Shodhbodhalaya: An International Peer reviewed Multidisciplinary Journal
Volume 4 | Issue 2 | ISSN: 2584-1807 | (https://shodhbodh.com/)

The Impact of AI-Driven Personalisation on Consumer Trust, Perceived Value, and Customer Loyalty in Indian E-Commerce

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Abstract

These days, AI is an increasingly prominent figure in ecommerce, influencing recommendations, adaptive interfaces, personalised offers, virtual assistants and predictive content. The systems can do much to cut down search effort as well as increase relevance, but they rely on lots of consumer information and can cause privacy issues that lead to loss of trust. This analytical study examines the impact of the personalisation quality and recommendation relevance on perceived value, privacy concern on consumer trust and perceived value and consumer trust on customer loyalty in the Indian ecommerce industry. A cross-sectional quantitative design was determined for 312 online shoppers that had experienced AI recommendations in the last year. A structured five point likert scale was used to assess six constructs. The reliability of all scales was satisfactory. The perceived value was greatly enhanced by personalisation quality, in particular by recommendation relevance, which had the greater impact. Perceived value positively influenced consumer trust, whereas privacy concern negatively did. Consumer trust was the most significant factor affecting customer loyalty. The results indicate that the elements of effective personalisation are not necessarily those of intensity: they are relevant recommendations, user friendly data usage, consumer control and reliable platform behaviour. E-commerce companies must, therefore, integrate privacy protection, personalisation transparency and recommendation precision to generate long-term loyalty, not just short-term convenience, from their algorithms.

Keywords: artificial intelligence; personalisation; recommendation relevance; privacy concern; consumer trust; customer loyalty; e-commerce

1. Introduction

AI has emerged as a key enabler of today's ecommerce landscape. Recommendation engines suggest products, predictive systems tailor offers, chatbots answer questions, and adaptive interfaces adjust content based on users' browsing and purchasing patterns. These apps can enhance the consumer experience by eliminating information overload and helping focus on products more likely to align with consumer needs. Marketing research sees AI not as a mere automation solution, but as a means to reconceptualize the customer experience and customer relationships (Ameen et al., 2021; Huang & Rust, 2021; Davenport et al., 2020).

Relevance is the driving force behind the commercial potential of personalisation driven by AI. In online markets, consumers are faced with thousands of products, reviews and promotional messages. Identifying the right choices can save time, reduce mental strain and boost confidence in the buying process. But the same system can be intrusive when consumers are not aware of how their data has been gathered, merged, or derived. Personalisation can thus be paradoxical – the more useful data it is able to use to make a recommendation, the more privacy concern and distrust it can produce. Consumer experiences with AI encompass cognitive, emotional, and relational reactions, as highlighted by Puntoni et al. (2021), and privacy assurances, reactances, and trust are pivotal to personalised digital services, as noted by Chen and Sun (2022) and Zeng et al. (2022).

From personalized product feeds to algorithmic recommendations, sponsored suggestions, dynamic notifications, and AI-supported customer service, Indian e-commerce users are exposed to a range of personalization elements, all of which are common. These features may be more or less relevant to the shoppers depending on their preferences, technology readiness, level of privacy expectations, and experiences with the platform. The use of chatbots, AI for retention, conversational commerce, and anthropomorphic assistants have been explored in Indian-origin scholarship (Kasilingam, 2020; Singh et al., 2023; Jham et al., 2023; Balakrishnan & Dwivedi, 2024). But a clear empirical chain between the personalisation quality and the relevance of the recommendations and value, trust and loyalty still needs to be established. While many studies focus on intention to adopt or purchase, the long-term loyalty needs relational explanation.

The research problem is that ecommerce companies may be able to expand their number of personalised interactions, without simultaneously enhancing the value and trust of those interactions for consumers. The incorrect recommendation can indicate poor understanding, as can the correct recommendation made to an extent that is not anticipated. The real question for management is not whether personalisation is beneficial, but how it can be beneficial without being too personal, intrusive, or suspicious of privacy. This study focuses on the issue when the quality of personalisation and relevance of recommendation generates the perceived value, and the Privacy concern leads to a decrease of trust, while the perceived value strengthens trust, and trust leads to customer loyalty. The research is not limited to a specific city, state or region but is centered around Indian online shoppers.

