Keywords: AI Powered Shopping, Experiences, Emotional Engagement, Trust, Purchase Intention, On, line Fashion Retailing, UTAUT2 and S-O-R Theory

European Journal of Prosthodontics and Restorative Dentistry (2026) 34 (7s), 751–761

An Integrated S-O-R and UTAUT2 Framework for Examining the influence of AI-Powered Shopping Experiences on Emotional Engagement, Trust, and Purchase Intention in Online Fashion Retailing

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Abstract
The increasing use of artificial intelligence (AI) in online fashion retailing is transforming consumers' shopping experiences, yet the psychological mechanisms through which AI-enabled features influence purchase intention remain insufficiently understood. This study integrates the Stimulus–Organism–Response (S-O-R) paradigm with specific UTAUT2 components to investigate the effects of Performance Expectancy, Effort Expectancy, Hedonic Motivation, and Consumer Trust on Emotional Engagement and Purchase Intention. Customers in Kozhikode District, Kerala, India, who had used online platforms with AI-enabled features like chatbots, visual search, virtual try-ons, personalised offers, and personalised recommendations to buy fashionable clothing participated in a quantitative, cross-sectional study. A structured seven-point Likert-scale questionnaire was used to gather data, and SmartPLS's Partial Least Squares Structural Equation Modelling (PLS-SEM) was used for analysis. The results demonstrate that consumer trust, hedonic motivation, performance expectancy, and effort expectancy all have a major impact on emotional engagement. Purchase intention is strongly predicted by emotional engagement. Effort Expectancy and Hedonic Motivation have an indirect impact on Purchase Intention thru Emotional Engagement, but Performance Expectancy and Consumer Trust have substantial direct and indirect impacts. By showing that emotional engagement serves as a crucial mechanism connecting AI-enabled retail perceptions with purchase intention, the study expands on the S-O-R and UTAUT2 views. The results indicate that in order to develop emotionally compelling AI-powered buying experiences, online fashion businesses need combine practical utility, ease of engagement, enjoyment, and trust.

Received:21-06-2026
Revised:28-07-2026
Accepted:05-08-2026
Doi: 10.1922/ejprd.v34i7s.1694

INTRODUCTION

Artificial intelligence (AI) has emerged as a revolutionary force in the retail industry by providing intelligent, data-driven, and highly personalised shopping experiences. The way consumers find, assess, and buy things has been completely transformed by AI-powered technologies like conversational chatbots, virtual try-on apps, personalised recommendation systems, and predictive analytics. These technologies promote merchants' competitive advantage in increasingly digital marketplaces by improving customer convenience, decision quality, and seamless interactions (Jasim et al., 2026; Magano & Rebelo, 2026). AI has developed from a technology advancement into a strategic tool that influences customer experiences and purchase behaviour as online shopping continues to grow internationally. Online fashion retailing provides a particularly pertinent environment for examining AI-enabled consumer behaviour among digital retail industries. Instead of only serving practical needs, fashion purchases are highly sensory and emotionally motivated, reflecting consumers' identities, lifestyles, and self-expression. AI-powered chatbots, virtual fitting rooms, intelligent styling assistants, and personalised product recommendations are just a few examples of the personalised and interactive shopping experiences that fashion consumers are demanding.

Research has continuously shown that AI-powered ecommerce solutions increase customer experiences by providing intelligent decision support, improved personalisation, and effective customer service. While AI chatbots offer real-time support and enhance service responsiveness, personalised recommendation systems make product recommendations more relevant. Similarly, by enabling customers to see things before making a purchase, virtual try-on solutions boost their confidence and delight. When taken as a whole, these AI capabilities increase consumer engagement, perceived value, and trust—all of which have an impact on purchase intention (Jasim et al., 2026; Qi et al., 2026).

There are still significant research gaps in spite of these developments. First, the majority of research focuses more on system performance and technology adoption than on the psychological processes by which AI affects customer behaviour. Second, despite the fact that emotional involvement is crucial to fashion consumption, little empirical research has been done on its mediating function in AI-enabled retail settings. Third, only a small number of research have looked at the combined impact of trust and emotional engagement on purchase intention. Instead, trust has often been studied separately. Additionally, prior research has typically used technology acceptance models or the Stimulus–Organism–Response (S–O–R) theory independently, which has limited a thorough knowledge of both technical acceptance and psychological reactions. Lastly, despite the quick expansion of AI-enabled fashion e-commerce, there is still little empirical data from emerging markets, especially India and tier-II cities like Kozhikode. In order to fill in these gaps, this study creates and tests an integrated framework that combines the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) with the Stimulus–Organism–Response (S–O–R) theory to explain how AI-powered shopping experiences affect emotional engagement, trust, and purchase intention among Kozhikode District online fashion consumers. In addition to offering useful insights for fashion retailers looking to provide individualised, reliable, and emotionally compelling purchasing experiences, the results are anticipated to add to the expanding body of research on AI-enabled consumer behaviour.

