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Article

Factors Influencing Consumer Buying Intention Toward AI-Powered Shopping: An Extended UTAUT Approach

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Abstract: Artificial intelligence (AI) has changed e-commerce by making personalized recommendations, virtual assistants, and automated decisions possible, which has reshaped how people shop online. Despite these advances, we still do not fully understand what drives consumers to buy through AI-powered shopping. This study looks at the factors that influence consumer buying intention by expanding the Unified Theory of Acceptance and Use of Technology (UTAUT) to include Perceived Ease of Use, Attitude, Perceived Risk, and Trust in AI. We surveyed 432 people and analyzed the results using covariance-based Structural Equation Modeling (CB-SEM). The findings show that Performance Expectancy ($\beta = 0.318$, $p < 0.001$), Social Influence ($\beta = 0.238$, $p < 0.001$), Hedonic Motivation ($\beta = 0.306$, $p < 0.001$), and Perceived Ease of Use ($\beta = 0.294$, $p < 0.001$) all have a significant positive effect on Behavioral Intention. Behavioral Intention, in turn, strongly increases Consumer Buying Intention ($\beta = 0.535$, $p < 0.001$). On the other hand, Effort Expectancy, Attitude, and Perceived Risk did not have a significant impact, while Facilitating Conditions and Trust in AI were linked to lower Behavioral Intention. These results expand the UTAUT framework by adding AI-specific factors and offer practical advice for retailers and e-commerce platforms that want to encourage more consumers to use AI-powered shopping by improving usability, features, and the overall user experience.
Keywords: Artificial Intelligence, AI-Powered Shopping, Extended UTAUT, Consumer Buying Intention, Behavioral Intention, Structural Equation Modeling (SEM), E-commerce.

1. Introduction

Artificial intelligence (AI) is changing digital commerce by reshaping how people use online shopping platforms. Tools like recommendation systems, chatbots, virtual assistants, predictive analytics, and personalized marketing help retailers offer more customized shopping and work more efficiently. These tools quickly analyze large amounts of consumer data to suggest products, answer questions, and send targeted offers, which helps keep customers engaged and satisfied. As more businesses use AI, it is important to understand what affects whether consumers accept AI-powered shopping . E-commerce has grown worldwide, especially after the COVID-19 pandemic, leading to more use of AI technologies. AI now helps with pricing, customer service, fraud detection, inventory, and advertising , not just product recommendations. These changes make shopping easier and more efficient for consumers. Still, not everyone is comfortable with AI-powered shopping, since decisions depend on more than just technology—they are also shaped by psychological, behavioral, and social factors.

Researchers use several theories to explain why people adopt new technology. One of the most widely used is the Unified Theory of Acceptance and Use of Technology (UTAUT). This model says that people are most likely to use a technology if they expect it to help them, find it easy to use, feel social pressure to use it, and have the support they need . UTAUT has been used to study technology adoption in areas like mobile banking, e-learning, healthcare, government services, and online shopping, and it often predicts user acceptance well. The rapid growth of AI-powered applications has brought new aspects of consumer behavior that the original UTAUT framework does not fully address

. Unlike traditional information systems, AI technologies can make decisions on their own, offer personalized suggestions, and predict what users might want, all of which directly affect what people buy . As a result, consumers now judge AI systems not just by how useful or easy they are to use, but also by how much they trust them, the risks they perceive, their emotional reactions, and their overall attitudes toward AI. Recent research shows that these psychological factors are important in shaping whether consumers are willing to use AI-based services, especially in online shopping . Trust is a key factor in AI adoption research because consumers depend on AI systems to recommend products, handle payments, and manage personal information. People are more likely to use AI-powered shopping tools if they see them as reliable, transparent, and able to protect their privacy . On the other hand, worries about algorithmic bias, data privacy, cybersecurity, and lack of transparency can lower trust and make people less willing to use these technologies . Perceived risk also plays a big role in online shopping, as uncertainty about AI recommendations, misuse of data, and automated decisions can make consumers hesitant to buy with AI help . These points show that traditional technology acceptance models should include psychological factors specific to AI.

