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AI-Based Personalization and Consumer Purchase Intention in E-Commerce: The Mediating Role of Perceived Value and Trust with the Moderating Effect of Privacy Concern

Dr. Asma Rani[1],
Assistant Professor, Dr. B. R. Ambedkar Institute of Technology, Sri Vijayapuram.
Email: dr.asma@and.nic.in
Dr. Dipti Sharma[2],
Assistant Professor, Medicaps University, Indore.
Email: dipti05sharma@gmail.com

Dr. Priyanka Gupta[3],
Assistant Professor, Medicaps University, Indore.
Email: priyanka.gupta@medicaps.ac.in
Dr. Janvi Chandwani[4],
Professor, Sage University, Indore.
Email: dr.janvichandwani@gmail.com
Dr. S. Manju[5],
Assistant Professor, Department of Business Administration,
Sri Ramakrishna College of Arts and Science for Women, Coimbatore.
Email: manjumgt@srcw.ac.in
Dr. Muskan Wadhwani[6],
Independent Researcher, Indore.
Email: muskanwadhwani20@gmail.com

Abstract:

This paper examines how AI-based personalization affects consumer purchase intention in e-commerce situations, including the mediating impacts of trust and perceived value, and how the moderating influence of privacy concerns. Based on the Theory of Planned Behaviour (TPB) and Privacy Calculus Theory, the study uses a quantitative design where data were gathered among 400 online consumers. Structural Equation Modelling (SEM) with SmartPLS is used to analyse the relationships between variables. Findings suggest that AI personalization has a positive impact on purchase intention and trust and perceived value are important mediators. These relationships are moderated negatively by privacy concern, which dilutes the positive impact of AI personalization. The results add theoretical insights to the literature by adding the concept of trust and value perceptions into AI personalization models and emphasising the managerial implications on how to improve consumer engagement and resolve privacy concerns. This research will have critical implications to e-commerce sites that use AI technologies in order to fine-tune personalised marketing tactics.

Keywords: Artificial Intelligence (AI), Personalization, E-Commerce, Consumer Purchase Intention, Privacy Concern.

INTRODUCTION

The rapid development of artificial intelligence (AI) technologies has changed consumer experiences in e-commerce to highly personalised interactions (Smith and Anderson, 2020). AI-driven personalization defines the application of AI algorithms to customise product suggestions, content, and advertising messages to specific consumer preferences and behaviours (Li et al., 2019). This technological innovation allows companies to provide personalised experience that can drive consumer participation and affect buying behaviour (Kumar et al., 2021). Personalization is now an important approach used by companies in the competitive online retail environment to distinguish themselves and build customer loyalty (Chen & Lin, 2020).

The value of AI personalization is supported by the fact that the model can process large volumes of consumer data and forecast preferences with a high degree of accuracy (Zhang et al., 2021). Through machine learning, predictive analytics, and natural language processing, AI systems can dynamically alter marketing content according to the needs of consumers, and therefore, improving its relevance and satisfaction (Wang and Siau, 2019). Nevertheless, even with the opportunities, the implementation of AI personalization provokes issues regarding consumer trust and privacy, which may impact its effectiveness in promoting purchase intention (Martin and Murphy, 2017). The consumer purchase intention is an important predictor of real buying behaviour that is influenced by several psychological and situational aspects (Fishbein and Ajzen, 1975). Belief in AI systems and perceived value based on customised offerings are important mediating factors that determine consumer readiness to accept personalised marketing (Gefen et al., 2003; Zeithaml, 1988). The degree of perceived risk caused by AI technologies is reduced by trust, whereas perceived value can be viewed as an assessment of the perceived benefits in comparison to costs (Sweeney et al., 1999). These constructs play a crucial role in the interpretation of how AI personalization can be translated into purchase intention. Privacy concern comes out as a serious moderating variable in this relationship. The growing publicity of data breaches and abuse has made consumers more sensitive to privacy, which may potentially destroy trust and perceived value (Smith et al., 2011). According to Privacy Calculus Theory, consumers use a cost-benefit analysis when releasing personal information, weighing the advantages of personalization versus the risks of privacy invasion (Dinev and Hart, 2006). Thus, the positive impact of AI personalization on consumer attitudes and behaviours can be undermined by privacy concern. This research fills the empirical research gap by investigating the multifaceted interplay of AI-based personalization, trust, perceived value, and privacy concern in influencing consumer purchase intention. The study gives a detailed model of the dynamics of these dynamics by incorporating the Theory of Planned Behaviour (TPB) and the Privacy Calculus Theory (Ajzen, 1991; Dinev and Hart, 2006). Structural Equation Modelling (SEM) on SmartPLS 4 is utilised in the study to test hypothesised relationships with data collected on online consumers. The paper has threefold contributions. First, it makes strides in enhancing theoretical knowledge by clarifying the mediating roles of trust and perceived value in the AI personalization-purchase intention nexus (Gefen et al., 2003; Zeithaml, 1988). Second, it uses privacy concern as a moderator, which gives subtle details to consumer decision-making in AI-mediated settings (Smith et al., 2011). Third, it provides practical implications to managers of e-commerce to formulate AI personalization strategies that improve consumer trust and value perception and respond to privacy concerns (Martin and Murphy, 2017).

