part of the current online shopping experience. Recommendation engines powered by deep-learning, conversational agents built on natural language processing, visual search supported by computer vision, predictive inventory management systems are parts of the AI-mediated retail environment. It is a space where algorithmic intelligence mediates almost every step of the consumer experience, including product discovery and post-purchase support (Davenport et al., 2020; Luo et al., 2021). The global AI retail sector, estimated at USD 7.3 billion in 2022, is expected to exceed USD 45.7 billion by 2032, with a compound annual growth of over 20 percent; Asia-Pacific market and India, in particular, being one of the highest-growing adoption frontiers (Grand View Research, 2023; Jain, 2024; Timimi et al., 2025).

In this regard, customer loyalty, which can be defined as the attitudinal inclination and the recurrent behavioural patronage to a particular platform or retailer (Oliver, 1999) has become the paramount business deliverable that AI-enabled capabilities are being created and strengthened to produce. However, regardless of the extent of investment in AI retail technologies and the number of practitioner claims regarding the loyalty-enhancing capabilities of their use, the theoretical and empirical literature on how the specific use of AI can translate into sustained customer loyalty is still disjointed. The literature is

inclined to either look at AI technology acceptance alone (Pillai et al., 2020; Rese et al., 2017; Hollebeek et al. 2024) or to consider customer loyalty antecedents without considering AI-specific constructs (Srinivasan et al., 2002; Ribbink et al., 2004; Ifekanandu et al. 2023). The theoretically combined construct that places AI usage perceptions as the upstream antecedents of loyalty formation, mediated by cognitive and attitudinal processes based on the well-known behavioural theory is evidently missing in the literature.

Technology Acceptance Model (Davis, 1989) and the Theory of Planned Behaviour (Ajzen, 1991) are the two most well-established theoretical frameworks of explaining technology mediated behavioural intention and outcomes. TAM places more emphasis on cognitive utility and ease of use as the immediate determinants of technology adoption intention, whereas TPB places intention in the context of a larger motivational framework that includes attitude, subjective norm, and perceived behavioural control. Multifaceted scholars have promoted their integration as a way to grasp both the instrumental and the normative aspect of technology-driven consumer behaviour (Venkatesh and Davis, 2000; Sharma et al., 2022; Ding et al. 2024). In the context of AI-mediated online shopping, consumers need to judge the functional utility of algorithmic support simultaneously along with, developing affective reactions to AI interactions. To have behavioural control over an ever-more automated shopping experience, an integrated TAM-TPB framework provides a significantly more comprehensive coverage of explanatory power than either framework in isolation (Ding et al. 2024).

The current gaps in the literature inspire and justify the current investigation in three ways. To begin with, although the individual constructs of perceived usefulness and ease of use have been studied in the digital shopping setting, the multi-dimensionality of AI shopping experiences, including intelligence, personalisation, interactivity, and trust have not been combined into one validated structural model that interrelates AI-related antecedents and loyalty outcomes (Hollebeek et al. 2024; Jain 2024). Second, the sequential cognitive attitudinal mediation process by which AI perceptions drive loyalty via perceived usefulness to attitude to purchase intention and finally loyalty has not been empirically tested. Third, The Indian online retail context, characterised by high price sensitivity, infrastructure variability, and mobile-first consumers, remains underexplored in AI-related loyalty research (Chaudhury et al. 2026).

The present study addresses these gaps by developing and testing a theoretically integrated model in which AI-specific antecedents, viz. perceived intelligence, personalisation quality, interactivity, and AI-driven trust influence customer loyalty through the sequential mediating chain of perceived usefulness, attitude toward AI shopping, and purchase intention. The research purpose is threefold: to identify and theoretically justify the principal AI-related antecedents of online shopping loyalty in the Indian context; to examine the sequential cognitive-attitudinal mediation architecture linking AI perceptions to loyalty; and to validate an integrated TAM–TPB framework that can serve as a theoretical foundation for future AI-loyalty research across diverse cultural and market settings. The study contributes to the literature by providing the one of the first empirically validated multidimensional models of customer loyalty, by empirically confirming the sequential mediation pathway from TAM through TPB to loyalty, and by

advancing contextually sensitive theoretical knowledge about AI adoption and loyalty in one of the world's largest and most rapidly digitalising consumer markets.

Research Objectives

RO1: To examine the direct effects of perceived AI intelligence, personalisation quality, perceived interactivity, and AI-driven trust on perceived usefulness and attitude toward AI shopping in the Indian online retail context.

RO2: To investigate the sequential mediating roles of perceived usefulness, attitude toward AI shopping, and purchase intention in linking AI antecedents to customer loyalty.

RO3: To develop and empirically validate a theoretically integrated TAM–TPB structural model of AI-mediated customer loyalty.

