

THE IMPACT OF ARTIFICIAL INTELLIGENCE ON GENERATION Z'S ONLINE FASHION PURCHASE INTENTIONS

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Abstract

This study examines how Artificial Intelligence affects consumer buying intentions in the online fashion industry. The main objective of this study is to understand how AI-related factors impact attitudes toward using AI and decisions when buying fashion products online. The study expanded the Technology Acceptance Model (TAM) by adding two key elements: AI-driven Personalization and Trust in AI. This additional focus helps investigate the buying intentions of Gen Z in relation to online fashion. A quantitative approach was taken, using a cross-sectional research design. Data collected from consumers who had recently purchased fashion products through online. The analysis employed Partial Least Squares Structural Equation Modelling (PLS-SEM) using Smart PLS 4 software. The results indicate that AI-driven personalization, perceived ease of use, perceived usefulness, and trust in AI all significantly affected consumers' attitudes toward AI and influenced their buying intentions. Among these variables, Trust in AI had the strongest direct and indirect effect on buying intentions. The study also showed that attitude plays a partial mediating role between AI factors and purchase decisions. The findings suggest that AI technologies should be personalized, easy to use, beneficial, and trustworthy to positively influence online shopping behaviour. This research is important for online fashion retailers as it offers practical advice to improve AI systems for better consumer engagement and greater purchasing intentions. Overall, the study provides valuable insights by expanding the TAM model and demonstrating how AI can shape modern consumer behaviour in digital retail environments.

Keywords: Artificial Intelligence, Purchase Intention, TAM, Fashion, Attitude.

INTRODUCTION

The rapid growth in digital technologies witnessed significant changes in the digital retail environment, especially in the fashion industry. Digital technologies are quickly changing the online fashion retail, especially through the use of artificial intelligence. AI also changing how consumers interact with e-commerce fashion platforms. Among these consumers, Generation Z (Gen Z) are digital natives who born between 1997 and 2012 (Liu et al., 2023) emerge as a highly influential segment. These young consumers are comfortable with technology and expecting features like personalization, honesty, and smooth digital experiences (Francis & Hoefel, 2018; Kavitha & Joshith, 2024). In fashion e commerce, AI technologies like personalized recommendation systems, chat bot enabled customer care, and visual search capabilities are being utilized to provide extremely engaging shopping experiences (Kumar et al., 2024; Zhang & Liu, 2024). While such personalization provides enhanced value, it also creates transparency and data privacy issues that are especially relevant for Gen Z consumers (Ding et al., 2024; Ionescu, 2024). AI also supports Gen Z's need for fast, creative, and unique shopping experiences (Kumar et al., 2024). As online fashion shopping becomes more intelligent and enjoyable, it is important to study what factors influence Gen Z's buying decisions in the digital fashion market.

This study used the Technology Acceptance Model (TAM), developed by (Davis, 1989), for investigating buying intention of Gen Z online fashion consumers. TAM constructs that are, Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) are not sufficient to explain all of the changes created by AI. However, the increasing dependence on AI has also created consumer trust and data privacy concerns that affect online consumer purchasing decisions (Cvetkovic et al., 2025). Trust in AI is a critical factor influencing consumer adoption

(Thiebes et al., 2021). Data privacy concerns and transparency continue to make it more difficult for acceptance of AI (Guerra-Tamez et al., 2024). On the other hand, personalization using AI can understand consumer choices and can improve satisfaction and engagement (Ding et al., 2024; Ranjan & Upadhyay, 2025). While recent studies have extended the Technology Acceptance Model (TAM) to include factors such as perceived usefulness, ease of use, and trust in the context of AI adoption in retail (Hossain & Biswas, 2024; Ibrahim et al., 2024), few have examined how trust and personalization that is the two AI-specific constructs, that can be jointly integrated into TAM to better explain online fashion consumers' purchase intentions. This study aims to investigating how trust in AI and personalization influence Gen Z online fashion consumers' buying intentions within an extended TAM framework. This study proposed a model that integrates all these factors to provide a comprehensive understanding of AI's role in shaping consumer buying intention (Kim, 2025; Liu et al., 2023; Lopes et al., 2024).

LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

Previous research consists with the gap of integrating AI trust and personalization as independent variables within the TAM framework in the context of online fashion shopping. So it is essential to construct comprehensive models that simultaneously assess these AI-specific constructs alongside traditional TAM components (PU, PEOU). There is also exists geographical gap for this study particularly in a culturally and economically heterogeneous country like India.

