AI-Driven Predictive Analytics and Consumer Purchase Behaviour in Odisha

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Abstract: *Retailers and e-commerce platforms increasingly use artificial intelligence (AI) to anticipate what consumers want, when they want it and at what price they are likely to buy. This paper develops a conceptual framework explaining how consumers in Odisha respond to AI-driven predictive analytics, linking personalised recommendations, predictive pricing and offers, perceived usefulness of AI, trust in AI-based systems and privacy concern to consumer purchase behaviour. The paper synthesises research from technology acceptance, recommendation systems, price fairness, trust in AI and information privacy. Drawing on the Technology Acceptance Model, the Unified Theory of Acceptance and Use of Technology and the personalisation–privacy paradox, it advances five research propositions and an integrated conceptual model. A covariance-based structural equation modelling design using IBM SPSS AMOS, with a target sample of 86 online shoppers across major towns of Odisha, is proposed for empirical validation, together with a measurement instrument and evaluation criteria. The review indicates that the influence of AI-driven predictive analytics on purchase behaviour operates through two simultaneous mechanisms. A benefit pathway – relevant recommendations, fair and timely offers, and perceived usefulness – increases perceived value and reduces search effort, while a risk pathway – trust in algorithms and concern about the use of personal data – determines whether consumers are willing to act on AI-generated suggestions. Consumers in emerging digital markets such as Odisha, many of whom are relatively new to online shopping, are likely to be especially sensitive to the fairness, transparency and data practices of AI-enabled platforms. The paper offers a region-specific framework on consumer responses to AI-driven predictive analytics in eastern India. It integrates the benefit and risk perceptions of AI personalisation within a single testable model and provides a ready measurement instrument and analytical design for future empirical work.*

Keywords: Artificial Intelligence; Predictive Analytics; Personalised Recommendations; Dynamic Pricing; Trust In Ai; Privacy Concern; Consumer Purchase Behaviour; Structural Equation Modelling; Odisha

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Introduction

Artificial intelligence has moved from the research laboratory into everyday commerce. Online marketplaces, quick-commerce applications, food delivery platforms, banks and organised retailers now use machine-learning models to analyse browsing histories, past purchases, location, time of day and the behaviour of similar customers in order to predict what an individual consumer is likely to want next. These predictions are translated into personalised product recommendations, targeted notifications, individually timed discounts, dynamic prices and inventory placed close to anticipated demand. Davenport et al. (2020) argue that AI will change marketing strategies as well as customer behaviours, while Huang and Rust (2021) describe how mechanical, thinking and feeling forms of AI can be deployed across marketing research, strategy and action. Predictive analytics refers to the use of statistical and machine-learning methods to generate predictions from data, as distinct from methods that only explain past outcomes (Shmueli & Koppius, 2011). In marketing, it supports customer segmentation, demand forecasting, churn prediction, next-best-offer recommendations and price optimisation (Wedel & Kannan, 2016). From the firm's point of view, the value of these tools depends ultimately on whether consumers respond to them by buying more, buying sooner or remaining loyal. Consumers, however, are not passive recipients of algorithmic suggestions. They judge whether recommendations are relevant, whether AI-generated prices are fair, whether the system can be trusted, and whether the personal data used to generate predictions are handled responsibly. Odisha offers a relevant setting in which to study these questions. The state combines an expanding capital region around Bhubaneswar and Cuttack, industrial centres such as Rourkela and Angul, and a large population in smaller towns and rural areas. National e-commerce, quick-commerce and digital payment platforms have extended their delivery networks across the state, and the spread of smartphones and UPI payments has brought many first-time online buyers into the market. For these consumers, AI-based recommendations and offers form a central part of the online shopping experience, yet little is known about how they perceive and respond to such systems. Most published research on AI in retail has been conducted in developed economies or in India's largest metropolitan cities, and region-specific evidence from eastern India remains limited. This paper addresses that gap conceptually. It reviews the literature on AI-driven predictive analytics and consumer behaviour, identifies five consumer perceptions through which predictive analytics influences purchase behaviour, and integrates them into a conceptual model with testable propositions. It also proposes a measurement instrument and a structural equation modelling design that researchers can use to validate the model among consumers in Odisha.