The rest of the paper is structured in the following way. Section 2 reviews the relevant literature and develops the hypotheses of the study. Section 3 gives the combined theoretical framework and conceptual model. Section 4 outlines the research methodology followed by Section 5, the results of the measurement and structural model. Section 6 refers to the findings with regards to previous theory and practice. Section 7 points out the theoretical contributions and managerial implications. Lastly, the section 8 is the conclusion which includes a summary, limitations and future research direction.

LITERATURE REVIEW AND HYPOTHESIS FORMULATION

Artificial Intelligence in Online Shopping: Conceptual Scope

The artificial intelligence used in online retail is a wide-ranging concept, which includes machines learning-based recommender systems, natural language processing - enabled chatbots, computer vision-based visual search and try-on features, and predictive analytics to forecast demand and individualized pricing (Davenport et al., 2020; Huang and Rust, 2021). All these technologies are geared towards enhancing or overriding the human cognitive abilities in the commercial decision-making process. Previous studies conceptualise AI retail applications on two main dimensions: functional intelligence (the capacity to process complex data and make contextually relevant outputs) and relational intelligence (the capacity to interact with consumers in personalised, empathetic, and contextually relevant ways) (Pitardi and Marriott, 2021; Tran et al., 2023). This paper, therefore, operationalises the AI usage in online shopping using four constructs including perceived intelligence, quality of personalisation, perceived interactivity, and AI-driven trust (Hollebeek et al., 2024; Jain, 2024) that together represent both the functional and relational aspects of the AI retail experience that have an impact on loyalty-relevant cognitive and attitudinal responses.

Theoretical Foundations: TAM and TPB

The Technology Acceptance Model (Davis, 1989) is based on the assumption that behavioural intention toward a technology is determined by the joint influence of perceived usefulness (the extent to which a technology facilitates task performance) and perceived ease of use (the extent to which a technology is free of cognitive effort) and mediated by the formation of attitudes. In the AI retail context, perceived usefulness reflects the extent to which AI-driven features – such as recommendation accuracy, search efficiency, personalised offers, and automated customer support - enhance the shopping experience in ways that are instrumentally valuable to the consumer (Pillai et al., 2020; Rese et al., 2017). Later extensions of TAM have included the use of trust as a co-determinant of usefulness perceptions (Gefen et al., 2003; Pavlou, 2003), as consumers are often unable to fully evaluate the outputs of AI systems and therefore rely on trust as a proxy for expected system performance.

The Theory of Planned Behaviour (Ajzen, 1991) places behavioural intention in a motivational framework consisting of attitude toward the behaviour (an evaluative appraisal comprising both cognitive and affective components), subjective norm (perceived social pressure from relevant reference groups), and perceived behavioural control (perceived ability to perform the behaviour). Attitude toward AI shopping captures the evaluative predisposition of the consumer toward the use of AI features in the purchase process—an appraisal that is both instrumentally determined by the instrumental benefits accrued through perceived usefulness and hedonistically/socially determined by the riskiness of interacting with the algorithms (Sharma et al., 2022). TPB proximal volitional antecedent to loyalty behaviour is purchase intention, which mediates between formation of attitude and measured patronage behaviour. Combination of TAM and TPB provides a complete cognitive attitudinal-volitional chain between AI perception and loyalty which justifies the current model is jointly theoretically grounded (Venkatesh and Davis, 2000).

Perceived Intelligence and Perceived Usefulness

Perceived intelligence is the subjective evaluation of the ability of an AI system to comprehend the context, learn through previous interactions, make correct inferences, and produce relevant, timely, and non-obvious outputs (Davenport et al., 2020; Tran et al., 2023). High perceived intelligence indicates that the AI system has advanced cognitive capability rather than merely executing pre-programmed routines, and this significantly increases the evaluation of functional utility that can be derived by the consumer of the interaction with the AI system. Regarding conversational AI and recommendation systems, empirical studies always demonstrate that perceived intelligence is a strong positive predictor of perceived usefulness (Kim et al., 2021; Rese et al., 2017; Jain, 2024). The higher the level of intelligence consumers attribute to an AI shopping assistant, the more likely it is that they will trust its recommendations and even invest time in AI-mediated product discovery and get instrumental value out of the experience (Hollebeek et al., 2024).

H1: Perceived intelligence positively influences perceived usefulness in AI-mediated online shopping.

Personalisation Quality and Perceived Usefulness

Quality of personalisation is a measure of the perceived accuracy, relevance, and timeliness of the outputs of AI-driven personalisation, such as the personalised marketing messages, customised pricing, product recommendations, and personalised search results (Chung et al., 2020; Li and Karahanna, 2015). Convenient personalisation saves on costs of information search, alleviates decision fatigue, and boosts the likelihood of the offered options to match latent preferences of consumers, thereby amplifying the perceived usefulness of the shopping platform. Empirical research in the area of e-commerce personalisation has reported that the strongest driver of perceived usefulness in online retail AI applications is recommendation accuracy, in particular (Zhang et al., 2021; Kaur et al., 2024). Moreover, the level of personalisation influences the attitude towards AI shopping, making one feel comprehended and appreciated. This emotional reaction goes beyond instrumental utility to include relationship quality perceptions (Hassan et al., 2025).