1.1 Research Objectives

1. To examine the influence of personalisation quality and recommendation relevance on the perceived value of AI-enabled e-commerce experiences.
2. To assess the effects of privacy concern and perceived value on consumer trust in e-commerce platforms.
3. To determine the influence of consumer trust on customer loyalty in Indian e-commerce.

2. Review of Literature and Hypothesis Development

2.1 AI-Driven Personalisation and the E-Commerce Experience

AI-powered personalisation is the process of tailoring content, recommendations, communications and interfaces based on consumer data and predictive algorithms, without the need for manual effort. It is not the same as a simple segmentation, since it is possible to update the outputs continuously at the individual level. According to Davenport et al. (2020), AI is transforming marketing by predicting, automating and providing personal support to make decisions. Huang & Rust propose a marketing strategy that has mechanical, thinking intelligence and feeling intelligence each serving a separate marketing role. In e-commerce, the personalisation mainly involves the application of pattern recognising capabilities of thought intelligence and pattern-to-consumer communication in the interface.

Research into customer experience has shown that the usefulness of AI is subjective based on the customer's perception of the customer journey. While Ameen et al. (2021) demonstrate that AI can enhance experience by offering convenience and responsiveness, consumer characteristics and ethics play a role in its outcome. At the same time, Hoyer et al. (2020) state that new technologies are changing the way customers experience the pre-purchase, purchase, and post-purchase phases of the customer journey. Puntoni et al. (2021) highlight the fact that consumers can interact with AI in empowering, replacing, monitoring or interacting manner. These experiences give rise to the fact that the same personalisation option can be seen as positive by one customer and negative by another.

Personalisation quality is the overall assessment of whether a platform knows your preferences, reacts accordingly and offers a seamless, personalised experience. With regard to recommendation relevance, it is more limited and focuses on the appropriateness of recommended products in the context of existing demands, preferences and buying situations.

Necula and Păvăloaia (2023) demonstrate that advanced AI techniques are being increasingly applied to the study of e-commerce recommendations, but that does not necessarily mean that the results are accepted by the consumers. Bunea et al. (2024) have found that usefulness and concerns influence perceptions of AI in online shopping, while Hossain and Biswas (2024) have shown the impact of technology acceptance in AI-based shopping platforms. To the consumer, the recommendation must be of value, and not just algorithmically generated.

2.2 Perceived Value Created by Personalisation and Relevance

Perceived value is the judgment a customer makes about the benefits he or she has received compared to the effort, time, data giving, monetary and/or psychological costs of an interaction. The utilitarian value can be achieved by AI personalisation, where it cuts down on search time, makes products fit, and helps in comparing. Can add hedonic value – make discovery more fun, relational value – make site seem attentive. AI technology stimuli is linked to smart customer experience by Gao et al., (2022) and the perception of easy browsing is related to customer experience and engagement by Lopes et al., (2025). Yrjölä et al. (2025) also list several retail value propositions related to AI.

Recommendation relevance is expected to directly influence the perceived value since it dictates whether the consumer is given any assistance that is actionable. Weird suggestions place attention cost and can lower trust of the platform. Suitable recommendations guide the consumers to find alternative products, to compare the two, and to make a choice. Trzebiński et al. (2023) reveal how learning ability influences the reaction to online recommenders, while Bergner et al. (2023) illustrate how conversational AI's modality influences the consumer-brand relationship. If consumers feel the AI system is learning correctly and is communicating in a meaningful way, the personalised interaction is a value proposition to the platform.

Personalisation quality should also enhance value as there is consistency between touchpoints, minimising friction. A consumer can assess not just a specific product recommendation but also the consistency of search results, reminders, service messages and offers. Ranieri et al. (2024) reveal some positive and negative influences of chatbot service on customer experience, and Nicolescu and Tudorache (2022) demonstrate that the HCI factors play a prominent role in AI customer service. Thus, personalisation should be planned, comprehensible and manageable. High-quality personalisation is expected to bring a perceived value increase and relevant recommendations should do so by bringing an added value contribution that is more immediate.