The Technology Acceptance Model (TAM), introduced by Davis (1989), explains technology adoption based on perceived usefulness (PU) and perceived ease of use (PEOU). In the context of AI-enabled e-commerce, various research has studied variables such as trust, personalization, and interactivity to find more accurate adoption behaviour (Massoudi et al., 2024).

(Ibrahim et al., 2024) analysed TAM in AI contexts and emphasized that consumer types (early adopters vs. laggards) significantly moderate AI adoption behaviour. Their study underlined the need for contextualized TAM frameworks, particularly when user groups are technology-savvy, such as Gen Z.

Perceived Usefulness (PU) is the extent to which a person thinks that using AI will improve their shopping performance (Choi et al., 2023; Davis, 1989). AI-driven features like personalized recommendations, virtual try-ons, and smart sizing tools significantly enhance PU by making decision-making easier and increasing purchase accuracy (Pookulangara et al., 2021). (Yeo et al., 2022) found that AI tools positively affect purchase decision by providing relevant product recommendations. (Hossain & Biswas, 2024) showed how AI-driven shopping sites in Bangladesh improve PU by simplifying product searches. Consumer attitudes vary based on the accuracy and relevance of AI (Liu et al., 2023). (Manida, 2025) investigated how important PU is in influencing consumer behaviour, particularly on digital platforms where AI integration can enhance shopping experiences. (Ibrahim et al., 2024) discussed how PU continues to be a key factor in user adoption and positive attitudes, especially when AI is seen as leading to meaningful results. This implies there is a positive connection between PU and consumer attitudes in AI-driven settings.

H₁: Perceived Usefulness (PU) positively influences consumers' attitude.

Perceived ease of use refers to how effortlessly consumers interact with AI tools. (Chie et al., 2024) found that user-friendly AI interfaces, such as chatbots and voice assistants, enhance adoption. (Pookulangara et al., 2021) studied how AI-powered sizing technologies make fitting easier, which improves perceived ease of use. However, complicated AI features may discourage users who are not very tech-savvy (Ibrahim et al., 2024). (Jeong & Roh, 2016) expanded the Technology Acceptance Model (TAM) to include smart fashion products. They confirmed that ease of use encourages adoption. Recent research shows that having an intuitive AI design is essential for Gen Z and Millennial shoppers (Ruiz-Viñals et al., 2024). (Martínez Puertas et al., 2024) found that how easily users can interact with AI systems affects their attitudes. This supports TAM's relevance in AI contexts. (Liébana-Cabanillas et al., 2018) observed that simplicity and seamless user experience booster positive attitude towards digital payment systems.

H₂: Perceived Ease of Use (PEOU) positively influences consumers' attitude.

Trust in AI refers to confidence that consumers' have regarding reliability, fairness, and secured data usage of AI applications (Hossain & Biswas, 2024; Thiebes et al., 2021). (Sadiq et al., 2025) found that AI-driven social commerce adoption depends on perceived trust. (Chie et al., 2024) emphasized that secure AI interactions strengthen trust in e-commerce platforms. Technology Acceptance Model (TAM) and its extensions have consistently found trust as a prerequisite for the development of positive attitudes. Trust enhances perceived usefulness and ease of use, thus influencing users' attitudes toward AI applications (Fiftem et al., 2025). In fashion e-commerce, AI trust in technology enhances consumer comfort and acceptance, resulting in a positive attitude toward the technology (Alkudah & Sciences, 2024; Yeo et al., 2022).

H₃: Consumer Trust in AI positively influences consumers' attitude.

(Kim, 2025) identified that when customers are satisfied that AI systems are competent and safe, they will buy. When customers perceive AI technologies as trustworthy, they will be positively inclined toward the technologies and thus become predisposed to use the tools easily in online buying scenarios (Fiftem et al., 2025; Yeo et al., 2022).

H₄: Consumer Trust in AI positively influences consumers' Buying Intentions.

AI-driven personalization means how much people believe AI technology can tailor experiences to fit their individual needs and preferences (Sharma & Sharma, 2024). This includes showing product suggestions, offers, or services based on each person's likes, needs, and behaviour. AI achieve this by studying data such as what users have searched for, bought before, and their basic details. This helps create more relevant and useful interactions, which can make customers feel more satisfied and engaged (Alkudah & Sciences, 2024; Ding et al., 2024; Yeo et al., 2022).