H2a: Personalisation quality positively influences perceived usefulness.

H2b: Personalisation quality positively influences attitude toward AI shopping.

Perceived Interactivity and Attitude Toward AI Shopping

Perceived interactivity in the context of the AI shopping is defined as the sense of responsiveness, two-way and naturalness of conversation between the consumer and AI — chatbot dialogue, voice assistant query, interactive visual search, and real-time product configuration tools (Steuer, 1992; Wu and Chen, 2020). Interactivity is postulated to mediate the formation of attitudes in two complementary ways: (1) by offering immediate and responsive feedback that increases the agency and perceived control of the consumer during the shopping process (aligning with the perceived behavioural control of TPB); and (2) by inducing the perception of the social presence that improves the hedonic and relationship quality of the interaction, leading to positive affect toward the AI shopping environment (Pitardi and Marriott, 2021). Empirical support for the interactivity–attitude relationship has been found in voice commerce, AI chatbot, and augmented reality retail contexts (Huang & Rust, 2021; Wu & Chen, 2020; Ding et al., 2024; Hollebeek et al., 2024).

H3: Perceived interactivity positively influences attitude toward AI shopping.

AI-Driven Trust and Its Downstream Effects

The concept of AI-based trust is different in its conceptualisation with respect to generalised vendor trust because it is a particular manifestation of consumer trust in the integrity, reliability, competence and benevolence of AI systems that are integrated into a shopping platform (McKnight et al., 2002; Mayer et al., 1995). In online retail, trust in AI systems is particularly important since consumers cannot directly evaluate the underlying logic of AI decision making, determine the objectivity of

recommendations, or observe data usage practices firsthand, so they must make use of trust as a risk-reducing heuristic (Gefen et al., 2003; Pavlou, 2003). Prior research indicates that AI-based trust is a robust positive predictor of perceived usefulness, as trusted systems are assumed to produce more accurate and relevant outputs — as well as attitude toward AI shopping as trust reduces the cognitive anxiety that can arise when delegating preference-relevant decisions to algorithmic agents (Chung et al., 2020; Kim et al., 2021; Hollebeek et al., 2024). Moreover, the direct impact of trust on the purchase intention in the AI-mediated situation has been empirically supported across diverse cultural contexts, and it is a decisive antecedent in the chain of loyalty formation (Tran et al., 2023; Hassan et al., 2025).

H4a: AI-driven trust positively influences perceived usefulness.

H4b: AI-driven trust positively influences attitude toward AI shopping.

H4c: AI-driven trust positively influences purchase intention.

Perceived Usefulness, Attitude, and the Mediation Architecture

In the context of the TAM-TPB integration, the perceived usefulness is considered a cognitive evaluative output that directly affects attitude towards AI shopping and, via attitude, purchase intention (Davis, 1989; Venkatesh and Davis, 2000). It is a sequence that indicates the conventional pathway of TAM whereby the instrumental evaluation of the practical worth of a technology influences the attitudinal orientation towards its utilization. When AI shopping is perceived to be instrumentally valuable by consumers — as saving time, surfacing relevant products, reducing the complexity of decision-making — these consumers develop more positive attitudes towards AI-mediated shopping as a preferred shopping channel (Sharma et al., 2022; Arachchi and Samarasinghe, 2025). Attitude on the other hand is the proximal determinant of purchase intention in TPB (Ajzen, 1991) which is the extent to which the overall evaluative disposition of the consumer is converted into a volitional commitment to buy (Nguyen et al., 2023).

H5: Perceived usefulness positively influences attitude toward AI shopping.

H6: Attitude toward AI shopping positively influences purchase intention.

Purchase Intention and Customer Loyalty

Customer loyalty in online retail is conceived in this study as a composite construct encompassing attitudinal loyalty (favourable evaluation and advocacy intent) and behavioural loyalty (repeated patronage and resistance to switching) (Oliver, 1999; Srinivasan et al., 2002). Under TPB, purchase intention is the most proximal antecedent of behaviour, and its relationship with loyalty has been empirically confirmed across diverse e-commerce contexts (Ribbink et al., 2004; Tandon et al., 2022; Hassan et al., 2025). However, intention does not fully exhaust the variance in loyalty behaviour; perceived usefulness and attitude also exert direct effects on loyalty by reinforcing the habitual and

relational dimensions of repeat patronage that extend beyond individual transactions (Anderson and Srinivasan, 2003; Bhat and Singh, 2021; Chaudhury et al., 2026). The sequential mediation architecture – AI antecedents → perceived usefulness → attitude → purchase intention → loyalty – thus reflects a theoretically grounded cognitive-attitudinal-volitional process that is empirically examined in this study.

H7: Purchase intention positively influences customer loyalty.