1.1 Literature Review

The effects of AI-powered personalisation on consumers' perceived risk, shopping experience, buy intention, and recommendation intention in online fashion retailing were examined by Jasim et al. (2026). A key psychological component in AI-enabled commerce, according to the study, is trust. However, the study mostly relied on the Value-Based Adoption Model and Trust Theory, and emotional engagement was not investigated. The results indicate that in order to provide a more thorough explanation of consumer behaviour, emotional mechanisms and more expansive theoretical stances like S-O-R and UTAUT2 must be included.

Zaman et al. (2025) used a longitudinal research design to investigate consumers' aspirations to adopt AI-enabled services in international online fashion businesses. The results showed that while privacy concerns mitigated these associations, users' inclinations to adopt AI-enabled services were highly influenced by trust, transaction utility, and product uniqueness. The study mostly concentrated on technology acceptance rather than customers' emotional reactions, despite the fact that it offered insightful information about the adoption of AI services. This makes it possible to look at both trust and emotional engagement when describing purchase intention.

The impact of AI on Generation Z customers' brand trust and purchase behaviour in a variety of industries, including fashion, was examined by Guerra-Tamez et al. (2024). According to the study, consumers' confidence in AI suggestions was bolstered by transparency, and brand trust and purchase decisions were positively impacted by AI-enhanced personalisation. However, sector-specific insights were constrained by the multi-industry design, underscoring the necessity for studies that solely concentrate on online fashion shopping.

Supartha et al. (2026) used the Stimulus–Organism–Response framework to investigate how AI personalisation and content marketing affect consumer trust and purchasing decisions. The findings demonstrated that AI personalisation greatly increased customer trust, which in turn affected purchasing decisions. The study limited its explanatory breadth by excluding emotional engagement and tech

In order to determine the factors impacting consumers' use of AI-based virtual assistants in retail, Blut et al. (2024) performed a meta-analysis of 244 independent samples. According to the study, anthropomorphism, pricing value, social influence, support, and trust all had a major impact on the adoption of AI through both emotional and cognitive reactions. The meta-analysis did not particularly look into online fashion retail or buy intention, but it did confirm the significance of emotional reactions in AI interactions. These results lend credence to the addition of emotional engagement in research on AI-enabled commerce. nology acceptance dimensions, although validating trust as a significant mediator.

1.2 Statement of the problem

The psychological mechanisms through which AI-powered shopping experiences influence consumers' purchase intentions have received relatively little attention, despite the growing adoption of AI in fashion e-commerce. Instead, research has mostly concentrated on technology adoption, personalisation effectiveness, or system performance (Guha et al., 2021; Huang & Rust, 2021). Specifically, consumer trust has frequently been studied separately rather than as a complementing mechanism impacting purchase intention, and emotional engagement—which is essential to fashion consumption—remains understudied in AI-enabled shopping settings (Blut et al., 2024; Guha et al., 2021). Additionally, prior research has mostly used technology acceptance models or the Stimulus–Organism–Response (S–O–R) theory independently, which has led to a limited understanding of how technological stimuli simultaneously influence consumers' emotional reactions and behavioural intentions (Venkatesh et al., 2012).

Thus, by creating and empirically testing an integrated S-O-R-UTAUT2 framework to explain consumers' purchase intents toward AI-enabled online fashion shopping in Kozhikode District, this study aims to close these theoretical and contextual gaps.

1.3 Research Objectives

1. To investigate the influence of AI-powered shopping experiences on emotional engagement.
2. To examine the influence of emotional engagement on trust.
3. To examine the influence of trust on purchase intention.
4. To test mediation effects.

2. THEORETICAL FRAMEWORK

2.1 AI in Fashion Retail

Artificial Intelligence (AI) has shifted from being an optimisation tool for back-office processes to the main driver of front-end consumer interactions in digital fashion retail (Gao, 2025). Consumer decisions in high involvement categories such as apparel are highly influenced by subjective perceptions of aesthetic, fit and emotion. Artificial intelligence (AI) tools reproduce offline retail interactions and utilise hyper-scale personal data to bridge the experiential gap that is intrinsic to e-commerce.