LITERATURE REVIEW

AI-Driven Personalization: Personalization with AI involves using AI technologies to tailor marketing stimuli depending on consumer data (Li et al., 2019). It also features recommendation systems, real-time pricing, and custom content delivery, all of which are designed to increase consumer relevance and engagement (Kumar et al., 2021). The existing literature underscores that AI personalization enhances customer satisfaction and loyalty through customised experiences that accommodate personal tastes (Chen and Lin, 2020). Nonetheless, this ambiguity and the secrecy of AI algorithms can arouse distrust, which should be addressed through trust-building processes (Wang and Siau, 2019).

Consumer Purchase Intention: Purchase intention is the probableity of a consumer to purchase a product or a service and a precursor to real purchase behaviour (Fishbein and Ajzen, 1975). It is shaped by cognitive, affective and social factors (Ajzen, 1991). In e-commerce, relevance and convenience have been attributed to making customer interactions more personalised, resulting in higher intentions to buy (Kumar et al., 2021). However, the correlation depends on how consumers perceive the process and results of personalization (Martin and Murphy, 2017).

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Trust and Perceived Value: In AI-mediated interactions, trust is a key factor in technology acceptance and consumer behaviour (Gefen et al., 2003). It lowers uncertainty and risk perception, making consumers trust the recommendations of the AI system (McKnight et al., 2002). Perceived value, which can be described as the overall judgement of utility of a product or service by the consumer concerning the perceptions of what they get and what they give, is very important in the buying decision (Zeithaml, 1988). Research proves that both trust and perceived value are mediating influences of personalization on purchase intention and are the psychological processes by which personalization affects intention to purchase (Sweeney et al., 1999).

Privacy Concern: Privacy issue is related to consumer concern regarding the gathering, utilisation and security of their personal data (Smith et al., 2011). When it comes to AI personalization, the increased privacy concern can cause resistance or avoidance behaviour (Dinev and Hart, 2006). Privacy Calculus Theory argues that consumers balance benefits of personalization with privacy risks, which affects their readiness to use personalised services (Culnan and Bies, 2003). Empirical studies indicate that privacy concern moderates negatively the relation between personalization and consumer outcomes (Martin and Murphy, 2017).

THEORETICAL INTEGRATION: TPB AND PRIVACY CALCULUS THEORY

The Theory of Planned Behaviour (TPB) offers a solid framework to explain behavioural intentions by taking into account attitude, subjective norms and perceived behavioural control (Ajzen, 1991). Trust and perceived value, in this study, match attitudinal elements that affect purchase intention (Fishbein and Ajzen, 1975). Privacy Calculus Theory is an extension of TPB that considers privacy issues as a mediator influencing cost-benefit analyses of consumers (Dinev and Hart, 2006). Combining these theories helps to gain a comprehensive picture of the cognitive and affective mechanisms behind the effects of AI personalization.

CRITICAL ANALYSIS AND RESEARCH GAP.