2.3 Privacy Concern, Consumer Trust, and Loyalty

A privacy concern is an apprehension regarding the collection, usage, sharing, safety and inference of personal data. AI systems can rely on prior browsing history, click patterns, geo-location data, purchase history, and more, but users might not be aware of what information led to a recommendation. The challenge of personalising web content while accommodating privacy concern and consumer reactance is discussed by Chen and Sun (2022). Framing of privacy policies has a significant impact on concerns and reactions, as illustrated by Zeng et al (2022). Kronemann et al. (2023) also show anthropomorphism and personalisation have a positive effect on disclosure and privacy concern is still a significant factor. These results suggest that the reverse side of the coin also holds true; in other words, when the personalisation is more accurate than the consumer is expecting, it can have a negative impact on trust.

Consumer trust is a readiness to trust the platform despite doubts. Trust has a range of components in AI-influenced commerce, such as believing in the competence of recommendations, data security, transaction reliability, and equity. According to Cheng and Jiang (2022), the marketing activities of AI chatbots affect the relationships between customers and brands, and Lee et al. (2022) confirm that the use of chatbots based on AI can help to promote brands cognitively and affectively. Youn and Jin (2021) conclude that parasocial interaction and ideology lead to a difference in trust of using a chatbot for managing relationships. Therefore technical accuracy is not enough to ensure trust; transparency, perceived benevolence and consumer perception of the system operating within a range of acceptability are also crucial components.

Customer loyalty encompasses the repeat buyer, the continued use of the platform, favourable recommendations and resistance to platform switching. AI can help build loyalty when it is always valuable and eliminates uncertainty. According to Maduku et al. (2024), AI-powered digital assistants have the power to evoke emotional responses, engagement, and customer loyalty. Huh et al. (2023) link voice assistants to positive technology and brand loyalty, while Jham et al. (2023) demonstrate the influence of trust and psychological distance on consumer interactions with anthropomorphic assistants. On the other hand, if they don't like the privacy or the recommendations haven't been successful, the relationship can suffer. So the mechanism between perceived value and loyal customers will be assumed to be trust.

2.4 Research Framework and Hypothesis Development

The plan is to introduce a value-creation path and a risk-control path. Value-creation antecedents are personalisation quality and recommendation relevance. Perceived value refers to the first impression the consumer has regarding the value created by AI. Risk of privacy concerns is one of the risk evaluations that should reduce consumer trust. Useful and coherent interactions should be a strong indicator of competence, and therefore enhance trust as perceived value. Trust then breeds loyalty, which diminishes uncertainty and builds trust in the next interaction. This structure aligns with the research which suggests that AI customer experience can be divided into four components: usefulness, emotion, privacy, and outcomes of the relationship (Ameen et al., 2021; Pizzi et al., 2023; Teepapal, 2025).

The value of personalisation is expected to improve perceived value due to less effort and better fit on the adaptive experiences. The relevance of the recommendations will be further expected to increase the perceived value by providing relevant recommendations that can support choice. Weak perceived control is likely to result in reduced trust if privacy concern is an issue. Repeated useful interactions are expected to help build trust, as they will make people feel that the platform is competent and reliable. Last but not least, consumer trust will lead to loyalty as the buyers will be more likely to return to, reorder, and recommend the platform they feel is reliable.

2.5 Research Hypotheses

1. H1: Personalisation quality has a significant positive influence on perceived value.
2. H2: Recommendation relevance has a significant positive influence on perceived value.
3. H3: Privacy concern has a significant negative influence on consumer trust.
4. H4: Perceived value has a significant positive influence on consumer trust.
5. H5: Consumer trust has a significant positive influence on customer loyalty.

3. Methodology

3.1 Research Design

This study is of quantitative type, explanatory and cross-sectional research design. The unit of analysis is the individual Indian online shopper who has seen the AI product recommendations/personalised content on an e-commerce website over the last year. The design explores value-creation pathway and a pathway for privacy risk to build trust and loyalty.

3.2 Variables and Measurement

Six constructs are included in this study, all of which are related to each other, namely personalisation quality, recommendation relevance, privacy concern, perceived value, consumer trust and customer loyalty. Four statements are used to assess each construct, on a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). Items were created using the synthesis of the latest research related to AI Customer Experience, Recommendation Systems, Privacy, Trust and Loyalty (Ameen et al., 2021; Chen & Sun, 2022; Necula & Păvăloaia, 2023; Maduku et al., 2024). Demographic measures include gender, age and education level, occupation, and monthly personal income. Usage measures include shopping frequency, and frequency of using personalised recommendations.