- AI Personalisation: Existing fashion platforms apply deep learning models to collect real-time behavioural vectors, such as dwell time, click paths, hover interactions, etc., as well as the historical transaction data. AI personalisation is not based on static demographic segmentations, but it dynamically curates individual user feeds by changing the layout of the site, colour schemes, and promotional offers based on the predicted micro-intent.
- Recommendation Engines: Modern fashion recommendation systems have gone beyond traditional collaborative filtering and rely on hybrid models that incorporate computer vision. Such algorithms analyse item-specific features (e.g., silhouette, pattern, neckline, fabric texture) and user's behavioural history to generate personalised outfit combinations, style recommendations, and cross-category "complete the look" suggestions (Gao, 2025).
- Conversational Agents & Chatbots: Virtual assistants that use Large Language Models (LLM) and Natural Language Processing (NLP) function as digital personal stylists. In addition to providing style advice, real-time inventory checks, and conversational cross-selling, they go beyond prewritten Customer Service FAQs to understand unclear aesthetic enquiries.
- Visual Search: To locate identical or aesthetically comparable fashion goods inside a retailer's catalogue, customers can upload photographs (screenshots, social media postings, real-world photos) to visual search engines. Deep convolutional neural networks (CNNs) overcome text-based query constraints by transforming pictures into high-dimensional feature vectors, greatly lowering search friction for visual-first consumers.
- Virtual Try-On (VTO): VTO technology projects 2D clothing pictures onto 3D body avatars or live camera feeds using augmented reality (AR), computer vision, and Generative Adversarial Networks (GANs) or diffusion models (Gao, 2025). Fit and style ambiguity is the biggest barrier to online fashion selling, and VTO tackles it.

2.2 AI-Powered Shopping Experience

The multifaceted, technology-mediated customer journey known as the AI-Powered Shopping Experience (AIPSE) is characterised by artificial intelligence capabilities that proactively personalise, streamline, augment, and enrich consumer interactions across pre-purchase, purchase, and post-purchase touchpoints (Gao, 2025).

Dimensions

- Informational Value (Utility): The extent to which AI technologies improve decision-making efficiency and lower cognitive search costs by delivering precise, customised, and timely product information.
- Aesthetic/Visual Engagement: The sensory immersion and richness of perception offered by visual AI techniques (e.g., VTO, high-resolution visual matching).

- Relational/Conversational Interactivity: The response of AI conversational agents that is real-time, bidirectional, and human-like.
- Convenience/Effort Reduction: The smooth reduction of operational friction in the processes of product assessment, checkout, and discovery.

2.3 Emotional Engagement

The degree of a customer's emotive, psychological, and sensory connection with a brand or platform throughout the purchasing process is known as emotional engagement, and it is typified by sentiments of delight, excitement, immersion, and ambient warmth (Mehrabian & Russell, 1974).

Dimensions

- Positive Affect: The instantaneous feeling of happiness, enjoyment, and excitement brought on by extremely specific visual cues.
- Immersion (Flow State): When a customer is completely absorbed in the interactive visual shopping environment, they are in a state of profound cognitive absorption (Gao, 2025).
- Social Connectedness/Warmth: The conversational comfort and felt human presence that intelligent AI agents provide.

2.4 Customer trust

According to Gao (2025), trust is a multifaceted construct in an AI-mediated retail setting that represents a consumer's readiness to rely on an entity based on expectations of competence, integrity, and compassion.

- Trust in AI (Algorithmic Trust): Consumer faith in the accuracy, privacy protections, dynamic processing capabilities, and impartiality of the underlying technology is known as algorithmic trust. It represents the conviction that the AI system will consistently carry out its duties without making mistakes or abusing customer data.
- Trust in the Platform (Institutional/Vendor Trust): The conviction that the fashion e-commerce vendor as a whole conducts business morally, safeguards financial transactions, fulfils delivery commitments, and upholds reasonable return policies (Gao, 2025).
- Trust in Recommendations (Output Trust): The subjective conviction that the particular products, sizes, styles, and outfit combinations recommended by the algorithm actually correspond with the customer's actual personal style and fit criteria, as opposed to commercial agendas or inventory clearance objectives.

2.5 Purchase Intention

The deliberate, probabilistic assessment and willingness of a customer to carry out a transaction to obtain a fashion item from the online retail platform is known as purchase intention (Gao, 2025; Venkatesh et al., 2012).

Purchase intention is the main downstream predictor of actual transactional behaviour, according to traditional consumer behaviour research. Risk reduction, brand attitude, platform trust, and perceived value all directly influence purchase intention in e-commerce settings (Gao, 2025).

2.6 Theoretical Foundation of UTAUT2

Technology adoption frameworks are extended into consumer situations by the Unified Theory of Acceptance and Use of Technology 2 (Venkatesh et al., 2012). It suggests that structural views of the technology's usefulness, operational simplicity, social drives, and inherent hedonic worth are what motivate people to embrace and use it.