In fashion e-commerce, AI personalization tools like product recommendation systems, chatbots, and virtual try-on options help improve the overall shopping experience. These features not only make the platforms more useful but also shape how consumers feel about them and whether they decide to make a purchase (Hossain & Biswas, 2024; Li et al., 2024).

H₅: AI-driven Personalization positively influences consumers' attitude.

H₆: AI-driven Personalization positively influences consumers' Buying Intentions.

In online fashion shopping, personalization based on AI enhance customer experience through the application of features like recommendation systems, chatbots, and virtual fitting, which influence the perceived usefulness of websites as well as consumers' attitude and purchase intentions (Hossain & Biswas, 2024; Li et al., 2024).

H₇: Consumer Attitude mediates the relationship between AI-driven Personalization and Buying Intentions.

H₈: Consumer Attitude mediates the relationship between Trust in AI and Buying Intentions.

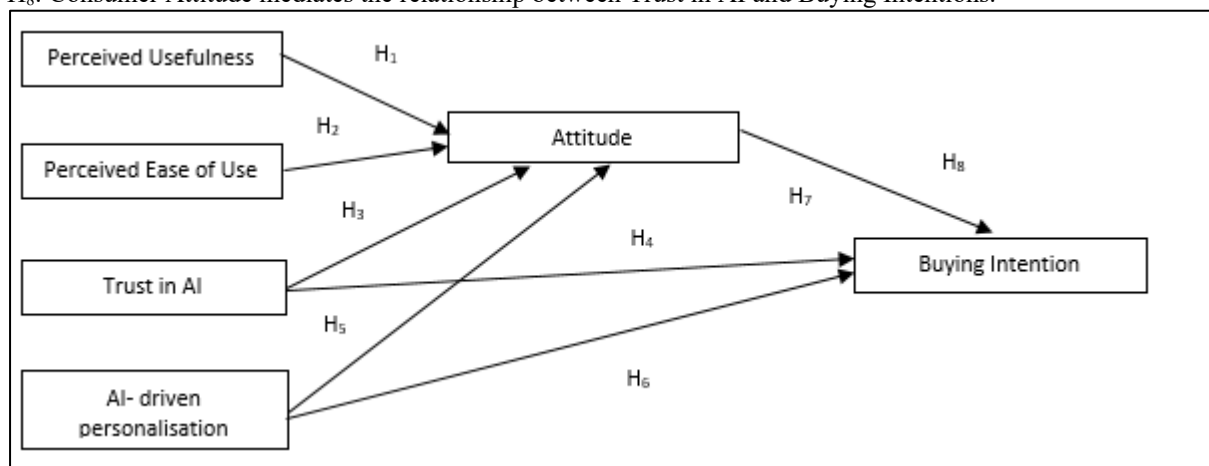


Figure 1: Proposed Conceptual Model

METHODS

This study adopted quantitative approach to understand the behaviour of Gen Z online consumer. A cross-sectional research design was chosen for this study because it allows researchers to collect data from respondents at a single point in time, making it efficient for examining attitudes and behaviours (Creswell, 2014). The target population includes Gen Z individuals aged 18 to 28 who purchase fashion products online at least one time within a month and purposive sampling technique is adopted for selecting respondents (Etikan, 2016). Population area consists with Kozhikode district in Kerala, India. Data were collected using structured questionnaire with 29 questions including 3 demographic questions. Five-point Likert scale is used for measuring constructs. A total of 406 responses were collected, out of which 390 valid responses were selected for final analysis after data cleaning and screening which is considered sufficient for using PLS-SEM for data analysis (J. F. Hair et al., 2019) and also adequate as per Cochran's equation.

The data was analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM), which is well-suited for predictive research and is effective even with complex models and relatively small sample sizes (J. F. Hair et al., 2021). The analysis was carried out in two stages, with the first stage focusing on the assessment of the measurement model. In this stage reliability and validity of the constructs were examined using indicator reliability (outer loadings), internal consistency reliability (Cronbach's alpha and composite reliability), convergent validity (Average Variance Extracted), and discriminant validity (Fornell-Larcker criterion and HTMT ratios). Second stage was Structural Model Assessment (J. Hair & Alamer, 2022). Here the relationships among constructs were tested by evaluating path coefficients and coefficient of determination (R^2). Bootstrapping with 10,000 resamples was performed to test the significance of the path coefficients. Smart PLS 4.0 software was used to perform the analysis.