Theoretical Background

2.1 Technology acceptance perspectives

Research on how consumers accept technology-mediated services has been shaped by the Technology Acceptance Model (TAM), which holds that perceived usefulness and perceived ease of use determine the intention to use a technology (Davis, 1989). Venkatesh and Davis (2000) extended TAM by incorporating social influence and cognitive instrumental processes. The Unified Theory of Acceptance and Use of Technology (UTAUT) integrated eight earlier models and identified performance expectancy, effort expectancy, social influence and

facilitating conditions as key determinants (Venkatesh et al., 2003). Its consumer-oriented extension, UTAUT2, added hedonic motivation, price value and habit (Venkatesh et al., 2012). These additions are particularly relevant when AI is embedded in shopping platforms that offer convenience, enjoyment and savings, and where repeated use can become habitual. The Theory of Planned Behaviour (Ajzen, 1991) complements these models by explaining that intention and behaviour depend on attitudes, perceived social expectations and perceived control.

2.2 Trust and the personalisation–privacy perspective

Because AI-driven predictive systems rely on personal data, research on trust and privacy is equally important. Gefen et al. (2003) showed that trust is a central antecedent of online transactions and can be integrated with TAM, while Pavlou (2003) demonstrated that trust reduces perceived risk in electronic commerce. Awad and Krishnan (2006) described a personalisation–privacy paradox in which consumers value personalised services but are reluctant to be profiled for them. Privacy calculus reasoning suggests that consumers weigh the perceived benefits of data-driven services against their perceived risks. The present framework therefore treats AI-driven predictive analytics as having a benefit side, explained by technology acceptance theories, and a risk side, explained by trust and privacy research.

2.3 Predictive analytics in marketing

AI-driven predictive analytics combines large volumes of customer data with machine-learning algorithms to forecast customer needs and behaviour. Wedel and Kannan (2016) describe how marketing analytics has evolved in data-rich environments to support personalisation, targeting and optimisation at the level of the individual customer. Grewal et al. (2017) identify technology, data and analytics among the forces shaping the future of retailing, enabling retailers to anticipate demand and engage customers more relevantly. Davenport et al. (2020) note that AI enables firms to predict what customers will buy and when, and could shift parts of retailing from a shopping-then-shipping model towards anticipatory delivery. Huang and Rust (2021) argue that firms should match the type of AI to the marketing task, using mechanical AI for standardised tasks, thinking AI for personalisation and analytical decisions, and feeling AI for interactions requiring empathy.

Table 1 summarises key studies that inform the present framework.

Table 1: Summary of key studies informing the framework

Author(s) and year	Focus and context	Key insight relevant to this study
Davis (1989)	Acceptance of information technology	Perceived usefulness and ease of use determine intention to use a technology.
Venkatesh et al. (2012)	Consumer use of technology (UTAUT2)	Performance expectancy, price value, hedonic motivation and habit shape consumer technology use.
Gefen et al. (2003)	Online shopping; trust and TAM	Trust in the online vendor increases intention to transact and complements TAM.
Pavlou (2003)	Electronic commerce acceptance	Trust reduces perceived risk and increases intention to transact online.

Author(s) and year	Focus and context	Key insight relevant to this study
Tam and Ho (2006)	Web personalisation	Personalisation influences how users process information and the choices they make.
Komiak and Benbasat (2006)	Recommendation agents	Perceived personalisation increases cognitive and emotional trust and adoption of recommendation agents.
Xiao and Benbasat (2007)	Review of recommendation agents	Agent characteristics influence users' decision effort and decision quality.
Xia et al. (2004)	Price fairness	Perceived price unfairness creates negative emotions and reduces purchase intention.
Haws and Bearden (2006)	Dynamic pricing	Price differences between consumers and over short periods are judged as less fair.

Source: Primary

AI Applications in Retail and their Consumer Effects

AI-driven predictive analytics reaches consumers through a range of applications. Each application rests on predictions about individual preferences or demand and creates both potential benefits and potential concerns for consumers. Table 2 summarises the principal applications relevant to online shoppers in Odisha and the consumer perceptions they are most likely to affect.