Performance Expectancy (PE):

The extent to which a customer thinks utilising AI fashion technologies (such as visual search and automated suggestions) can help them locate clothes more quickly and precisely (Venkatesh et al., 2012). It Acts as the user experience's functional foundation.

Expectancy of Effort (EE):

It refers to how simple it is for customers to engage with AI interfaces (Venkatesh et al., 2012). Emotional engagement and platform trust are destroyed by high operational effort, which creates cognitive friction.

Motivation by Hedonism (HM):

The satisfaction that comes from utilising AI shopping solutions (Venkatesh et al., 2012). At its core, fashion buying is hedonistic and dynamic. The intrinsic joy of engaging with new AI systems is captured by HM.

2.7 Theoretical Foundations of S-O-R Theory

The Stimulus-Organism-Response (S-O-R) model, which has its roots in environmental psychology (Mehrabian & Russell, 1974), postulates that environmental cues (Stimuli) function as inputs that modify an individual's internal emotional and cognitive state (Organism), which in turn drives downstream approach or avoidance behavioural outcomes (Response). The internet interface serves as an atmospherically rich shop environment in digital fashion retail (Gao, 2025; Mehrabian & Russell, 1974).

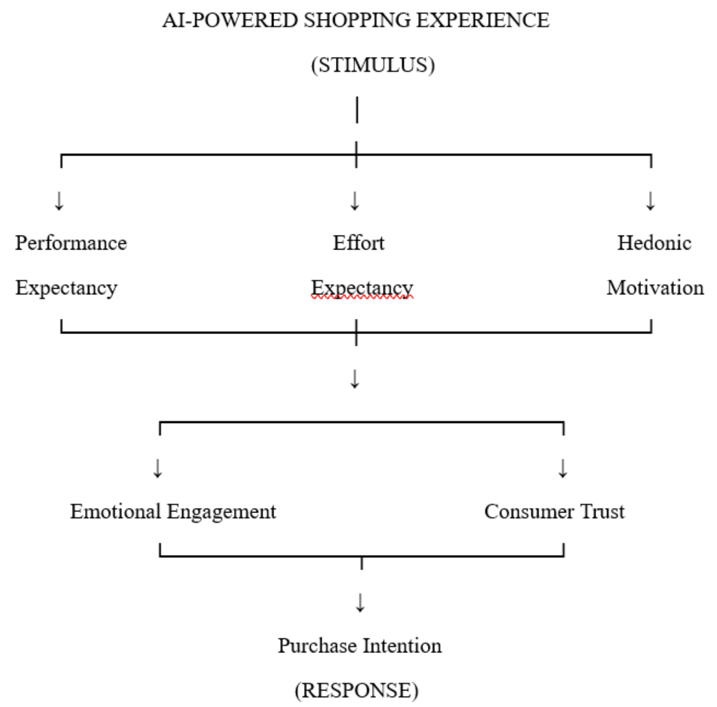
Stimulus: The AI interface's features, functional design, technological characteristics, and intelligence.

Organism: The consumer's emotional responses (Emotional Engagement) and internal cognitive assessment (Trust constructs) brought on by such technological stimuli.

Response: The last behavioural vector that arises from the internal psychological state is Purchase Intention. The macro-architectural framework required to sequence technical features into psychological states and ultimately transactional reactions is provided by S-O-R (Gao, 2025).

3. CONCEPTUAL FRAMEWORK

AI-powered features constitute external stimuli that shape consumers' perceptions of the usefulness, ease of use, and enjoyment of the online shopping experience. These technology-related evaluations, represented by performance expectancy, effort expectancy, and hedonic motivation, subsequently influence consumers' emotional engagement and trust, which in turn shape their intention to purchase fashion apparel online.



Conceptual Model

4. HYPOTHESES DEVELOPMENT

H1a: Performance expectancy has a positive effect on consumer trust in AI-powered online fashion retailing.

H1b: Performance expectancy has a positive effect on consumers' emotional engagement with AI-powSered online fashion retailing.

H2a: Effort expectancy has a positive effect on consumer trust in AI-powered online fashion retailing.

H2b: Effort expectancy has a positive effect on consumers' emotional engagement with AI-powered online fashion retailing.

H3a: Hedonic motivation has a positive effect on consumer trust in AI-powered online fashion retailing.

H3b: Hedonic motivation has a positive effect on consumers' emotional engagement with AI-powered online fashion retailing.

H4a: Consumer trust has a positive effect on purchase intention in online fashion retailing.

H4b: Emotional engagement has a positive effect on purchase intention in online fashion retailing.