Besides trust and perceived risk, researchers now highlight the importance of ease of use, enjoyment, and consumer attitudes in shaping how people decide to use AI shopping tools . People are more likely to try AI technologies when they are easy, intuitive, and fun to use. AI apps that offer engaging and personalized shopping experiences can boost motivation and make people more likely to use them. Attitudes toward AI also affect how consumers judge AI recommendations and whether they use these tools in their shopping . These psychological factors add to traditional UTAUT models by including emotional and experience-based aspects of technology acceptance. While past studies have looked at technology acceptance in online shopping, there are still some gaps. Many have focused on traditional online shopping instead of AI-powered environments . Also, most research uses the original UTAUT model and does not include AI-specific factors that matter to today's consumers. Often, studies look at trust, perceived risk, or attitude separately instead of combining them in one model. As a result, we still do not know much about how technology, psychology, and experience together affect buying decisions in AI shopping, especially in developing countries where AI use is still growing.

This study aims to address these gaps by proposing and testing an Extended UTAUT model. The model combines the original UTAUT constructs with perceived ease of use, trust in AI, perceived risk, and attitude to better explain why consumers choose to buy through AI-powered shopping. Here, behavioral intention acts as the link between these technological and psychological factors and consumers' purchase decisions. The research uses Structural Equation Modeling (SEM) to analyze survey responses from 432 participants. By doing so, the study expands the use of the UTAUT framework in AI-driven retail and offers evidence about which technological, behavioral and psychological factors matter most for consumer buying intention. The results of this study provide both theoretical and practical value. On the theoretical side, the research adds to technology acceptance literature by including AI-specific factors in the UTAUT framework, giving a fuller picture of how consumers behave in AI-powered shopping. On the practical side, the findings offer useful guidance for e-commerce platforms, online retailers, AI developers, and digital marketers who want to boost consumer acceptance of AI shopping tools by improving system design, personalizing customer experiences, and building trust.

2. Data Collection and Preparation

This study used a quantitative cross-sectional survey to explore what affects consumer buying intentions for AI-powered shopping. Data came from people who had used or were familiar with AI shopping tools like recommendation systems, virtual assistants, and chatbots. The researchers distributed a structured questionnaire both online and offline to reach more participants. The questionnaire had two parts. The first part asked for demographic details like gender, age, education, income, job, and location. The second part focused on the main factors from the Extended UTAUT model, including Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, Perceived Ease of Use, Attitude, Perceived Risk, Trust in AI, Behavioral Intention, and Consumer Buying Intention. All questions used a five-point Likert scale from 1 (Strongly Disagree) to 5 (Strongly Agree).

After checking the questionnaires for completeness and consistency, 432 valid responses were kept for analysis. Before testing the hypotheses, normality was assessed. The results showed no major data quality problems, so the dataset was suitable for further analysis. Next, the reliability and validity of the measurement model were checked using Cronbach's alpha, Composite Reliability, Average Variance Extracted and Confirmatory Factor Analysis . The hypotheses as mentioned in the conceptual framework (Figure 1) were then tested with covariance-based Structural Equation Modeling.