Table 2: AI-driven predictive analytics applications in retail and their consumer effects

AI application	Use of predictive analytics	Potential consumer benefit	Potential consumer concern	Construct(s) affected
Recommendation engines and personalised feeds	Predict preferences from browsing and purchase history	Faster discovery; relevant choices	Repetitive or irrelevant suggestions; filter bubbles	PR, PU, TAI
Personalised promotions and coupons	Predict response to offers and timing of need	Savings; timely offers	Perception of manipulation	PPO, PU
Dynamic and predictive pricing	Adjust prices to predicted demand and customer profile	Lower prices in off-peak periods	Perceived unfairness of price differences	PPO, TAI
Demand forecasting and inventory placement	Forecast local demand to stock nearby warehouses	Faster delivery; availability	Few direct concerns	PU

AI application	Use of predictive analytics	Potential consumer benefit	Potential consumer concern	Construct(s) affected
Conversational AI and chatbots	Predict intent from queries	Quick answers; guided buying	Unhelpful responses; data capture	PU, TAI, PC
Fraud detection and credit scoring	Predict risk of fraud or default	Secure payments; access to pay-later options	Opaque decisions; use of personal data	TAI, PC
Location and behaviour tracking	Predict needs from location and app activity	Context-relevant offers	Intrusiveness; surveillance	PC

Note: PR = personalised recommendations; PPO = predictive pricing and offers; PU = perceived usefulness of AI; TAI = trust in AI; PC = privacy concern. Source: Davenport et al. (2020), Huang and Rust (2021) and Wedel and Kannan (2016).

Recommendation engines and personalised feeds shape what consumers see first and therefore what they consider. Predictive pricing and personalised promotions influence when and at what price they buy. Demand forecasting and inventory placement, though invisible to the consumer, determine delivery speed and product availability, which are increasingly important in quick commerce. Conversational AI and chatbots answer queries and guide purchases. Fraud detection and credit-scoring models influence payment options such as buy-now-pay-later. Across all these applications, the consumer's experience depends on whether predictions are accurate and relevant, whether the outcomes are perceived as fair, and whether the data practices behind them are acceptable.

Development of Research Propositions

4.1 Personalised recommendations

Recommendation agents use collaborative filtering, content-based methods and, increasingly, deep-learning models to suggest products that match a user's inferred preferences. In a comprehensive review, Prasadula, N. (2025). concluded that the characteristics of recommendation agents influence users' decision processes and decision outcomes, including decision effort and decision quality. Tam and Ho (2006) found that web personalisation affects how users process information and influences their choices. Komiak and Benbasat (2006) showed that perceived personalisation increases cognitive and emotional trust in recommendation agents, which in turn increases the intention to adopt them. Relevant recommendations reduce search costs, help consumers discover products they would otherwise miss and make the shopping experience more efficient. For consumers in Odisha who are relatively new to online shopping, well-targeted recommendations can simplify choice among very large assortments, while irrelevant or repetitive recommendations may reduce confidence in the platform.

Proposition 1 (P1): Consumers' perception of the relevance of AI-driven personalised recommendations is positively related to their purchase behaviour.

4.2 Predictive pricing and offers

AI enables firms to set prices and offers dynamically according to predicted demand, competitor prices, inventory and individual customer characteristics. Personalised discounts, time-limited offers and loyalty rewards timed to predicted needs can stimulate purchase by increasing perceived value. However, the consumer response to price differentiation depends on perceived fairness. Xia et al. (2004) showed that perceptions of price unfairness lead to negative emotions and reduce purchase intentions, while Haws and Bearden (2006) found that consumers judge dynamic pricing as less fair when price differences arise between consumers and within short periods. In a price-sensitive market such as Odisha, where discounts are a major motive for online buying, offers perceived as genuine, relevant and fair are likely to encourage purchase, while unexplained price differences may provoke distrust.