RESULT

Table 1: Demographic Descriptive Statistics

Profile	Frequency	Percent
Gender		
Male	127	32.6

	Female	263	67.4
Educational Qualification	SSLC or Below	4	1.0
	Higher Secondary	23	5.9
	UG	270	69.2
	PG and above	93	23.9
Occupation	Govt. Employees	18	4.6
	Private Employees	177	45.4
	Own Business	47	12.1
	Student	119	30.5
	House wife	29	7.4

Table 4.1 shows that majority (67.4%) of respondents are females. Most were undergraduates (69.2%), followed by postgraduates (23.9%). Regarding occupation, private employees dominated (45.4%), followed by students (30.5%), business owners (12.1%), housewives (7.4%), and government employees (4.6%).

Table 2: Reliability and Convergent Test results

	Cronbach's alpha	Composite reliability (rho_c)	Average variance extracted (AVE)
AI-driven Personalization	0.846	0.891	0.622
Attitude	0.831	0.887	0.663
Buying Intention	0.819	0.881	0.649
Perceived Ease of Use	0.869	0.910	0.717
Perceived Usefulness	0.870	0.910	0.717
Trust in AI	0.885	0.916	0.686

Table 2 shows the results of reliability and convergent validity for the six constructs included in the conceptual model. The Cronbach's alpha values, which range from 0.819 to 0.885, indicate a high level of internal consistency among the measurement items. As these values are above the recommended threshold of 0.70, they confirm strong internal reliability. Similarly, the composite reliability (rho_c) values, all above 0.88, provide further evidence of construct reliability (J. F. Hair et al., 2019).

The Average Variance Extracted (AVE) values fall between 0.622 and 0.717, which are well above the minimum required value of 0.50, thereby confirming convergent validity (Fornell & Larcker, 1981). These results confirm that the measurement model is both reliable and valid, making it suitable for further analysis using PLS-SEM.

Table 3: Heterotrait-Monotrait Ratio (HTMT)

	AI-driven Personalization	Attitude	BI	PEOU	PU	Trust in AI
AI-driven Personalization						
Attitude	0.550					
BI	0.610	0.648				
Perceived Ease of Use	0.208	0.424	0.408			
Perceived Usefulness	0.407	0.558	0.457	0.398		
Trust in AI	0.474	0.528	0.653	0.368	0.527	

Table 3 depicts discriminant validity by using the Heterotrait-Monotrait Ratio (HTMT). It is a robust method recommended by (Henseler et al., 2015). All HTMT values varied from 0.208 to 0.653, well below the conservative threshold of 0.85, confirming the constructs are statistically different. The highest value of correlation of 0.653 between Buying Intention and Trust in AI indicates a moderate but acceptable relationship. This confirms that despite the two constructs being related, they are different from one another. These findings confirm discriminant validity among study variables that are AI-driven Personalization, Attitude, Buying Intention, Perceived Ease of Use, Perceived Usefulness, and Trust in AI.

Table 4: Fornell- Larcker Criterion

	AI-driven Personalization	Attitude	Buying Intention	PEOU	PU	Trust in AI
AI-driven Personalization	0.788					
Attitude	0.466	0.814				
Buying Intention	0.511	0.542	0.805			
PEOU	0.188	0.370	0.351	0.847		
PU	0.354	0.497	0.397	0.345	0.847	
Trust in AI	0.415	0.464	0.558	0.327	0.456	0.828

Table 4 displays discriminant validity through the Fornell-Larcker criterion, where the square root of a construct's Average Variance Extracted (AVE) should be higher than its correlations with other constructs (Fornell & Larcker, 1981). On the table, the diagonal elements (e.g., 0.788 for AI-driven Personalization, 0.814 for Attitude) are higher than the respective inter-construct correlations, validating each construct having higher variance with its indicators than with the others. This establishes the requirement of discriminant validity. Results validate guidelines by (J. F. Hair et al., 2019), validating the distinctiveness of all the constructs on the measurement model.