2.1 Conceptual Framework

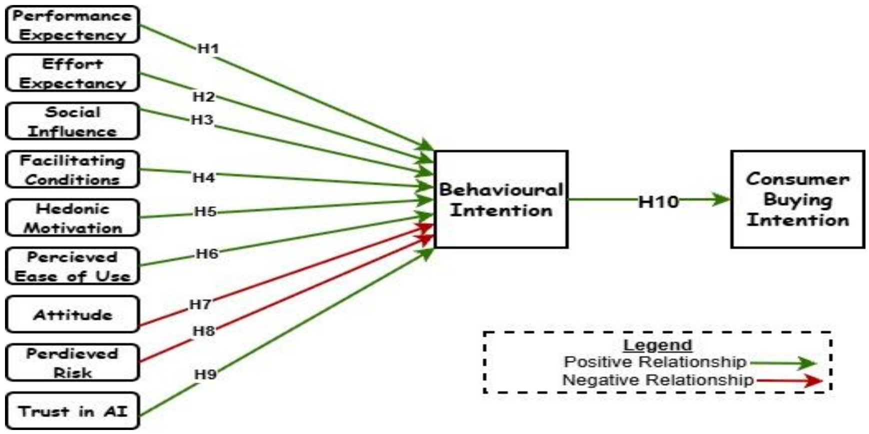


Figure 1.Conceptual Framework of the study

3. Methodology

Statistical analyses were carried out Pythons's semopy library . First, descriptive statistics summarized the respondents' demographic characteristics and the distribution of study variables. Before estimating the model, the dataset was checked and normality using descriptive measures. Because the study used ordinal data on a five-point Likert scale, non-parametric tests were used to examine differences in consumer buying intention across demographic groups. The Mann–Whitney U test compared gender-based differences , while the Kruskal–Wallis H test was used for variables with more than two categories , such as age, education, income, occupation, and location. All statistical analyses used a significance level of 5% ($p < 0.05$).

The internal consistency of the measurement scales was subsequently evaluated using Cronbach's alpha (α) and Composite Reliability (CR) (Adamson & Prion, 2013). Cronbach's alpha was calculated as

$$\alpha = \frac{k}{k-1}\left(1-\frac{\sum_{i=1}^{k}\sigma_i^2}{\sigma_T^2}\right),$$

where k represents the number of measurement items, σ_i^2denotes the variance of each item, and σ_T^2i is the total variance of the scale. Composite Reliability was computed as

$$CR = \frac{\sum {\lambda_i}^2}{\sum {\lambda_i}^2 + \sum \theta_i},$$

where $\lambda_i$is the standardized factor loading and $\theta_i$represents the measurement error. Values exceeding 0.70 were considered indicative of satisfactory reliability.

The validity of the measurement model was assessed using Confirmatory Factor Analysis (CFA). Convergent validity was evaluated through standardized factor loadings, Composite Reliability (CR) and Average Variance Extracted (AVE), where AVE was calculated as

$$AVE = \frac{\sum \lambda_i^2}{n},$$

with $\lambda_i$representing the standardized factor loading and n denoting the number of indicators for each construct. Model adequacy was examined using multiple goodness-of-fit indices, including the Comparative Fit Index (CFI), Tucker–Lewis Index (TLI), Goodness-of-Fit Index (GFI), Adjusted Goodness-of-Fit Index (AGFI), Normed Fit Index (NFI), and the Root Mean Square Error of Approximation (RMSEA) (West et al., 2023).

Following the validation of the measurement model, the proposed hypotheses were tested using covariance-based Structural Equation Modeling (CB-SEM). The structural model can be expressed as

$$\eta = B\eta + \Gamma\xi + \zeta,$$

where η denotes the endogenous latent variables, ξ represents the exogenous latent variables, B is the coefficient matrix among endogenous constructs, Γ is the coefficient matrix relating exogenous to endogenous constructs, and ζ is the structural error term. The significance of the hypothesized relationships was evaluated using standardized path coefficients (β), critical ratios (z-values), and corresponding p-values, with statistical significance established at $p < 0.05$.

4. Results and Discussion

This section shares the main findings from the statistical analyses and explains how they relate to the Extended UTAUT framework. It covers the respondent profile, reviews the measurement and structural models, and then interprets the hypothesized relationships.

4.1 Respondent Profile

Figure 2 presents the demographic characteristics of the respondents included in this study. A total of 432 valid responses were analyzed. Male respondents constituted 55.1% of the sample, while females accounted for 44.9%, indicating a relatively balanced gender distribution. Regarding residential location, 48.4% of the respondents were from rural areas, followed by 27.5% from semi-urban areas and 24.1% from urban areas. In terms of educational attainment, the majority (53.2%) possessed a master's degree or higher, whereas 25.7% were graduates and 20.8% had completed higher secondary education. Nearly half of the respondents (44.4%) reported a monthly income below ₹10,000, and students represented the largest occupational group (50.5%), followed by government employees (25.7%) and private-sector employees (17.8%). These findings indicate that the study captured responses from consumers with diverse demographic backgrounds, providing an appropriate sample for examining AI-powered shopping behavior.