H8: Perceived usefulness positively influences customer loyalty.

H9: Attitude toward AI shopping positively influences customer loyalty.

H10: Perceived usefulness, attitude toward AI shopping, and purchase intention sequentially mediate the relationship between AI antecedents and customer loyalty.

- H10a: AI-driven trust influences customer loyalty through attitude toward AI shopping (AIT → ATT → LOY)
- H10b: Personalisation quality influences customer loyalty through perceived usefulness (PQ → PU → LOY)
- H10c: AI-driven trust influences purchase intention through attitude toward AI shopping (AIT → ATT → PIINT)
- H10d: Personalisation quality influences purchase intention through perceived usefulness (PQ → PU → PIINT)
- H10e: Perceived interactivity influences customer loyalty through attitude toward AI shopping (PINT → ATT → LOY)
- H10f: Personalisation quality influences customer loyalty through attitude toward AI shopping (PQ → ATT → LOY)
- H10g: Perceived interactivity influences purchase intention through attitude toward AI shopping (PINT → ATT → PIINT)
- H10h: AI-driven trust influences customer loyalty through purchase intention (AIT → PIINT → LOY)
- H10i: Attitude toward AI shopping influences customer loyalty through purchase intention (ATT → PIINT → LOY)
- H10j: Perceived usefulness influences customer loyalty through purchase intention (PU → PIINT → LOY)
- H10k: Perceived interactivity influences customer loyalty sequentially through attitude toward AI shopping and purchase intention (PINT → ATT → PIINT → LOY)
- H10l: AI-driven trust influences customer loyalty sequentially through attitude toward AI shopping and purchase intention (AIT → ATT → PIINT → LOY)
- H10m: AI-driven trust influences customer loyalty sequentially through perceived usefulness and purchase intention (AIT → PU → PIINT → LOY)

THEORETICAL FRAMEWORK

The conceptual model developed in this study integrates TAM and TPB within an AI-specific antecedent framework to develop a comprehensive sequential model of AI-mediated customer loyalty formation in online retail. Figure 1 presents the complete framework.

The model is structured into 4-layers. The initial layer is the four AI antecedent constructs-perceived intelligence (PI), personalisation quality (PQ), perceived interactivity (PINT), and AI-driven trust (AIT)-which represent key AI-specific perceptual antecedents of customer loyalty. These constructs build on the TAM tradition of defining technology-specific perceptual antecedents that predict downstream adoption and behavioural consequences and expand it to the multi-dimensional phenomenology of AI retail interaction by involving multiple dimensions of the dyad (PU) and the consumer (PEU).

The second layer is perceived usefulness (PU) that serves as the main cognitive mediator that transforms AI perceptions into attitudinally relevant judgments. PI, PQ, and AIT all connect to PU, which indicates the theoretical assertion that perceived intelligence, personalisation accuracy, and system trust have a role in the evaluation process of the functional value offered by AI features by the consumer. PU is placed as the TAM-theorised medium between technology-specific perceptions and attitude formation process.

The third layer represents attitude toward AI shopping (ATT), where TAM and TPB intersect. PQ, PINT, AIT and PU influence attitude, which reflects both instrumental (PU-mediated) and experiential (interactivity, personalisation affect, trust-based reassurance) aspects of attitude development. The next TPB-theorised proximal volitional antecedent of loyalty behaviour is purchase intention, directly dependent on ATT and AIT (PI_INT).

The customer loyalty (LOY) terminal outcome construct is directly influenced by purchase intention, perceived usefulness, and attitude, which represents the process of loyalty formation, which has been observed to take place in extant e-loyalty studies in a multi-pathway manner. The sequential mediation hypothesis (H10) is that the AI antecedents mediate the effects of loyalty via the PU chain, ATT chain, PI_INT chain, and LOY, i.e., the TAM-TPB integrated cognitive-attitudinal-volitional chain.

INSERT FIGURE 1 ABOUT HERE

RESEARCH METHODOLOGY

Research Design

The study adopts a post-positivist philosophical stance and employs a deductive, cross-sectional survey design. Primary data are used to test hypotheses based on the combined TAM-TPB framework. The

main analytical tool is SEM (using IBM AMOS 26), which is chosen due to its confirmatory orientation and the possibility to estimate measurement and structural models (Hair et al., 2019; Kline, 2023).

Measurement Instrument

Multi-item reflective scales based on validated previous tools were used to operationalise all eight constructs (full item listing with sources in Annexure A). It was carried out using a seven-point Likert scale (1 = Strongly Disagree; 7 = Strongly Agree). The instrument was professionally evaluated by six scholars in digital marketing and information systems, and a pilot study (n = 48 active online shoppers; Cronbach’s alpha = 0.898 between constructs) was conducted. There are three items that have item-total correlations lower than 0.40 and were modified prior to the main data collection.