Table 5: Collinearity Statistics Using VIF (Inner Model)

	VIF
AI-driven Personalization -> Attitude	1.260
AI-driven Personalization -> Buying Intention	1.365
Attitude -> Buying Intention	1.440
Perceived Ease of Use -> Attitude	1.184
Perceived Usefulness -> Attitude	1.388
Trust in AI -> Attitude	1.444
Trust in AI -> Buying Intention	1.362

Table 5 shows collinearity that was checked against Variance Inflation Factor (VIF) values to ascertain the absence of multicollinearity among predictor constructs in the inner model. All VIF values range from 1.184 to 1.444, far short of the commonly used cut-point of 5 (J. F. Hair et al., 2019) and even the more conservative cut-point of 3.3 (Diamantopoulos & Siguaw, 2006). These results affirm that collinearity is absent, and that predictors are sufficiently independently dispersed. This enhances the reliability and interpretability of path coefficients in the structural model.

Table 6: R² Results

	R-square	R-square adjusted
Attitude	0.401	0.395
Buying Intention	0.458	0.454

The R² values in table 6 indicate that the model explains 40.1% of variance in Attitude and 45.8% of variance in Buying Intention. All of the four AI constructs that is, personalization, perceived usefulness, perceived ease of use, and trust strongly predict consumer attitude and intention.

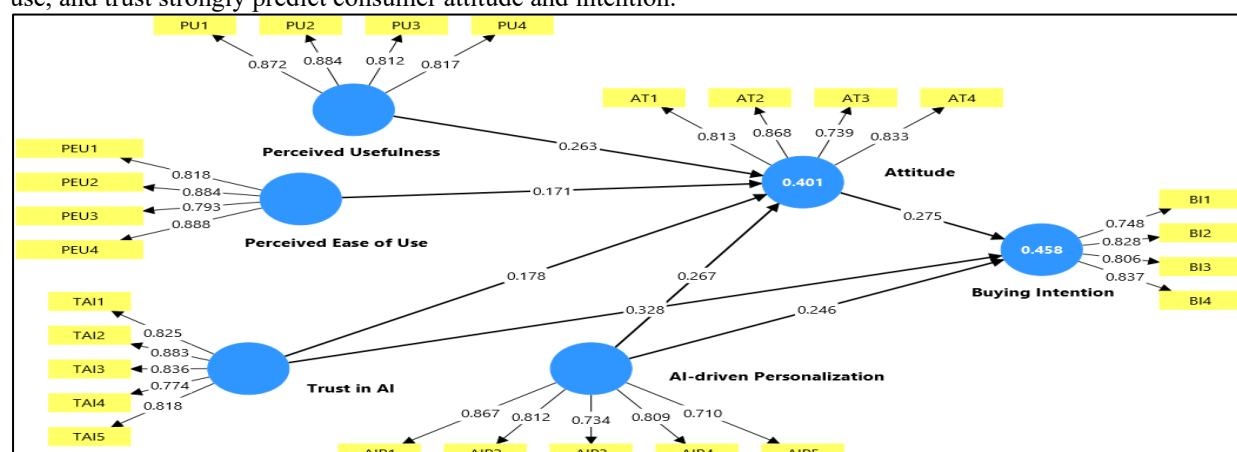


Figure 2: Measurement model assessment

Table 7: Path Coefficients

	Path coefficient	Standard deviation	T statistics	P values	Result
AI-driven Personalization -> Attitude	0.267	0.058	4.577	<0.001	Supported
AI-driven Personalization -> Buying Intention	0.246	0.049	5.049	<0.001	Supported
Attitude -> Buying Intention	0.275	0.055	4.973	<0.001	Supported
Perceived Ease of Use -> Attitude	0.171	0.051	3.380	<0.001	Supported
Perceived Usefulness -> Attitude	0.263	0.057	4.628	<0.001	Supported
Trust in AI -> Attitude	0.178	0.059	3.001	0.001	Supported
Trust in AI -> Buying Intention	0.328	0.045	7.359	<0.001	Supported

Table 7 confirms the structural model findings that all proposed relationships from H₁ to H₆ are significant, affirming the hypothesized paths. AI Personalization has a positive effect on Attitude and Buying Intention. Perceived Ease of Use and Perceived Usefulness both have a significant effect on Attitude. Trust in AI both has a significant effect on Attitude and Buying Intention. These are affirmed by recommendations by (J. F. Hair et al., 2019) and validate the application of PLS-SEM in modelling consumer behaviour in AI contexts.