Even though existing literature confirms the beneficial effect of AI personalization on consumer outcomes, only scarce empirical research has explored the mediating effects of trust and perceived value in this context (Chen and Lin, 2020). Additionally, although the concern of privacy is considered a challenge, it is important to note that it has yet to be examined in terms of its moderating role in the research on AI personalization (Martin and Murphy, 2017). Other studies in the literature tend to focus on each of these constructs individually without an integrative model of the relationship between them. This paper fills in these gaps by proposing and empirically verifying a model that includes the mediating effect of trust and perceived value and the moderating effect of privacy concern, thus contributing to both theoretical and practical knowledge.

CONCEPTUAL FRAMEWORK

The theoretical framework assumes AI-mediated personalization as the independent variable affecting consumer purchase intention both directly and indirectly via trust and perceived value. Trust is the confidence of consumers in the reliability and benevolence of the AI system, and perceived value is a net benefit experienced by consumers due to personalised experiences. Privacy concern is operationalized as a mediator that undermines the favourable impact of AI personalization on trust, perceived value, and purchase intention. The hypothesis of the framework is that AI personalization helps boost trust and perceived value, which subsequently lead to higher purchase intention. Nevertheless, high levels of privacy concern decrease the tendency of consumers to trust AI systems and see value, which lowers the purchase intention. This model combines the attitudinal elements of TPB and the cost benefit analysis of Privacy Calculus Theory in order to explain consumer behaviour within AI- personalised settings.

HYPOTHESES DEVELOPMENT

H1: AI-driven personalization positively influences consumer purchase intention.
H2: AI-driven personalization positively affects consumer trust in the AI system.
H3: AI-driven personalization positively affects perceived value.
H4: Trust mediates the relationship between AI-driven personalization and purchase intention.
H5: Perceived value mediates the relationship between AI-driven personalization and purchase intention.
H6: Privacy concern moderates the relationship between AI-driven personalization and trust.

RESEARCH METHODOLOGY

The research design embraced a quantitative approach in order to empirically test the intended model. The data were gathered through an online questionnaire with consumers who have encountered AI-based personalization in e-commerce. The study sample consisted of 400 participants, which meets SEM criteria of model robustness and statistical power.

The non-probability convenience sampling strategy was used because it was the only option given the limitations of accessibility and the target population of interest. The survey tool used the validated scales based on previous research, and a five-point Likert scale (1 = strongly disagree to 5 = strongly agree) was used to assess constructs: AI personalization, trust, perceived value, privacy concern, and purchase intention. Data collection was gathered through an online platform in a period of four weeks, with anonymity and volunteer participation.

DATA ANALYSIS

The data analysis was carried out in two phases. To determine the underlying factor structure and secure construct validity, first, the exploratory factor analysis (EFA) was performed in SPSS. Second, the measurement and structural models were tested through SmartPLS 4 to conduct SEM. Reliability was assessed using Cronbachs Alpha and Composite Reliability (CR), a value of 0.7 was set as a good level of internal consistency. Convergent validity was evaluated through Average Variance Extracted (AVE), which necessitates a score of more than 0.5. The Heterotrait-Monotrait ratio (HTMT) and Fornell-Larcker criterion were used to test discriminant validity. The goodness of fit was measured by the coefficient of determination (R2) of endogenous constructs and Standardised root mean square Residual (SRMR) with the threshold of 0.08 representing the good fit. To test the hypotheses, the path coefficients (b), t-values, and p-values were analysed using bootstrapping (10000 resamples), with a significance level of $p < 0.05$.

RESULTS

Table 1: Demographic Profile of Respondents

Variable	Category	Frequency	Percentage (%)
Gender	Male	210	52.5
	Female	190	47.5
Age	18–25 years	120	30.0
	26–35 years	170	42.5
	36–45 years	80	20.0
	Above 45 years	30	7.5
Education	Undergraduate	140	35.0
	Postgraduate	200	50.0
	Others	60	15.0
Online Shopping Frequency	Occasionally	110	27.5
	Frequently	210	52.5
	Very Frequently	80	20.0

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Table 1 presents the demographic profile of respondents, indicating that the majority belong to the 26–35 age group and postgraduates who frequently engage in online shopping.