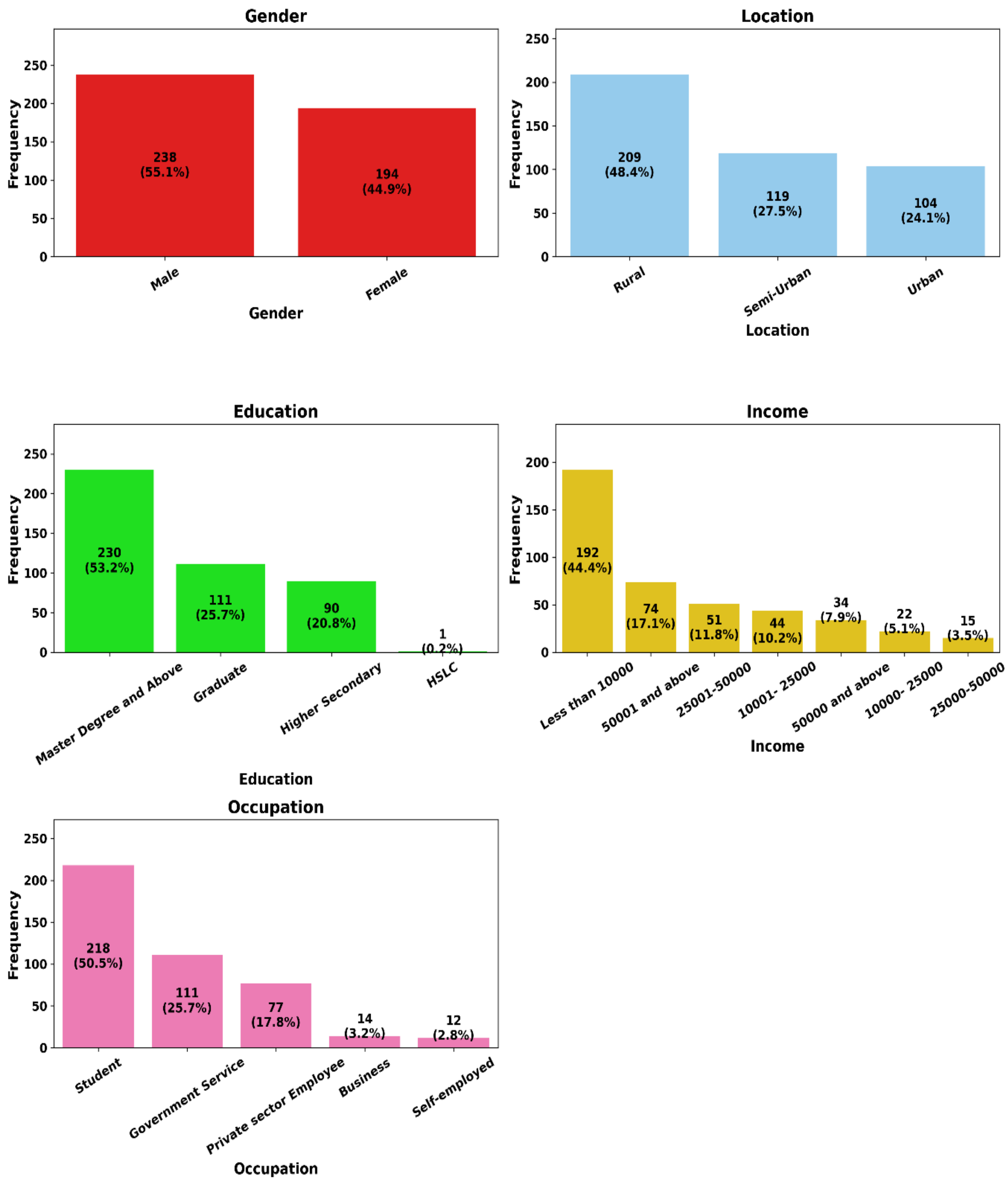


Figure 2.Demographic profile of respondents

Table 1.Results of the non-parametric tests

Variable	Test	Statistic	p-value	Significant
Gender	Mann-Whitney U	22006.5	0.401966962	No
Location	Kruskal-Wallis	0.524666	0.769254686	No
Age	Kruskal-Wallis	19.66535	0.76415215	No
Education	Kruskal-Wallis	2.672985	0.444837775	No
Income	Kruskal-Wallis	7.774358	0.255104942	No