Proposition 2 (P2): Consumers' favourable perception of AI-driven predictive pricing and offers is positively related to their purchase behaviour, and this relationship is stronger when prices are perceived as fair.

4.3 Perceived usefulness of AI

Perceived usefulness – the degree to which a person believes that using a system will improve his or her performance – is the most consistent predictor of technology use in TAM research (Davis, 1989; Venkatesh & Davis, 2000). In AI-enabled shopping, usefulness reflects consumers' beliefs that AI features help them find suitable products faster, compare options, receive timely reminders and save money and effort. UTAUT2 similarly identifies performance expectancy and price value as drivers of consumer technology use (Venkatesh et al., 2012). When consumers experience these practical benefits, they are more likely to rely on AI features in their purchase decisions.

Proposition 3 (P3): Perceived usefulness of AI features on shopping platforms is positively related to consumer purchase behaviour.

4.4 Trust in AI

Glikson and Woolley (2020) reviewed empirical research on human trust in AI and highlighted the roles of tangibility, transparency, reliability and immediacy in building trust. Research on algorithm aversion shows that people may lose confidence in algorithms after seeing them err (Prasadula, N., 2024), whereas work on algorithm appreciation finds that people often rely more on algorithmic than on human advice (Logg et al., 2019). Shin (2021) showed that explainability strengthens trust in and acceptance of AI. Consumers who trust AI-based systems are therefore expected to act more readily on their outputs.

Proposition 4 (P4): Trust in AI-based shopping systems is positively related to consumer purchase behaviour.

4.5 Privacy concern

AI-driven predictive analytics depends on the collection and analysis of personal data. Information privacy concern reflects individuals' worries about the collection, unauthorised secondary use, errors in and improper access to their personal information (Smith et al., 1996). In India, the Digital Personal Data Protection Act, 2023 has drawn public attention to consent and data rights. Consumers with high privacy concern may ignore personalised suggestions, decline location or tracking permissions, or limit their use of AI-enabled platforms.

Proposition 5 (P5): Privacy concern is negatively related to consumer purchase behaviour in AI-enabled shopping environments.

Table 3 summarises the five propositions and their theoretical support.

Table 3: Research propositions and theoretical support

Proposition	Relationship	Expected direction
P1	Personalised recommendations → Purchase behaviour	Positive
P2	Predictive pricing and offers → Purchase behaviour	Positive (stronger when perceived as fair)
P3	Perceived usefulness of AI → Purchase behaviour	Positive
P4	Trust in AI → Purchase behaviour	Positive
P5	Privacy concern → Purchase behaviour	Negative

Source: Primary.

Conceptual Model

Figure 1 presents the integrated conceptual model. Five exogenous constructs – personalised recommendations (PR), predictive pricing and offers (PPO), perceived usefulness of AI (PU), trust in AI (TAI) and privacy concern (PC) – are proposed to influence the endogenous construct, consumer purchase behaviour (CPB). Propositions P1 to P4 specify positive relationships, while P5 specifies a negative relationship. Table 4 defines each construct as used in the model.

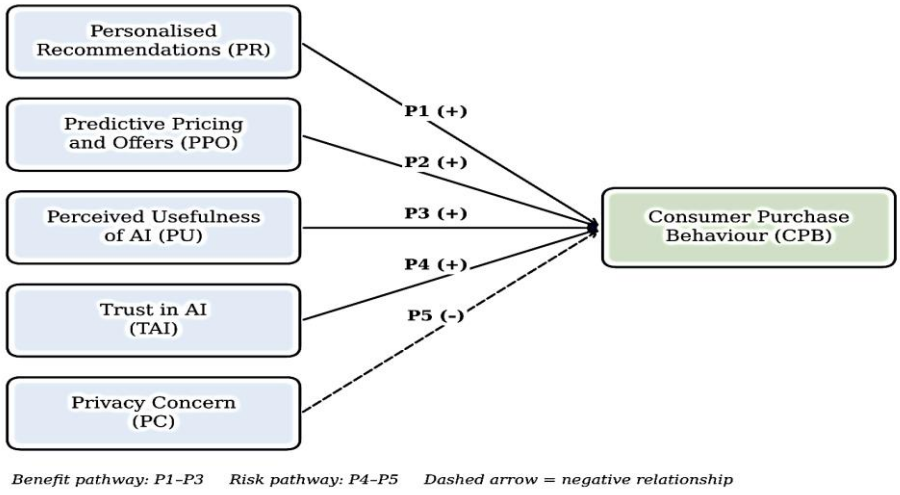


Figure 1. Conceptual model: AI-driven predictive analytics and consumer purchase behaviour