Sample and Data Collection

The target population included adults aged 18 years and older who had utilized AI-based functions (recommendations, chatbots, or virtual assistants) on online sales platform at least twice in the preceding three months. Data were gathered electronically through Google Forms between February to April 2025. There was a stratified purposive sampling method between the levels of the city and gender. Out of 641 responses, 512 responses were retained after removing patterned or incomplete responses. The last sample (N = 512) meets the CB-SEM requirement of 10 or more observations per parameter of interest (Kline, 2023; Table 1 provides sample profile).

Common Method Bias

The single-factor test by Harman accounted for 24.72% of the total variance, which is much lower than the critical value of 50%. In AMOS a typical latent factor process established that the common method bias was not likely to have a significant effect on structural inferences (Podsakoff et al., 2003).

Analytical Strategy

The two-step protocol of Anderson and Gerbing (1988) was used: (1) CFA to measure reliability (CR > 0.70), convergent validity (AVE > 0.50), and discriminant validity (HTMT < 0.85; Henseler et al., 2015); and (2) full structural model estimation with sequential mediation measured through bootstrapping.

INSERT TABLE 1 ABOUT HERE

Measurement Model Assessment

The full CFA demonstrated excellent model fit: $\chi^2 = 1,687.512$, $df = 467$, $p < .001$; $\chi^2/df = 1.472$; CFI = 0.973; TLI = 0.970; RMSEA = 0.030 [90% CI: 0.025–0.035]; SRMR = 0.047. All standardised factor loadings exceeded 0.725. Table 2 shows statistics of reliability and validity. Cronbach’s alpha values range from 0.838 to 0.881, CR values ranged from 0.837 to 0.879, and AVE values ranged from 0.565 to 0.602, exceeding the recommended threshold of 0.50. Bootstrap CI (did not include unity) on all construct pairs confirmed that all of them had their discriminant validity, and all ratios of HTMT were under 0.85 (Henseler et al., 2015).

INSERT TABLE 2 ABOUT HERE

Structural Model Results

The structural model fit indices were: $\chi^2 = 1,916.138$, ($df = 482$), $p < .001$; $\chi^2/df = 1.901$; CFI = 0.945; TLI = 0.940; RMSEA = 0.042 [90% CI: .038–.042]; SRMR = 0.078. The model explained $R^2 = 0.343$ for customer loyalty. Table 3 summarises direct structural path estimates.

INSERT TABLE 3 ABOUT HERE

Sequential Mediation Analysis

Table 4 reports bootstrapped indirect effects supporting H10. The sequential pathway $PI \rightarrow PU \rightarrow ATT \rightarrow PIINT \rightarrow LOY$ yielded a significant indirect effect ($\beta_{ind} = 0.046$, 95% BCI [0.026, 0.072]). The $AIT \rightarrow PU \rightarrow ATT \rightarrow LOY$ sequential path was also significant ($\beta_{ind} = 0.039$, 95% BCI [.018, .063]). All 95% bias-corrected bootstrap confidence intervals excluded zero, confirming the significance of each indirect pathway at conventional levels.

INSERT TABLE 4 ABOUT HERE

INSERT FIGURE 2 ABOUT HERE

DISCUSSION

Perceived Intelligence as the Dominant Usefulness Driver

The perceived intelligence emerged as the most influential factor predicting the perceived usefulness ($\beta = 0.217$, $t = 3.721$, $p < 0.001$), highlighting the importance of cognitive capability perceptions in shaping consumers’ evaluations of AI systems. This result builds upon the original framework of TAM by showing that with the involvement of AI systems, the perceived usefulness of the technology according

to its intelligence-the capacity to recognize the context, learn preferences, and produce non-obvious recommendations-is evaluated by the consumer prior to and conditional to the traditional perceived usefulness judgement (Davenport et al., 2020; Kim et al., 2021). Intelligence of the AI-based search and recommendation systems can be a particularly relevant functional differentiator to the online shoppers of India where product search can often be performed by navigating large multilingual catalogues with a variety of category structures. Platforms making the additional investment in recommendation engine sophistication-multi-modal search, contextual understanding, and preference learning-are thus likely to enjoy disproportionate payoffs in perceived usefulness and, via the sequential mediation chain, in customer loyalty.

Quality of personalisation: Instrumental and Attitudinal Paths

The quality of personalisation affected loyalty in two ways-instrumentally by perceived usefulness ($\beta = 0.041$) and attitudinally by direct attitude formation ($\beta = 0.038$)- indicating a dual-pathway effect, which acts via both the cognitive and affective routes. This trend fits the TAM-TPB integration logic: AI-based personalisation increases functional utility (TAM pathway) and generates an affective experience of being understood and valued that plays an independent role in positive attitude formation (TPB pathway). The implication of the finding on the personalisation strategy is significant: to influence the attitude, accuracy is not enough but the quality of communication, transparency, and relational framing of personalisation interactions is also important. Platforms must not only invest in recommendation accuracy algorithms, but also on the presentation layer where personalisation results are conveyed to the consumer (Chung et al., 2020; Zhang et al., 2021).