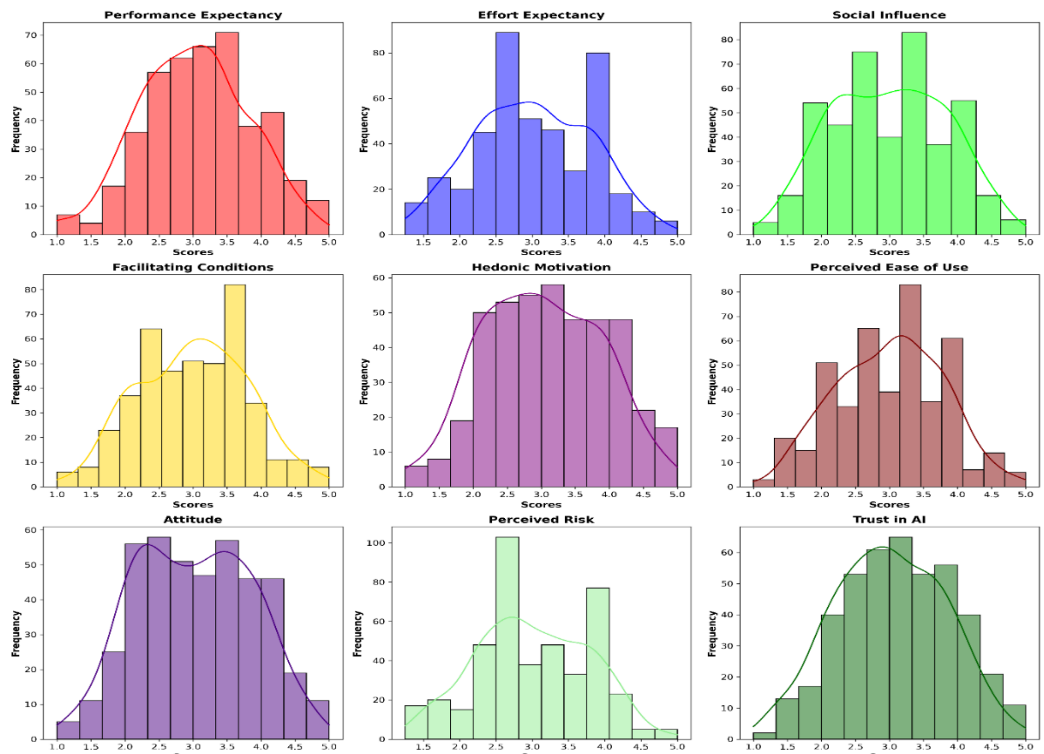
Occupation	Kruskal-Wallis	3.051959	0.549168096	No

To examine whether consumer buying intention differed across demographic groups, non-parametric statistical tests were performed.

Table 1 presents the results of the Mann–Whitney U and Kruskal–Wallis tests examining demographic differences in consumer buying intention. The findings reveal that gender, age, education, income, occupation, and residential location do not significantly influence consumer buying intention ($p > 0.05$). These results suggest that consumers exhibit relatively homogeneous purchasing intentions across different demographic categories, implying that AI-powered shopping behavior is influenced more strongly by psychological and technological factors than by demographic characteristics. Consequently, demographic variables were not incorporated as explanatory variables in the structural model.

4.2 Measurement Model Assessment

Prior to assessing the reliability and validity of the measurement model, the normality of the observed variables was assessed through histograms. Figure 3 displays the distribution of the latent constructs incorporated in the proposed model. The histograms demonstrate that the observed variables exhibit approximately bell-shaped distributions with only minor deviations from normality. Since slight departures from normality are common in behavioral studies employing Likert-scale measurements, the observed distributions do not indicate any substantial violations of the normality assumption.