3.3 Sample and Sampling

312 eligible respondents were specified and are within the recommended limit of 250-350 respondents for the intended regression models.

3.4 Data Collection Procedure

After informed consent, the instrument given. Randomly ordered construct statements follow questions for screening and profile. Use a small sample of 25-30 eligible shoppers for a pilot test to check for understanding and time to complete the questionnaire. Duplicate, substantially incomplete cases, patterned answers and answers that are too fast eliminated by data-quality procedures. No names, phone numbers, exact addresses or payment info taken.

3.5 Methods of Data Analysis

Frequency, percentage analysis - describes the sample. Response patterns are described item-wise in terms of percentages, means and standard deviations, and the internal consistency of the responses is assessed with Cronbach's alpha. Pearson correlations look at associations between constructs. Multiple regression tests H1 and H2 to see how well perceived value can be predicted based on personalisation quality and recommendation relevance. A second multiple regression examines the predictive power of privacy concern on perceived value on consumer trust (H3 and

H4). Simple regression test H5: predicting customer loyalty from consumer trust. A 5% significance level is applied to the beta coefficient, and it is standardised.

4. Data Analysis and Results

4.1 Demographic Profile

Table 1. Demographic and Usage Profile of the Study

Variable	**Category**	**Frequency**	**Percentage**
Gender	Male	149	47.8
	Female	157	50.3
	Prefer not to disclose	6	1.9
Age	45 years and above	28	9.0
	18-24 years	99	31.7
	35-44 years	62	19.9
	25-34 years	123	39.4
Education	Undergraduate	145	46.5
	Up to higher secondary	34	10.9
	Professional/doctoral	28	9.0
	Postgraduate	105	33.7
Occupation	Student	56	17.9
	Salaried employee	169	54.2
	Self-employed/business	60	19.2
	Other economically active	27	8.7
Monthly personal income	Below ₹25,000	80	25.6

	₹25,001-₹50,000	108	34.6
	Above ₹75,000	52	16.7
	₹50,001-₹75,000	72	23.1
Online shopping frequency	3-5 times a month	99	31.7
	More than 5 times a month	70	22.4
	1-2 times a month	110	35.3
	Less than monthly	33	10.6
Use of personalised recommendations	Sometimes	111	35.6
	Rarely	42	13.5
	Often	101	32.4
	Very often	58	18.6

Note. n = 312. Percentages may not total exactly 100 because of rounding.

The samples are diverse in age, education, occupation and income and shopping frequency. The 25-34 age group and salaried employees are the largest, and the other categories are significant examples of younger and older, students and self-employed, and other economically active shoppers. The vast majority of respondents report seeing personalised recommendations “sometimes” or “often”, with slight minority portions reporting seeing personalised recommendations “rarely” or “very frequently”.

Shodhbodhalaya: An International Peer reviewed Multidisciplinary Journal
Volume 4 | Issue 2 | ISSN: 2584-1807 | (https://shodhbodh.com/)

4.2 Descriptive and Reliability Analysis

Table 2. Item-Wise Analysis of Personalisation Quality

Item	SD %	D %	N %	A %	SA %	Mean	SD
PQ1. The platform adapts its content to my preferences.	9.0	17.3	28.2	25.0	20.5	3.3	1.2
PQ2. Personalised features are consistent across my shopping journey.	8.3	18.9	24.7	29.8	18.3	3.3	1.2
PQ3. The platform appears to understand my changing interests.	8.7	17.9	26.0	28.2	19.2	3.3	1.2
PQ4. The level of personalisation improves my shopping experience.	8.7	18.9	26.0	24.7	21.8	3.3	1.2

Scale: 1 = Strongly disagree to 5 = Strongly agree.

The mean of the item responses for personalisation quality is 3.31 with a standard deviation of 1.04. Agreements and disagreements included in the distribution; enough variation for testing the relationship. The four items are integrated and are kept as a composite measure.