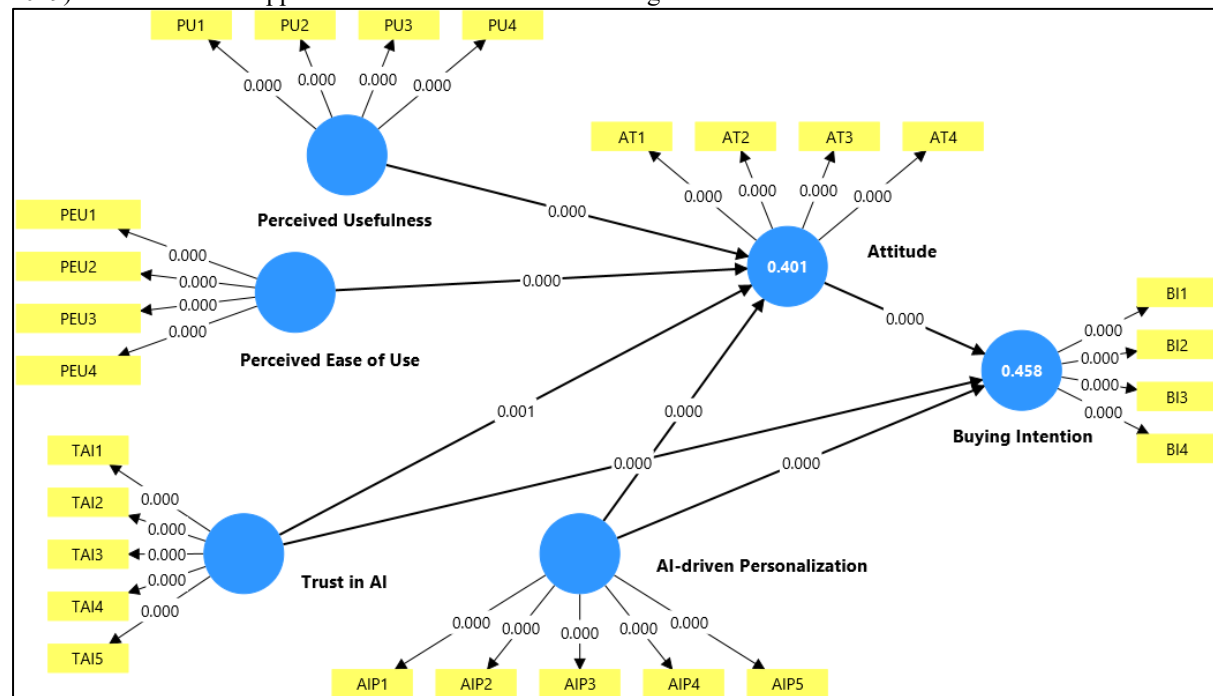


Figure 3: Measurement of structural model

Table 8: Mediation analysis

	Direct effect	95% confidence interval	Sig	Indirect effect	95% confidence interval	Sig
AI-driven Personalization -> Attitude -> Buying Intention	0.246	(0.165 to 0.324)	<0.001	0.073	(0.036 to 0.120)	0.002
Trust in AI -> Attitude -> Buying Intention	0.328	(0.253 to 0.401)	<0.001	0.049	(0.020 to 0.083)	0.006

Table 8 shows mediation test which confirms both direct and indirect effect are significant so AI-driven personalization and trust in AI has partial mediation effect on buying intention through attitude (Nitzl et al., 2016).

DISCUSSION

Path analysis of structural model confirm that the Technology Acceptance Model (TAM) theory is effective for the prediction of consumer buying intention influenced by AI in the context of fashion e-commerce. The model explains 40.1% of variance in Attitude and 45.8% in Buying Intention, representing moderate explanatory power (J. F. Hair et al., 2019). The results emphasize the significant influence of AI-related constructs such as AI driven Personalization, Perceived Ease of Use, Perceived Usefulness, and Trust in AI on consumer purchase intention towards fashion apparels. All the hypothetical relationships were statistically significant. Personalization through AI has highest direct and positive impact on both Attitude and Buying Intention (Li et al., 2024; Ranjan & Upadhyay, 2025)..

Attitude towards AI has significant partial mediating effect. This mediating role is also confirmed by significant indirect effects of AI Personalization and Trust in AI on Buying Intention through Attitude. This is consistent with the foundation theory of Davis' TAM (1989), and empirical research by (Manida, 2025) and (Ibrahim et al., 2024), who emphasized the pivotal role played by user attitudes in technology take-up.