5. RESEARCH METHODOLOGY

The study uses a quantitative, cross-sectional research approach to investigate how customers react to online fashion retailers' AI-enabled purchasing experiences. The study is carried out in Kozhikode District, Kerala, India, which offers a tier-II metropolis and rising market setting. Customers in Kozhikode District who have used online retail platforms with AI-enabled shopping features—such as AI-based product recommendations, personalised product suggestions, chatbots, visual search, virtual try-ons, personalised offers and promotions, and AI-curated fashion collections make up the target population. A purposive sampling technique is used to select respondents who meet the predefined eligibility criteria. As a screening criterion, respondents are asked whether they have encountered AI-enabled features such as personalised recommendations, chatbots, visual search, virtual try-on, or personalised product suggestions while shopping for fashion apparel online. A seven-point Likert scale, ranging from 1 = strongly disagree to 7 = strongly agree, is used to measure the constructs. Partial Least Squares Structural Equation Modelling (PLS-SEM) thru SmartPLS is used to analyse the data.

5.1 Measurement Instrument and Operationalisation of Variables

Item Code	Construct	Measurement Item	Source
PE1	Performance Expectancy	Using AI search or virtual try-on (VTO) helps me find fashion items faster.	Adapted/contextualised from Venkatesh et al. (2012)
PE2	Performance Expectancy	AI recommendations increase my chances of finding clothing that fits my style.	Adapted/contextualised from Venkatesh et al. (2012)
PE3	Performance Expectancy	AI features enhance the overall usefulness of my online fashion shopping experience.	Adapted/contextualised from Venkatesh et al. (2012)
PE4	Performance Expectancy	AI sizing and styling tools improve my shopping productivity.	Adapted/contextualised from Venkatesh et al. (2012)
EE1	Effort Expectancy	Interacting with AI features on this platform is clear and understandable.	Adapted/contextualised from Venkatesh et al. (2012)
EE2	Effort Expectancy	It is easy for me to become skillful at using visual search and VTO tools.	Adapted/contextualised from Venkatesh et al. (2012)
EE3	Effort Expectancy	I find the platform's AI interfaces flexible and easy to navigate.	Adapted/contextualised from Venkatesh et al. (2012)
EE4	Effort Expectancy	Learning to use new AI features requires minimal effort.	Adapted/contextualised from Venkatesh et al. (2012)
HM1	Hedonic Motivation	Using AI-powered visual features on this platform is enjoyable and fun.	Adapted/contextualised from Venkatesh et al. (2012)
HM2	Hedonic Motivation	Exploring personalised outfit recommendations provides me with entertainment.	Adapted/contextualised from Venkatesh et al. (2012)
HM3	Hedonic Motivation	Interacting with the AI interface is aesthetically pleasing.	Adapted/contextualised from Venkatesh et al. (2012)
HM4	Hedonic Motivation	I find using virtual try-on technology to be an exciting experience.	Adapted/contextualised from Venkatesh et al. (2012)
CT1	Consumer Trust	I trust that AI recommendations genuinely match my personal style preferences.	Adapted/contextualised from Gefen et al. (2003); Chen & Dhillon (2003)
CT2	Consumer Trust	I believe that the AI system handles my personal and fit data securely.	Adapted/contextualised from Gefen et al. (2003); Chen & Dhillon (2003)
CT3	Consumer Trust	The fashion advice provided by the platform's AI is reliable and accurate.	Adapted/contextualised from Gefen et al. (2003); Chen & Dhillon (2003)
CT4	Consumer Trust	I trust that the AI-powered platform keeps my interests in mind.	Adapted/contextualised from Gefen et al. (2003); Chen & Dhillon (2003)

Item Code	Construct	Measurement Item	Source
EME1	Emotional Engagement	I feel emotionally engaged when using AI-powered features for online fashion shopping.	Adapted/contextualised from Hollebeek et al. (2014)
EME2	Emotional Engagement	Using AI-powered features makes my online fashion shopping experience more emotionally engaging.	Adapted/contextualised from Hollebeek et al. (2014)
EME3	Emotional Engagement	I become emotionally involved when exploring AI-powered fashion recommendations.	Adapted/contextualised from Hollebeek et al. (2014)
EME4	Emotional Engagement	AI-powered features make me feel more connected to my online fashion shopping experience.	Adapted/contextualised from Hollebeek et al. (2014)
PI1	Purchase Intention	I intend to purchase fashion apparel through online platforms that provide AI-powered shopping features.	Adapted/contextualised from Pavlou (2003)
PI2	Purchase Intention	I am likely to purchase fashion apparel from an online platform that uses AI-powered features.	Adapted/contextualised from Pavlou (2003)
PI3	Purchase Intention	I would consider purchasing fashion apparel based on recommendations provided by AI.	Adapted/contextualised from Pavlou (2003)
PI4	Purchase Intention	I intend to continue purchasing fashion apparel online using AI-powered shopping features.	Adapted/contextualised from Pavlou (2003)