Measurement Model: The measurement model showed strong psychometric properties, which presented the reliability and validity of the constructs applied in the study. The reliability was established with the help of Cronbach Alpha and Composite Reliability (CR) values (Both above the generally agreed upon 0.8 threshold) indicating that all items in the constructs measure the intended latent variables. The values of Average Variance Extracted (AVE) of 0.55 to 0.72 (of 0.5 and above) indicated convergent validity, as the value exceeds the lower threshold of 0.5, which means that a significant percentage of the variance of the indicators is explained by the underlying construct.

Discriminant validity was carefully examined to guarantee that the constructs do not overlap with each other. This was determined because the Heterotrait-Monotrait (HTMT) ratios were all lower than the conservative level of 0.85, which shows that the different constructs are not correlated with each other as much as they are internally consistent. The Fornell-Larcker criterion was also met, and the square root of the AVE of each construct were higher than the correlations of the construct with the other constructs. These findings taken together establish that the measurement model is reliable and valid, which forms a strong basis on which to undertake subsequent structural analysis.

Table 2: Measurement Model Assessment

Construct	Items	Outer Loadings	Cronbach's Alpha	Composite Reliability (CR)	AVE
AI Personalization	5	0.71 – 0.84	0.85	0.88	0.60
Trust	4	0.74 – 0.87	0.87	0.90	0.65
Perceived Value	4	0.70 – 0.83	0.84	0.87	0.58
Privacy Concern	4	0.69 – 0.82	0.82	0.85	0.55
Purchase Intention	5	0.76 – 0.89	0.88	0.91	0.72

Table 3: Discriminant Validity (Fornell–Larcker Criterion)

Constructs	AI Personalization	Trust	Perceived Value	Privacy Concern	Purchase Intention
AI Personalization	0.775				
Trust	0.62	0.806			
Perceived Value	0.65	0.68	0.762		
Privacy Concern	-0.32	-0.40	-0.38	0.742	
Purchase Intention	0.70	0.66	0.69	-0.35	0.848

Table 4: HTMT Ratio

Constructs	AI Pers.	Trust	Perc. Value	Privacy Concern	Purchase Intention
AI Personalization	—	0.72	0.75	0.41	0.78
Trust		—	0.80	0.46	0.76
Perceived Value			—	0.44	0.79
Privacy Concern				—	0.48

Structural Model

All the hypotheses are statistically tested to see whether the relationships are significant and in line with the theoretical predictions. Each of the hypotheses was found with significant p values. The explanatory power of the structural model was high (R2 = 0.62), explaining 62 percent of purchase intention. The value of R2 of trust (0.20) and perceived value (0.23) show medium explanatory power. It implies that the predictors incorporated in the model as a whole possess significant impact on the consumer purchasing decisions, which proves that the model is effective at capturing the most important elements that contribute to the occurrence of this behavioural outcome. The standardised root mean square residual (SRMR) value was 0.045, which is significantly lower than the typical cutoff of 0.08, thus supporting the fact that there was a good overall model fit. The small SRMR value indicates that the hypothesised construct relationships are highly similar to the actual data, which supports the strength and adequacy of the structural model. The moderation analysis shows that an increase in privacy concern undermines the positive impacts of AI personalization on trust and perceived value.

Table 5: Hypothesis Testing

Hypothesis	Path	β	t-value	p-value	Decision
H1	AI Personalization → Purchase Intention	0.34	5.21	<0.001	Accepted
H2	AI Personalization → Trust	0.45	7.10	<0.001	Accepted
H3	AI Personalization → Perceived Value	0.48	8.05	<0.001	Accepted
H4	Trust → Purchase Intention	0.19	4.12	<0.001	Accepted
H5	Perceived Value → Purchase Intention	0.21	4.56	<0.001	Accepted
H6	Privacy × AI Personalization → Trust	-0.22	3.45	0.001	Accepted