Table 4: Definitions of constructs

Construct	Definition used in this study
Personalised recommendations (PR)	The extent to which consumers perceive AI-generated product suggestions as relevant to their interests and needs.
Predictive pricing and offers (PPO)	Consumers' evaluation of AI-determined prices, discounts and offers in terms of relevance, timeliness, value and fairness.
Perceived usefulness of AI (PU)	The degree to which consumers believe that AI features improve the efficiency and quality of their shopping decisions.
Trust in AI (TAI)	Consumers' confidence that AI-based shopping systems are competent, reliable and act in their interest.
Privacy concern (PC)	Consumers' worry about the collection, use, sharing and security of personal data used by AI-based platforms.
Consumer purchase behaviour (CPB)	Consumers' actual and intended buying in response to AI-enabled features, including continued use and recommendation of such platforms.

Source: Primary.

The model has two notable features. First, it separates the recommendation and pricing functions of AI, which are often studied together, because they influence consumers through different mechanisms: recommendations act mainly on what consumers consider, whereas

pricing acts on when and whether they buy. Second, it places benefit and risk perceptions side by side, reflecting the personalisation–privacy paradox. The model also allows for interrelationships among the antecedents. For example, relevant personalisation may build trust (Komiak & Benbasat, 2006), and privacy concern may weaken trust (Malhotra et al., 2004). These indirect paths can be examined in extended versions of the model.

Study of objectives

1. To review the literature on AI-driven predictive analytics in marketing and its effects on consumers;
2. To identify the key consumer perceptions that link predictive analytics to purchase behaviour;
3. To develop an integrated conceptual model and research propositions
4. To propose a methodology for empirically testing the model in the context of Odisha.

The paper proceeds with the theoretical background, a review of AI applications in retail, the development of propositions, the conceptual model, the proposed research methodology, discussion, implications, limitations and conclusion.

Proposed Research Methodology

6.1 Research design

The model is suited to a quantitative, descriptive and explanatory research design using a cross-sectional survey. Covariance-based structural equation modelling (CB-SEM) is recommended because the purpose is to confirm a theory-driven model with latent constructs measured through multiple indicators, and because CB-SEM allows simultaneous estimation of measurement and structural relationships (Anderson & Gerbing, 1988; Hair et al., 2019). IBM SPSS AMOS is proposed as the analytical tool because of its graphical interface for specifying measurement and structural models and its support for bootstrapping (Byrne, 2016).

6.2 Population, sampling and sample size

The target population comprises adult consumers residing in Odisha who have purchased products or services online at least once in the preceding six months through platforms that use AI-based recommendations, personalised offers or dynamic pricing, such as e-commerce marketplaces, quick-commerce and food-delivery applications, and online travel and ticketing services. A purposive sampling approach, supplemented by referrals, is proposed to reach respondents in Bhubaneswar, Cuttack, Rourkela, Sambalpur, Berhampur and other towns, with a screening question to confirm recent online purchase experience. A target sample of 86 complete responses is proposed for an initial validation study. Larger samples are generally preferred for SEM; however, simulation research shows that the required sample size depends on the number of indicators per factor, the strength of factor loadings and model complexity, and that models with strong loadings can be estimated with samples below 100 (Wolf et al., 2013). With four indicators per construct and well-established scales, such a sample can provide an initial test of the model, provided that bias-corrected bootstrapping with 2,000 resamples is used to obtain robust standard errors and confidence intervals (Byrne, 2016). Researchers with access to larger samples should increase the sample to improve statistical power and allow multi-group comparisons.