6. DATA ANALYSIS

6.1 Research Model

The suggested framework integrates the Stimulus-Organism-Response (S-O-R) logic with UTAUT2-related technological perceptions. Hedonic Motivation (HM), Consumer Trust (CT), Performance Expectancy (PE), and Effort Expectancy (EE) are all considered stimulus-related perceptions. Purchase Intention (PI) is the behavioural reaction, whereas Emotional Engagement (EME) is the organismic state.

6.2 Measurement Model Assessment

Every one of the six constructions has reflected specifications. Indicator loadings, Cronbach's alpha, composite reliability (CR), average variance extracted (AVE), and HTMT for discriminant validity were used to evaluate the measurement model.

Construct	Items	α	CR	AVE	Min loading	Max loading
PE	4	0.898	0.929	0.767	0.864	0.902
EE	4	0.904	0.933	0.777	0.871	0.886
HM	4	0.885	0.921	0.744	0.847	0.894
CT	4	0.886	0.921	0.746	0.851	0.882
EME	4	0.901	0.931	0.771	0.866	0.885
PI	4	0.901	0.931	0.771	0.872	0.885

Cronbach's alpha values vary from.885 to.901, composite reliability values range from.921 to.933, and indicator loadings are consistently high, ranging from roughly.847 to.902. Every AVE value is higher.74. When combined, these findings show convergent validity and good internal consistency. Therefore, the removal of an indication based just on low loading or insufficient dependability has no obvious measurement-model justification.

6.3 Discriminant Validity

Construct	PE	EE	HM	CT	EME	PI
PE	1.000	0.834	0.860	0.828	0.861	0.917
EE	0.834	1.000	0.756	0.784	0.797	0.801

HM	0.860	0.756	1.000	0.800	0.858	0.800
CT	0.828	0.784	0.800	1.000	0.834	0.900
EME	0.861	0.797	0.858	0.834	1.000	0.847
PI	0.917	0.801	0.800	0.900	0.847	1.000

The majority of construct pairings stay below.90, according to the HTMT matrix. While CT-PI is roughly.900, PE-PI is.917, which is higher than the widely used.90 screening standard. This suggests that special consideration should be given to the discriminant validity between these pairs. The conceptual connection between PE and PI may help to explain the comparatively high HTMT, as customers who find AI valuable may also naturally report greater purchase intentions.

6.4 Structural Model Assessment

The structural model accounts for 0.772 (77.2%) of the variation in purchase intention and 0.714 (71.4%) of the variance in emotional engagement. This suggests that the two endogenous constructs in the given sample are significantly explained by the suggested predictors.

Endogenous construct	R^2
Emotional Engagement	0.714
Purchase Intention	0.772

6.5 Collinearity

Endogenous	Predictor	VIF
EME	PE	3.492
EME	EE	2.631
EME	HM	2.788
EME	CT	2.668
PI	PE	3.707
PI	EE	2.730
PI	HM	3.095
PI	CT	2.860
PI	EME	3.499

The inner VIF values fall between 2.631 and 3.707. They continue to fall below the cautious cutoff point of 5, indicating that collinearity is not severe enough to compromise structural route interpretation.

6.6 Effect Sizes (f^2)

Endogenous	Predictor	f^2
EME	PE	0.061
EME	EE	0.038
EME	HM	0.110
EME	CT	0.072
PI	PE	0.194
PI	EE	0.009
PI	HM	0.000
PI	CT	0.192
PI	EME	0.021

Performance Expectancy has the most impact on Purchase Intention ($f^2 \approx .194$), closely followed by Consumer Trust ($f^2 \approx .192$). Hedonic Motivation has the most impact on Emotional Engagement ($f^2 \approx .110$), but this contribution is still rather little. The practical interpretation is that, while enjoyment seems more pertinent to the emotional stage of the shopping experience, utility and trust are especially significant for the ultimate desire to buy.

6.7 Hypothesis Testing

Path	β	SE	t	p	Decision
PE → EME	0.247	0.072	3.459	0.0007	Supported
EE → EME	0.169	0.062	2.715	0.0072	Supported
HM → EME	0.296	0.064	4.630	0.0000	Supported
CT → EME	0.234	0.063	3.746	0.0002	Supported
PE → PI	0.404	0.066	6.132	0.0000	Supported
EE → PI	0.077	0.057	1.354	0.1773	Not supported
HM → PI	0.001	0.060	0.018	0.9856	Not supported
CT → PI	0.353	0.058	6.101	0.0000	Supported
EME → PI	0.129	0.064	2.021	0.0447	Supported

The findings demonstrate a distinct distinction between purchase intention indicators and emotional engagement predictors. EME is positively and statistically significantly correlated with PE, EE, HM, and CT. While EE and HM have no discernible direct influence on PI, PE and CT are substantial positive predictors. EME itself is significant at the 5% level and shows a positive correlation with PI.