Table 3. Item-Wise Analysis of Recommendation Relevance

Item	SD %	D %	N %	A %	SA %	Mean	SD
RR1. Recommended products are relevant to my current needs.	7.4	21.2	24.4	24.7	22.4	3.3	1.2

Volume 4 | Issue 2 | ISSN: 2584-1807 | (https://shodhbodh.com/)

RR2. Recommendations match my tastes and past choices.	9.0	20.2	25.3	25.6	19.9	3.3	1.2
RR3. The platform helps me discover suitable products.	9.9	17.9	26.6	23.4	22.1	3.3	1.3
RR4. Recommended items reduce the time needed to search.	9.6	19.9	25.3	25.0	20.2	3.3	1.3

Scale: 1 = Strongly disagree to 5 = Strongly agree.

The mean and SD of the item responses for recommendation relevance are 3.29 and 1.07 respectively. The distribution includes agreement as well as disagreement, providing adequate variability to test relationships. The four items are cohesive and kept as a composite measure.

Table 4. Item-Wise Analysis of Privacy Concern

Item	SD %	D %	N %	A %	SA %	Mean	SD
PRC1. I am concerned about how the platform collects personal data.	11.2	19.6	26.6	23.4	19.2	3.2	1.3
PRC2. I worry that my shopping behaviour is monitored too closely.	12.8	21.2	23.4	24.4	18.3	3.1	1.3
PRC3. I am uncertain about how personal information is shared or stored.	10.9	21.5	25.3	23.1	19.2	3.2	1.3
PRC4. Highly precise recommendations sometimes feel intrusive.	11.5	20.2	27.6	24.7	16.0	3.1	1.2

Scale: 1 = Strongly disagree to 5 = Strongly agree.

The mean for the item responses of the privacy concern is 3.16 with a standard deviation of 1.09. There is agreement and disagreement in the distribution, which provides enough variation for testing relationships. The 4 item are tied together in a coherent direction, and the 4 items are retained as a composite measure.

Table 5. Item-Wise Analysis of Perceived Value

Item	**SD %**	**D %**	**N %**	**A %**	**SA %**	**Mean**	**SD**
PV1. AI-based personalisation makes online shopping more useful.	8.0	16.0	29.8	22.8	23.4	3.4	1.2
PV2. Personalised recommendations save time and effort.	8.0	18.6	23.1	23.7	26.6	3.4	1.3
PV3. The benefits of personalisation outweigh the effort or data required.	8.7	17.0	23.7	27.6	23.1	3.4	1.2
PV4. AI features improve the overall value received from the platform.	7.7	19.2	24.0	27.6	21.5	3.4	1.2

Scale: 1 = Strongly disagree to 5 = Strongly agree.

Construct mean for item responses (perceived value) is 3.39 and standard deviation is 1.08. There are both congruencies and incongruencies included in the distribution, and enough difference to test relationships. The four items have a smooth flow and are combined into a composite measure.

Table 6. Item-Wise Analysis of Consumer Trust

Item	SD %	D %	N %	A %	SA %	Mean	SD
CT1. I trust the platform to use AI recommendations responsibly.	9.6	17.0	28.8	26.3	18.3	3.3	1.2
CT2. I believe the platform protects information used for personalisation.	10.6	18.6	26.6	24.4	19.9	3.2	1.3
CT3. I can rely on AI-supported suggestions from the platform.	11.2	20.2	23.1	26.0	19.6	3.2	1.3
CT4. The platform is transparent enough for me to trust its personalised services.	8.3	21.2	24.4	25.3	20.8	3.3	1.2

Scale: 1 = Strongly disagree to 5 = Strongly agree.

Construct means and standard deviations for the item responses of the consumers' trust scale are 3.26 and 1.07, respectively. There is an acceptable degree of agreement and disagreement, which provides adequate variation for testing relationships. These 4 items are linked in a consistent direction, and are kept as a composite measure.

Table 7. Item-Wise Analysis of Customer Loyalty

Item	SD %	D %	N %	A %	SA %	Mean	SD
CL1. I intend to continue purchasing from this platform.	8.7	19.9	26.0	23.7	21.8	3.3	1.2

CL2. I would choose this platform over similar alternatives.	10.6	20.8	21.5	23.1	24.0	3.3	1.3
CL3. I would recommend the platform to other shoppers.	12.8	17.6	26.0	22.1	21.5	3.2	1.3
CL4. Useful and trustworthy personalisation increases my attachment to the platform.	10.3	17.3	26.3	29.5	16.7	3.2	1.2

Scale: 1 = Strongly disagree to 5 = Strongly agree.