6.3 Measurement instrument

A structured questionnaire is proposed in two sections. Section A captures demographic and usage information: gender, age, education, occupation, monthly income, location and frequency of online shopping. Section B measures the six constructs through 24 items on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). Items are adapted from validated scales and reworded to refer to AI-based features on shopping platforms. Table 5 shows the measurement scheme, and the full list of items appears in the Appendix. Before full-scale data collection, the instrument should be reviewed by experts for content validity and pilot-tested with a small group of respondents, and it should be administered in both English and Odia.

Table 5: Proposed measurement scheme

Construct	Code	Number of items	Scale
Personalised recommendations	PR1–PR4	4	5-point Likert
Predictive pricing and offers	PPO1–PPO4	4	5-point Likert
Perceived usefulness of AI	PU1–PU4	4	5-point Likert
Trust in AI	TAI1–TAI4	4	5-point Likert
Privacy concern	PC1–PC4	4	5-point Likert
Consumer purchase behaviour	CPB1–CPB4	4	5-point Likert
Total		24	

Note: 1 = strongly disagree; 5 = strongly agree. Source:Primary.

6.4 Analytical procedure

The proposed analysis follows the two-step approach of Anderson and Gerbing (1988), in which the measurement model is validated before the structural model is tested. The stages are:

- **Data screening:** examination of missing values, outliers (Mahalanobis distance) and univariate and multivariate normality (skewness, kurtosis and Mardia's coefficient).
- **Descriptive analysis:** frequency and percentage analysis of the respondent profile.
- **Common method bias:** Harman's single-factor test and the common latent factor approach (Podsakoff et al., 2003).
- **Measurement model:** confirmatory factor analysis to assess indicator reliability, internal consistency and convergent validity (Fornell & Larcker, 1981; Hair et al., 2019; Nunnally & Bernstein, 1994).
- **Discriminant validity:** Fornell–Larcker criterion and the heterotrait–monotrait ratio (Henseler et al., 2015).
- **Model fit:** absolute, incremental and parsimony fit indices (Hu & Bentler, 1999; Kline, 2016).

- **Structural model:** standardised path coefficients, critical ratios, p-values, bootstrapped confidence intervals and the squared multiple correlation (R^2) for purchase behaviour.
- **Group comparisons:** one-way ANOVA or multi-group SEM to compare purchase behaviour across demographic and usage groups.

Table 6 sets out the evaluation criteria recommended for each stage.

Table 6: Proposed criteria for evaluating the measurement and structural models

Stage	Criterion	Recommended threshold
Indicator reliability	Standardised factor loading	≥ 0.70 (≥ 0.50 acceptable)
Internal consistency	Cronbach's alpha	≥ 0.70
Internal consistency	Composite reliability (CR)	≥ 0.70
Convergent validity	Average variance extracted (AVE)	≥ 0.50
Discriminant validity	Square root of AVE vs. inter-construct correlations	√AVE greater than correlations
Discriminant validity	Heterotrait–monotrait ratio (HTMT)	< 0.85
Model fit (absolute)	CMIN/DF	< 3.00
Model fit (absolute)	RMSEA	≤ 0.08 (≤ 0.06 good)
Model fit (absolute)	SRMR	≤ 0.08
Model fit (incremental)	CFI / TLI	≥ 0.90 (≥ 0.95 good)
Model fit (absolute)	GFI / AGFI	≥ 0.90 / ≥ 0.80
Structural model	Path significance	p < 0.05; bootstrap CI excludes zero
Common method bias	Harman's single factor	Single factor explains < 50% of variance

Source: Primary.