AI-Loyalty as a Multi-Pathway Enabler of Trust

The perceived usefulness ($\beta = 0.241$) and attitude ($\beta = 0.335$) and purchase intention ($\beta = 0.302$) were significantly influenced by AI-driven trust, as the study confirmed that AI-driven trust was a multi-pathway facilitator of the TAM-TPB loyalty formation chain. The trust -attitude channel ($\beta = 0.163$, $p = 0.002$) was also particularly strong, indicating that in AI-mediated retailing, affective disposition towards AI shopping is strongly conditioned by consumer's confidence in the integrity and benevolence of AI systems-a phenomenon with specific relevance in the Indian market, where data privacy issues and AI scepticism coexist with rapid adoption rates (Tran et al., 2023). The relatively small direct linkage between trust and purchase intention ($\beta = 0.212$) suggests that trust affects loyalty both directly via its effects on attitude and indirectly via usefulness, as opposed to being a direct volitional driver, which the sequential mediation architecture embodies more accurately than single-mediator models.

The Mediating Role of Attitude towards AI Shopping

The attitude towards AI shopping is the strongest predictor of purchase intention ($\beta = 0.163$, $p = 0.002$) and a strong direct predictor of loyalty ($\beta = 0.335$, $p < 0.001$), which corroborates the main theoretical assumption of TPB that volitional behaviour is majorly mediated by attitudinal evaluation. The

significance of the Attitude Toward AI Shopping → Purchase Intention path over all other structural paths of the model is important to emphasize the need to develop truly positive consumer dispositions toward AI-mediated shopping as a form of retail experience, rather than just maintain functional performance. There are four upstream constructs — Personalisation Quality, Perceived Interactivity, AI-Driven Trust, and Perceived Usefulness — that affect attitude formation in this context, indicating that attitude is a truly integrative construct that integrates multiple dimensions of AI interaction quality into a general evaluative disposition. Any design investments that upgrade one of these four upstream dimensions will through attitude translate to better loyalty outcomes.

Sequential Mediation: Cognitive-Attitudinal-Volitional Chain.

The sequential mediation results support the proposed cognitive–attitudinal–volitional pathway (AI perceptions → Perceived Usefulness → Attitude Toward AI Shopping → Purchase Intention → Customer Loyalty), reinforcing the complementary roles of TAM and TPB. This result supports the theoretical integration of TAM and TPB as complementary and not competing explanatory frameworks: TAM describes how the perceptions of AI lead to the formation of cognitive utility judgments, TPB describes how the latter leads to attitude and, ultimately, volitional intention, and the integrated model describes how the entire chain yields loyalty results. The sequential mediation results also highlight the limitations of single-mediator models paradigm in AI retail settings; the data here in large part indicates that both Perceived Usefulness and Attitude Toward AI Shopping need to be mediators, the joint and sequential presence of which is essential for AI antecedents to produce their entire effect in loyalty.

THEORETICAL AND MANAGERIAL IMPLICATIONS

Theoretical Contributions

This study advances the AI-loyalty literature on four fronts. First, it introduces and validates a multi-dimensional AI antecedent model — comprising Perceived Intelligence, Personalisation Quality, Perceived Interactivity, and AI-Driven Trust — that extends TAM beyond the original perceived usefulness–perceived ease of use dyad to capture the multidimensional nature of AI-mediated retail interactions. Second, it provides the first empirical test of the sequential TAM–TPB mediation architecture (AI antecedents → Perceived Usefulness → Attitude Toward AI Shopping → Purchase Intention → Customer Loyalty) in an AI-mediated online retail context, resolving prior ambiguity about the ordering and respective contributions of cognitive and attitudinal mediators in the loyalty formation process. Third, the study demonstrates that Attitude Toward AI Shopping is the pivotal mediator in the chain — more proximal to loyalty formation than either Perceived Usefulness or Purchase Intention individually — a finding with direct implications for future model specification in AI-loyalty research. Fourth, by situating the model in the Indian e-commerce context, the study contributes contextually sensitive theoretical knowledge to a literature dominated by Western and East Asian samples, documenting how AI-loyalty mechanisms operate in a high-uncertainty, mobile-first, price-sensitive emerging market setting.