Performance Expectancy→ Emotional Engagement (β = 0.247, p <.001): When consumers believe AI features are actually helpful, they seem to become more emotionally attached. This makes logical sense when it comes to fashion shopping: technologies that help with size, enhance suggestions, or lessen search effort may make the experience seem more fulfilling rather than just practical.

Effort Expectancy → Emotional Engagement (β = 0.169, p = 0.0072): Emotional engagement is also influenced by ease of contact. Customers may be more inclined to investigate and engage with AI interfaces when they are clear and simple to use.

Hedonic Motivation → Emotional Engagement (β = 0.296, p <.001): Among the four stimuli, this is the most powerful predictor of EME. The outcome implies that satisfaction is directly related to whether or not customers genuinely feel emotionally invested in AI-enabled fashion purchasing, rather than being only a nice supplementary feature.

Consumer Trust → Emotional Engagement (β = 0.234, p <.001): The emotional experience is also influenced by trust. When customers feel that suggestions are trustworthy and that personal or appropriate information is managed appropriately, they are more willing to participate.

Emotional Engagement → Purchase Intention (β = 0.129, p = 0.0447): Stronger purchasing intention is linked to emotional involvement, according to the positive connection. Although the effect is not as strong as the direct effects of PE and CT, it is still statistically significant, confirming the notion that one way that AI-enabled shopping experiences might influence behavioural intention is by emotion.

While, there is no significant difference between Effort Expectancy and Purchase Intention (β = 0.077, p = 0.1773). This does not negate the significance of usability. Instead, the outcome implies that convenience might not be enough to drive a purchase once consumers have formed their entire emotional response and taken into account utility and trust.

The relationship between purchase intention and hedonic motivation is not significant (β = 0.001, p = 0.9856). One explanation might be that while enjoyment motivates users to engage with AI capabilities, it does not necessarily translate into a willingness to spend money. In the end, utility, assurance, and trust may be more important when making a fashion buy than amusement.

6.8 Mediation Analysis

Predictor	Indirect effect	Boot LL	Boot UL	Direct effect	Direct p	Interpretation
PE	0.032	0.002	0.074	0.404	0.0000	Partial mediation
EE	0.022	0.001	0.051	0.077	0.1773	Indirect-only mediation
HM	0.038	0.004	0.074	0.001	0.9856	Indirect-only mediation
CT	0.030	0.002	0.065	0.353	0.0000	Partial mediation

The bootstrap confidence intervals for the indirect effects do not cross zero, and they are positive. This suggests that PE, EE, HM, and CT are connected to PI by a significant mechanism provided by EME. The trend is particularly instructive for EE and HM: their indirect effects thru EME are large, while their direct effects on PI are negligible. This fits the pattern of indirect-only mediation. Practically speaking, easiness and enjoyment seem to have an impact on purchase intention mostly after they have moulded the customer's emotional experience.

Significant direct and indirect effects are shown by PE and CT, suggesting partial mediation. Therefore, usefulness and trust are important in two ways: first, they can directly affect buy intention; second, they can reinforce purchase intention by boosting emotional involvement.

6.9 Predictive Assessment

PI indicator	RMSE	MAE	Mean benchmark RMSE	Q²_predict-style
PI1	0.746	0.615	1.157	0.584
PI2	0.728	0.591	1.103	0.565
PI3	0.807	0.640	1.198	0.546
PI4	0.705	0.548	1.127	0.609

A transparent prediction evaluation was carried out using a 10-fold cross-validation check. The model's RMSE is less than the simple mean benchmark for each of the four PI indicators, and all Q^2-style values are positive. This suggests that the out-of-sample prediction in this check is useful. Unless the same process is carried out in SmartPLS and the software output is replaced, these values—which are a cross-validation approximation—should not be referred to be official SmartPLS PLSpredict output.

7. DISCUSSION

7.1 Findings in Relation to S-O-R Theory

The S-O-R reasoning is broadly supported by the data. The AI-related perceptions denoted by PE, EE, HM, and CT serve as external stimuli linked to an internal emotional state (EME), which is linked to the behavioural reaction (PI). Because all four stimuli have substantial indirect effects thru EME, the mediation data support this explanation.