Perceived ease of use and perceived usefulness have a significant influence on Attitude. These findings are in line with previous studies (Kim, 2025; Liébana-Cabanillas et al., 2018), which argue that AI systems must be easy to use and beneficial to create positive user attitudes. In addition, Trust in AI also has a significant influence on Attitude and Buying Intention corroborating arguments by (Emon & Khan, 2025; Thiebes et al., 2021) that trust is the foundation for AI adoption and making buying decisions.

Generally, the findings confirm the TAM extension with AI-related constructs such as trust and personalization, as proposed by (Massoudi et al., 2024; Pramanik & Jana, 2025). The findings confirm that when consumers perceive AI technologies as beneficial, trustworthy, personalized, and user-friendly, they develop positive attitudes, which in turn significantly influence their purchase intention. This underlines the strategic importance of optimizing AI features in fashion e-shops to elicit consumer engagement and purchasing behaviour.

From the above evidences, several actionable suggestions are drawn to maximize AI adoption in fashion e-commerce. With the immense impact of personalization on attitude and purchasing intention, e-commerce websites need to invest in advanced AI algorithms offering hyper-personalized experiences (Li et al., 2024; Ranjan & Upadhyay, 2025). System usability needs to be maximized through offering intuitive and user-friendly interfaces, particularly among Gen Z buyers (Ibrahim et al., 2024; Kim, 2025). Functional benefits of AI, e.g., smart fitting or virtual fitting, need to be made more conspicuous so that perceived usefulness is maximized (Liébana-Cabanillas et al., 2018; Manida, 2025). With trust being at the centre of attitude and purchasing intention determination, companies need to offer transparency in AI operation and highlight data protection policies (Emon & Khan, 2025; Thiebes et al., 2021). Positive consumer attitudes, as a mediator of the impact of AI features on purchasing behaviour, need to be fostered through education content, influencer promotion, and emotionally intelligent AI interfaces (Francis & Hoefel, 2018; Kavitha & Joshith, 2024). Academics are also encouraged to extend the traditional Technology Acceptance Model through the inclusion of AI-specific constructs such as trust, awareness, and emotional responsiveness to better reflect modern consumer behaviour (Fiftem et al., 2025; Pramanik & Jana, 2025). These strategies collectively emphasize the importance of developing AI systems that are not only functional and easy to use but also trustworthy, engaging, and customer-focused.

CONCLUSION

The present study investigated the influence of artificial intelligence on consumer buying intention towards fashion apparels online. This study is based on Technology Acceptance Model (TAM) theory and 2 additional variables are integrated into this model namely AI driven Personalization and Trust in AI in TAM theory. This study analysed influence of all these 4 constructs that are AI driven Personalization, Perceived Ease of Use, Perceived Usefulness, and Trust in AI on buying intention through attitude towards AI. All the hypothetical relationships are analysed through Partial Least Squares Structural Equation Modelling (PLS-SEM) analysis using Smart PLS 4. The results indicate that AI-driven personalization and trust in AI have strong direct effects on buying intention. They also have indirect effects through attitudes toward AI, perceived ease of use, and perceived usefulness, which influence buying intention through attitude. Among these factors, trust in AI is the most influential on buying intention. These findings emphasize the importance of including trust-building methods and personalized AI features in online fashion retail platforms to effectively shape consumer purchase intentions.

Limitation and future research directions

While this study offers important insights into how artificial intelligence (AI) influences buying intentions in online fashion shopping, it has some limitations that should be addressed in future research. The study was conducted in a specific regional and cultural context, likely within a part of India that is Kozhikode district in Kerala. This limits the generalizability of the results to consumers in other countries or cultures. Future studies could investigate individuals from other regions, countries, or age groups to see if the results generalize to

populations. Second, although the model included two of the main AI-relevant variables AI-driven Personalization and Trust in AI, future studies could include other variables in order to have a better general idea of how AI influences purchasing intention. This study used a cross-sectional research design to understand attitude and intention. People's attitudes and intentions change as they get more experience with AI. So future studies could use longitudinal studies to investigate these longitudinal changes for a better understanding. Overall, this study sets a good foundation, and future research can build on it for further studies related with AI's role in shaping online shopping experiences.

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