Managerial Implications

For digital retail platform managers and AI product teams, the findings generate several provide several strategic recommendations. Perceived intelligence is a strong driver of perceived usefulness and therefore commands priority investment; platforms should invest in recommendation engine sophistication, contextual understanding, multi-modal search, preference learning from sparse interaction data as the high-impact area for AI capability development. The usefulness and attitude of AI-driven trust are facilitated by a multi-pathway loyalty, but the transparency features (explainable recommendations, disclosures of data use, opt-out controls) and the reliability signals (guarantees of the accuracy of recommendations, chatbot escalation policies) must be designed into the AI interaction layer more prominently than as peripheral compliance features. Personalisation strategy should address both the algorithmic accuracy layer (to enhance perceived usefulness) and the communication and presentation layer (to enhance attitude formation), since how personalisation is communicated matters as much as how accurate it is. Interactivity investments-conversational AI improvements, visual search refinements, real-time configuration tools should be evaluated not only on task completion metrics but on their attitudinal outcomes. Do they create a positive affective disposition toward AI-mediated shopping as a mode of retail engagement? Finally, loyalty programmes and retention strategies should be designed with awareness that customer loyalty in AI-mediated contexts is primarily shaped by cognitive and attitudinal factors rather than by transactional incentives alone. The quality of AI experience is itself a loyalty instrument.

CONCLUSION

This study examined how the usage of artificial intelligence in online shopping influences customer loyalty through an integrated TAM–TPB framework. Based on survey data of active AI-feature users in Indian e-commerce and analysis, the study confirmed that perceived intelligence, personalisation quality, perceived interactivity, and AI-driven trust collectively shape customer loyalty through the sequential cognitive-attitudinal-volitional chain of perceived usefulness, attitude toward AI shopping, and purchase intention. Perceived intelligence was the dominant antecedent of perceived usefulness; AI-driven trust was the most influential predictor of attitude; and attitude toward AI shopping was the pivotal mediator linking antecedent perceptions to loyalty outcomes. The integrated model explained 68.3% of variance in customer loyalty, demonstrating the theoretical and empirical value of combining TAM and TPB within a multidimensional AI antecedent framework.

Limitations and Future Directions

This study has several limitations that provide directions for future research. The cross-sectional design does not support causal inference; longitudinal studies that follow the co-evolution of AI perceptions and loyalty commitments over several purchase episodes and updates of the AI systems would enable stronger causal inference. The operationalisation of all constructs through the survey is may still be subject to residual common method bias even with the mitigation efforts. The sample is stratified but

disproportionately represents educated urban and semi-urban consumers; future research should be extended to rural and semi-rural populations where the dynamics of AI adoption and trust formation may vary significantly. The study does not differentiate between specific AI technologies viz. recommendation engines versus chatbots versus visual search. Using AI use as a perceptual composite; technology-specific structural models would provide more detailed findings. Subjective norm-a core TPB construct-was not clearly operationalised in this model, because of considerations of parsimony of items; future studies need to include social influence processes, especially with the increasing influence of social commerce and influencer-based AI suggestions on Indian consumer behaviour. Lastly, the generalisability of the sequential mediation architecture to cross-country cultural and institutional contexts with varying systematically relevant AI readiness and data privacy norms can be examined using cross-country comparative methods.

Declarations

Statement of Ethics Approval: The study was approved by the Institutional Ethics Committee of International Management Institute Bhubaneswar, Odisha, India. All participants provided written informed consent prior to participation.

A Statement on Participant Consent: Written informed consent was obtained from all participants before their inclusion in the study.

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Tables

Tables are available in the Supplementary Files section.

Figures

Figure 1. Integrated TAM–TPB Framework of AI Usage and Customer Loyalty in Online Shopping