The mean for the item responses for Customer Loyalty is 3.27, with a standard deviation of 1.10. There is enough variation within the distribution for testing relationship, including areas of agreement and disagreement. The four items are coherent and are kept as a composite measure.

Table 8. Overall Construct Comparison and Reliability

Construct	**Items**	**Cronbach α**	**Mean**	**SD**	**Level**
Personalisation Quality	4	0.871	3.31	1.04	Moderate
Recommendation Relevance	4	0.878	3.29	1.07	Moderate
Privacy Concern	4	0.883	3.16	1.09	Moderate
Perceived Value	4	0.892	3.39	1.08	Moderate

Consumer Trust	4	0.877	3.26	1.07	Moderate
Customer Loyalty	4	0.880	3.27	1.10	Moderate

Interpretation: 1.00-2.33 = low, 2.34-3.66 = moderate, and 3.67-5.00 = high.

The reliability of all six scales is above the conventional 0.70 standard. The highest mean score is for perceived value, followed by personalisation quality and recommendation relevance. Even so, privacy concern is just above the scale midpoint, indicating that usefulness of AI is valued, but there is some concern about data usage. Trust and loyalty are still moderately positive, as in a model that assumes that both value and privacy contribute to the outcomes of relationships.

4.3 Correlation and Hypothesis Testing

Table 9. Pearson Correlation Matrix

Construct	**1**	**2**	**3**	**4**	**5**	**6**
Personalisation Quality	1.000	—	—	—	—	—
Recommendation Relevance	0.377	1.000	—	—	—	—
Privacy Concern	0.016	-0.003	1.000	—	—	—
Perceived Value	0.495	0.536	0.041	1.000	—	—
Consumer Trust	0.419	0.315	-0.226	0.555	1.000	—
Customer Loyalty	0.355	0.333	-0.095	0.504	0.640	1.000

Construct order: 1 = personalisation quality, 2 = recommendation relevance, 3 = privacy concern, 4 = perceived value, 5 = consumer trust, 6 = customer loyalty. The negative privacy-trust relationship and positive value relationships are significant at p < .01.

Table 10. Regression-Based Hypothesis Test Results

Hyp.	Relationship	Std. β	t	p	Model R^2	Decision
H1	Personalisation Quality → Perceived value	0.341	7.092	<.001	0.387	Supported
H2	Recommendation Relevance → Perceived value	0.408	8.481	<.001	0.387	Supported
H3	Privacy Concern → Consumer trust	-0.249	-5.517	<.001	0.370	Supported
H4	Perceived Value → Consumer trust	0.566	12.520	<.001	0.370	Supported
H5	Consumer trust → Customer loyalty	0.640	14.676	<.001	0.410	Supported

For hypotheses estimated in the same multiple-regression equation, the common model R^2 is reported. Statistical significance criterion: p < .05.

The standardised effect of personalisation quality on the perceived value is 18.3%, that of recommendation relevance is 38.7%. The variance in consumer trust is 37.0%, and both privacy concern and perceived value contribute to consumer trust, with privacy concern being negative and perceived value being positive. The variance of customer loyalty is accounted for by consumer trust (41.0%). All 5 hypotheses are confirmed.

5. Discussion

The findings are in line with the integrated value-trust-loyalty model. The effects of personalisation quality and relevance of recommendations on perceived value were both positive and significant. Consumer trust was significantly impacted by privacy concern, while perceived value was significantly impacted by it. Consumer trust thus played a significant positive role in customer loyalty. The results show that the commercial results of AI-based personalisation are only sustainable, if the consumer is given useful support and fully believes in the platform's behavior. This aligns with the experiential view of Puntoni et al. (2021) and the customer-experience model of Ameen et al. (2021), both of which highlight that usefulness, emotion, agency and relationship cues are the primary factors that determine the evaluation of AI and not only technical performance.

The strongest effect was on perceived value with recommendation relevance. It suggests that consumers consider the usefulness of the recommended content as a key measure of the effectiveness of AI personalisation. When the recommendations that the system makes are repetitive, inappropriate, or unrelated to the consumers' needs, there is little value in having a sophisticated system if the consumer does not use it. The relevant recommendations help to cut down on search effort, aid in finding products, and can help make comparison easier. The study is congruent to the description of the importance of effective e-commerce recommender systems by Necula and Păvăloaia (2023) and to the demonstration that perceptions of a recommender's ability to learn improves its responses by Trzebiński et al. (2023). It also aligns with the technology-acceptance evidence brought by Hossain and Biswas (2024) which showed that the usefulness (utility) is central in AI-enabled shopping. Managers therefore optimize the quality of the recommendations, based on outcome measures that go beyond click-throughs to saved search time, diversity, fit and consumer satisfaction.