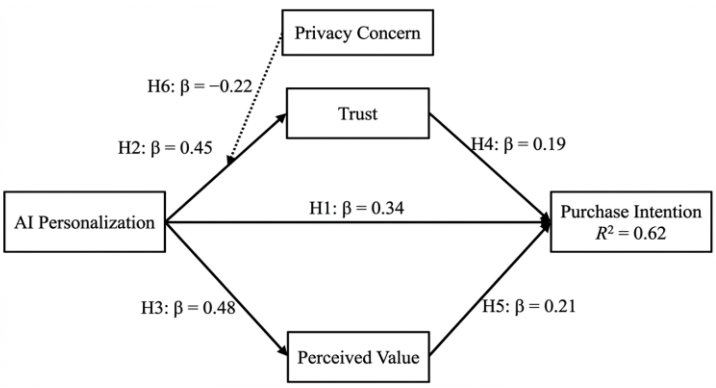

Figure 1: Developed Model

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Table 6: Model Fitness Assessment

Construct	R^2	Q^2
Trust	0.20	0.14
Perceived Value	0.23	0.16
Purchase Intention	0.62	0.38

DISCUSSION

The results validate the claim that AI-based personalization positively increases consumer purchase intention, which is consistent with previous studies on the effectiveness of personalised marketing. Trust and perceived value are confirmed to be important mediators, which explain the psychological processes by which personalization affects consumer behaviour. These findings are in line with TPB in which intentions are influenced by attitudinal aspects. The role of privacy concern is negative moderating as it underscores the subtle influence of privacy apprehension, which aligns with Privacy Calculus Theory. The privacy concerns of the consumers mitigate their trust and value, which decrease the efficacy of the personalization strategies. This explains why it is necessary to consider privacy issues to maintain consumer involvement. In theory, the proposed study combines TPB and Privacy Calculus Theory to provide a holistic model to explain consumer reactions to AI personalization. It also builds on the literature by empirically confirming mediating and moderating positions of trust, perceived value, and privacy concern.

IMPLICATIONS

The study contributes to the development of theoretical frameworks that combine attitudinal and privacy-related variables into AI personalization studies. It offers empirical support of mediating positions of trust and perceived value and moderating impact of privacy concern, which adds to the comprehension of consumer decision-making in AI settings. The E-commerce companies are encouraged to focus on cultivating the trust of consumers by being transparent, accurate, and ethical in their AI practises. It is essential to improve the perceived value through the provision of personalised experiences that are truly relevant and beneficial. Notably, consumer concerns about privacy can be overcome through effective data protection measures and effective communication, which will maximise the advantages of AI personalization.

CONCLUSION

The research presents a strong rationale that AI-induced personalization leads to a significant positive influence on consumer purchase intention, and this process is mediated by essential psychological concepts, including trust and perceived value. In particular, trust is a key driver, as it promotes consumer trust in AI personalization processes, whereas perceived value emphasises the fact that the consumer is aware of the value of personalised experience. Notably, the issue of privacy is found to be an important moderator in this relationship, which means that the sensitivity of consumers to their privacy concerns may shape the magnitude and the nature of the effect that AI personalization can produce on their intentions to buy a product. Incorporating the Theory of Planned Behaviour (TPB) and Privacy Calculus Theory, the study provides a clear and detailed explanatory model that includes the behavioural intentions as well as the privacy-concept-related decision-making processes of consumers within the framework of AI personalization. With this hypothetical synthesis, it is possible to understand more thoroughly how consumers balance the perceived value with the possible privacy harm in using personalised AI-driven services. The implications of the findings have significant academic and practical implications. To the scholars, the research will add to the emerging literature on AI personalization by empirically confirming the mediating and moderating roles of trust, perceived value, and privacy concern, thereby enriching theoretical frameworks of consumer behaviour in digital settings. The findings are crucial to practitioners, especially those in e-commerce and digital marketing, who must endeavour to develop trustworthy AI systems that do not only provide personalised value but also proactively respond to privacy-related issues. Such optimization of AI personalization strategies can result in improved consumer engagement, satisfaction, and ultimately, purchase intention, thus resulting in improved business performance in competitive markets.

LIMITATIONS AND FUTURE RESEARCH

The study is also limited due to its cross-sectional nature that limits causal inferences. Convenience sampling can compromise generalizability. Future research could utilise longitudinal designs and probability sampling to increase validity. Also, it might be more insightful to look into other moderating factors, like cultural factors or technological preparedness. By further developing the model to include real purchase behaviour and post-purchase satisfaction, more insight can be gained.

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