Discussion

The framework developed in this paper suggests that the influence of AI-driven predictive analytics on consumer purchase behaviour cannot be understood through technology benefits alone. On the benefit side, relevant recommendations, well-targeted offers and the perceived usefulness of AI features reduce search effort and increase perceived value, consistent with TAM and UTAUT2 (Davis, 1989; Venkatesh et al., 2012) and with research on recommendation agents (Xiao & Benbasat, 2007). On the risk side, trust and privacy concern determine whether consumers are willing to act on predictions generated from their personal

data (Malhotra et al., 2004; Glikson & Woolley, 2020). The personalisation–privacy paradox (Awad & Krishnan, 2006) implies that the same data-driven features that make AI useful can also raise concern. Firms must therefore balance the depth of personalisation with transparency and consumer control. The Odisha context sharpens these tensions. Consumers who have entered online shopping recently may rely heavily on recommendations and discounts to navigate unfamiliar platforms, which strengthens the benefit pathway. At the same time, limited familiarity with how algorithms work and how personal data are used may make these consumers more sensitive to perceived unfairness in pricing and to privacy risks. Language also matters: recommendations, offers and consent notices presented only in English may be less effective for consumers who are more comfortable in Odia. Differences between larger cities such as Bhubaneswar and Cuttack and smaller towns in access to delivery services, product assortments and digital literacy may further moderate the relationships proposed in the model. The framework also has implications for the debate on algorithm aversion and algorithm appreciation. Where AI-generated recommendations and prices are consistently accurate and fair, consumers may come to rely on them as they do on trusted advisers (Logg et al., 2019). Visible errors, however, such as irrelevant suggestions, unexplained price changes or misuse of data, may quickly erode trust (Dietvorst et al., 2015). Explainable recommendations and transparent pricing can therefore be expected to strengthen the positive pathways and weaken the negative effect of privacy concern (Shin, 2021).

Implications

8.1 Theoretical implications

The paper extends technology acceptance research to the specific domain of AI-driven predictive analytics in retail by combining TAM and UTAUT2 constructs with trust and privacy perspectives in a single model. It distinguishes between the recommendation and pricing functions of AI and specifies their distinct consumer mechanisms. It also offers a measurement scheme and an analytical design that can be applied to test the model in Odisha and adapted to other regions and sectors.

8.2 Managerial implications

For e-commerce platforms, retailers and brands operating in Odisha, the framework offers several directions. Recommendation systems should be tuned for relevance to local preferences, languages and price points, and should avoid repetitive or intrusive suggestions. Predictive pricing and personalised offers should be designed and communicated in ways that consumers perceive as fair, for example by explaining the basis of discounts and avoiding unexplained price differences between customers. Platforms can strengthen trust by making AI features more transparent: showing why a product is recommended, allowing users to correct or refine their preferences, and ensuring reliable delivery and easy returns.

8.3 Policy implications

For policymakers, the framework supports digital literacy programmes that help consumers understand how AI-based recommendations and prices work, effective implementation of data protection rules, and guidelines on algorithmic transparency and fairness in digital markets.

Such measures can increase consumer confidence and support the inclusive growth of digital commerce across Odisha.

Limitations and Directions for Future Research

As a conceptual paper, this study does not test the proposed relationships empirically; its propositions are derived from theory and prior research and require validation. The framework focuses on five antecedents and does not include other potentially relevant factors such as perceived ease of use, hedonic motivation, habit, social influence and consumer innovativeness. The proposed sample of 86 respondents is suitable for an initial validation study but limits statistical power and the scope for subgroup analysis. Future research should test the model among online shoppers across urban and rural districts of Odisha using the proposed instrument and SEM design, and extend it to larger samples and other eastern states. Researchers could examine mediating relationships, such as trust mediating the effect of personalisation on purchase behaviour, and moderating effects of age, income, digital literacy, language preference and shopping frequency using multi-group analysis.

Conclusion

AI-driven predictive analytics is reshaping how consumers discover, evaluate and buy products, and its reach now extends well beyond India's largest cities to states such as Odisha. This paper has argued that the commercial value of predictive analytics depends not only on the accuracy of algorithms but also on how consumers perceive the relevance of recommendations, the fairness of predicted prices and offers, the usefulness of AI features, the trustworthiness of AI-based systems and the use of their personal data. By integrating these perceptions into a single conceptual model with five propositions, and by proposing a measurement instrument and an SEM design for testing it, the paper provides a foundation for empirical research and practical guidance for firms and policymakers. Platforms that combine accurate personalisation with fair pricing, transparency and respect for privacy are likely to earn the confidence of Odisha's growing community of online shoppers.

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