Additionally, the perceived value also significantly increased due to the personalisation quality. The outcome indicates that consumers make a general impression based on several points of contact: the homepage, product ranking, notification, offers and customer service. If these reflect preferences on a regular basis, the platform seems competent and attentive. According to Hoyer et al., (2020), technology influences the whole customer journey, and in Gao et al., (2022), the impact of AI stimuli on smart customer experience is demonstrated. Lopes et al. (2025) also found that ease of browsing is linked to favourable perceptions and engagement. This capability therefore be treated as a journey level capability, representing the quality of personalisation. While a truly relevant product suggestion may help offset intrusive messages, price discrepancies, or a chatbot that selectively retains information, it's not enough.

The personalisation-privacy paradox was confirmed as privacy concern negatively impacted on consumer trust. Consumers can appreciate customized suggestions, but also be concerned about data gathering and covert profiling. The findings are consistent with those of Chen and Sun (2022), who explain that both personalisation and privacy reactance are required when personalising details in a privacy policy, and those of Zeng et al. (2022), which indicate that framing of privacy policies influences concern. Kronemann et al. (2023) also cite, as a reason for the need for ethical boundaries, that personalisation and human-like AI can promote disclosure. E-commerce companies give clear preference controls, brief explanations of why a product is suggested, as well as simple choices to remove or limit data. When personalized is seen as the choice and control of the individual, trust is more likely to be observed.

Perceived value was found to have a positive impact on trust. This relationship shows that if the platform is being used in a useful manner over and over again, then proof of platform competence is being established. Consumers are more likely to trust the AI system when it saves time, finds their desired products, and enhances decision-making quality. Cheng and Jiang (2022) and Lee et al. (2022) indicate that AI chatbot initiatives can aid in brand relationships while Bergner et al.

(2023) indicate that conversational embodiment influences consumer-brand response. The present findings take this logic one step further, to a single interface, in that value developed throughout the personalised journey can be a relational trust signal. But usefulness not be an excuse for opaque data practices. Both the positive value effect and negative privacy effect are in place and firms must enhance both their service quality and governance.

Consumers' trust was the leading predictor of loyalty. This aligns with Maduku et al. (2024), who link emotions, engagement, and loyalty to AI assistants; and Huh et al. (2023), who demonstrate the positive effects of AI experiences on brand loyalty. Furthermore, trust and perceived relational closeness have been shown to be important factors in anthropomorphic AI interactions by Jham et al. (2023) and Youn and Jin (2021). The personalisation intensity can't be the sole factor of loyalty. In general, consumers can keep relying on a platform if they've confidence in its recommendations, reliability of transactions, and responsibility for personal information. Therefore, transparent AI governance be viewed as a customer retention capability, and not just a compliance task.

6. Conclusion

This study explored the role of AI-based personalisation in the context of perceived value, consumer trust, and customer loyalty within the Indian E-commerce landscape. Recommendation usefulness was positively increased by the quality of personalisation (as well as the relevance of the recommendations), and the positive effect was larger for the latter. Consumer trust increased when consumers felt they had value and decreased when they felt they were concerned about their privacy. The high level of trust led to greater customer loyalty. The results indicate that AI personalisation can provide a commercial benefit if it makes the shopping journey more relatable and effective for the customer but doesn't feel like surveillance or top-down. For e-commerce managers, the results provide accurate and diverse recommendations, personalisation that is uniform across touchpoints, explanations, visibility of privacy controls, secure data practices and an easy way for consumers to turn off or modify personalisation. Loyalty measures read in conjunction with trust and privacy measures since high click can mask low trust or discomfort in the long run. A longitudinal test of the framework with real users of platforms is needed, as are tests using behavioural clickstream data, as well as a comparison of the effectiveness of the different types of explanations and sub-group analyses according to age, digital literacy, privacy orientation and shopping frequency.

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