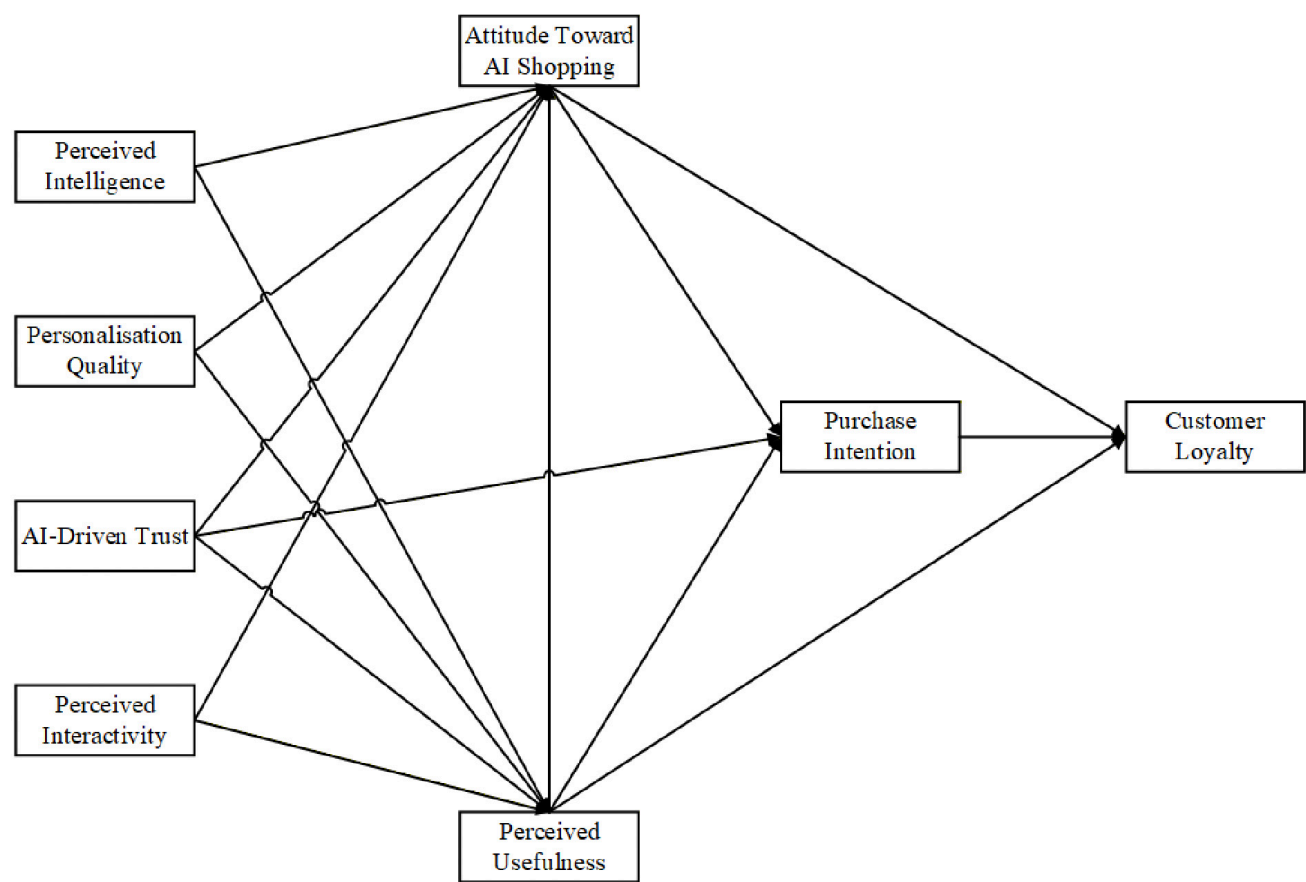


Figure 1

See image above for figure legend

Figure 2. Final Structural Model with Standardised Path Coefficients and R² Values

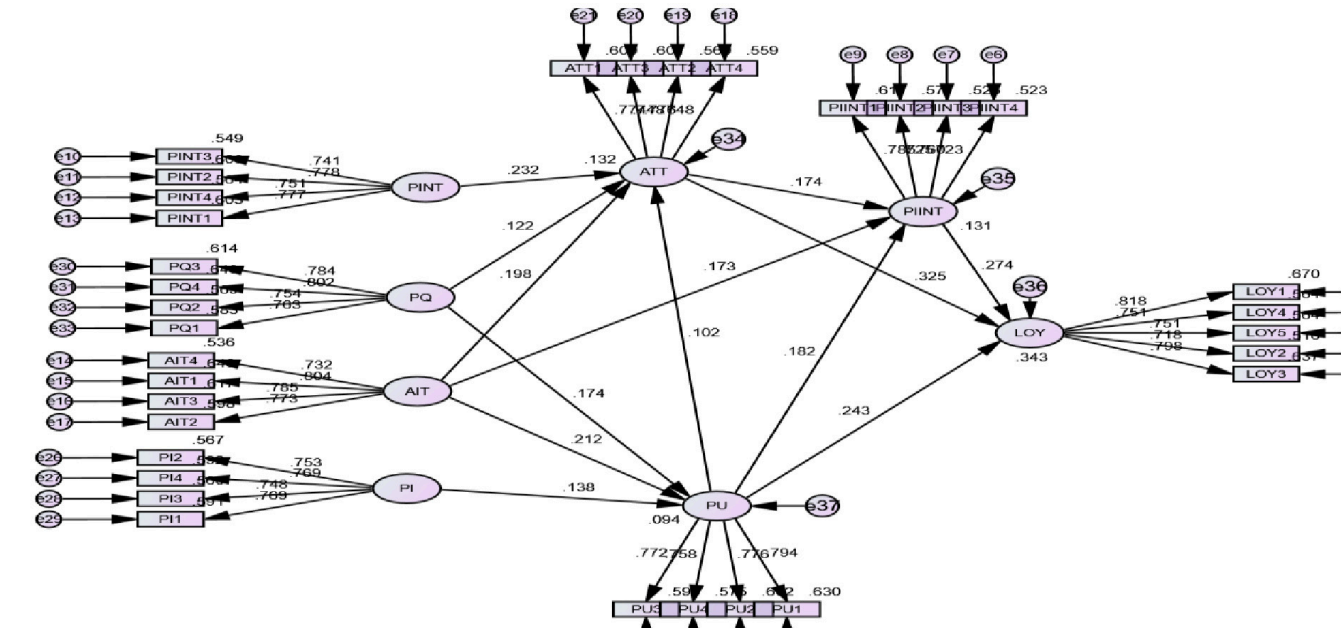


Figure 2

See image above for figure legend

Supplementary Files

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