The outcome demonstrates that technology adoption is more than just a cognitive process, which is very helpful for AI-enabled retail. Customers may be aware that an AI tool is practical or simple to use, but how the technology enhances the shopping experience may influence their decision to buy. This explanation aligns with previous S-O-R studies in online purchasing, wherein consumers' internal moods and subsequent behavioural intents have been connected to environmental and shopping cues.

7.2 Findings in Relation to UTAUT2

The results offer a sophisticated use of UTAUT2. Purchase intention and performance expectation are strongly correlated, which is in line with the importance of perceived utility in technology adoption studies. On the other hand, while both have a major impact on EME, Effort Expectancy and Hedonic Motivation do not significantly affect PI directly. This implies that customers could value an AI system because it is simple and entertaining, but these attributes might need to produce a favourable emotional experience before they transfer into a buy intention.

7.3 Consumer Trust as an AI-specific Stimulus

One of the model's most significant conclusions is consumer trust. Its indirect impact through EME is likewise noteworthy, and its direct impact on PI is nearly as great as that of PE. Customers may be required to rely on advice regarding body fit, personal style, and maybe sensitive personal data, which makes this especially likely in AI-enabled fashion purchasing. Similar to this, recent studies on virtual try-ons in online clothing purchasing look at characteristics including utility, trust, engagement, and user-friendliness as they relate to purchase intention (Kim & Forsythe, 2008; Chidambaram et al., 2024). Thus, the current data support the growing theory that the adoption of AI in retail depends on both convenience and system confidence.

8. Theoretical Contributions

- Applying S-O-R to AI-enabled retail: The model assigns purchase intention to the response component, emotional engagement to the organism component, and impressions of AI-related technologies to the stimulus component. This increases the direct applicability of S-O-R to AI-mediated fashion purchasing.
- Integrating UTAUT2 and S-O-R: By including technology-acceptance factors into an emotional process, the study goes beyond evaluating them as stand-alone predictors. The results demonstrate that PE, EE, and HM can affect the organismic state prior to the formation of purchase intention.
- Strengthening the importance of emotional engagement: Rather than being a descriptive result, the mediation findings present EME as a significant mechanism. Specifically, PE and CT have both direct and indirect impacts on PI, whereas EE and HM have an indirect impact thru EME.
- Stressing trust in addition to technological acceptance: Consumer Trust gives the UTAUT2-S-O-R framework an AI-specific relational dimension and shows that trust in AI suggestions and data management can coexist with utility and emotional experience in explaining purchase intention.

9. Practical Implications

- Online Shopping Sites
  Performance Expectancy has a big impact on Purchase Intention, thus e-commerce platforms should give priority to AI capabilities that offer evident functional value, especially personalised recommendations, visual search, size help, and virtual try-on.
- Stores that sell clothing
  Since Hedonic Motivation increases Emotional Engagement but does not directly transfer into Purchase Intention, fashion merchants should combine utilitarian usability with captivating AI experiences.
- AI Programmers
  Given the important role that consumer trust plays in purchase intention, AI developers should prioritise suggestion accuracy, user-friendly interfaces, dependable sizing help, and transparent data procedures.
- Online Advertisers
  Digital marketers could use emotional appeals to increase customer engagement while communicating the concrete advantages of AI-enabled purchasing, such as better product discovery, tailored suggestions, and decision help.

10. Conclusion

Consumer trust, hedonic motivation, performance expectancy, and effort expectancy all have a favourable impact on emotional engagement. Performance Expectancy and Consumer Trust have a direct impact on

Purchase Intention, whereas Effort Expectancy and Hedonic Motivation do not. Purchase intention is positively correlated with emotional engagement, which also acts as a mediator between purchase intention and the four sensory factors. Significant variation in both Purchase Intention and Emotional Engagement is explained by the model. Overall, the results indicate that a mix of practical utility, trust, and an emotionally engaging experience is necessary for effective AI-enabled fashion buying.

11. Future Research Directions

- To evaluate the generalisability of the connections between AI perceptions, trust, emotional engagement, and buy intention, future research might duplicate the suggested model across various retail industries and cultural situations.
- Longitudinal studies might look at how consumers' purchase intentions, trust, and emotional involvement change as they become more used to AI-enabled retail tools.
- To demonstrate stronger causal linkages, experimental research might compare AI-assisted and traditional online shopping experiences and vary elements like virtual try-on realism, suggestion accuracy, and personalisation.
- Instead of depending only on purchase intention, future research could expand the model by adding AI-specific elements like transparency, privacy concerns, perceived risk, and anthropomorphism as well as behavioural outcomes like actual usage, repeat purchases, and conversion behaviour.

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