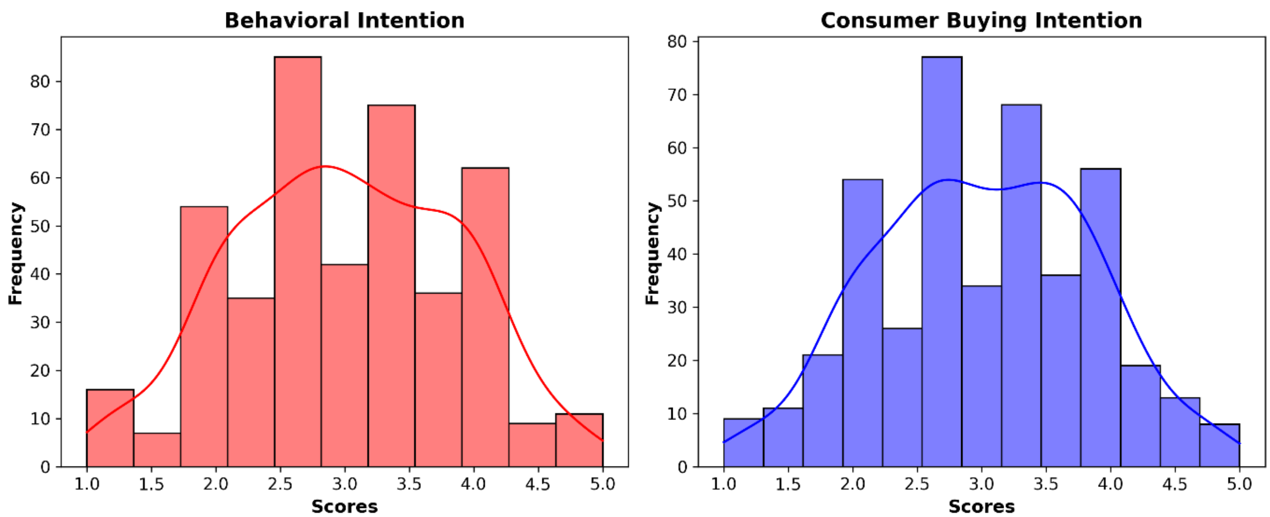


Figure 3.Histograms and normality assessment of latent constructs

After checking for normality, we assessed the reliability and convergent validity of the measurement model using Cronbach's alpha, Composite Reliability (CR), and Average Variance Extracted (AVE). Table 2 shows the results.

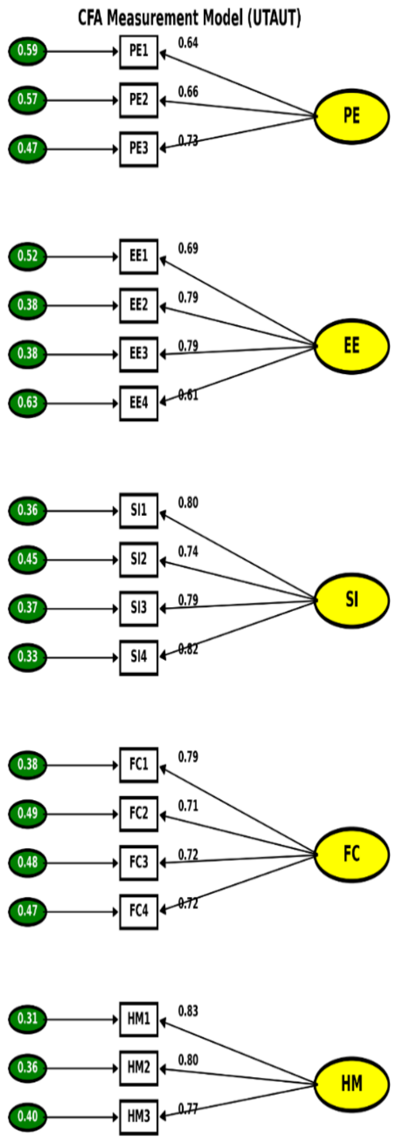
Table 2.Reliability and convergent validity of the measurement model

Statistic	**PE**	**EE**	**SI**	**FC**	**HM**	**PEOU**	**ATT**	**PR**	**TRUST**	**BI**	**CBI**
Cronbach's	0.715	0.81	0.867	0.825	0.843	0.841	0.923	0.785	0.751	0.893	0.89
AVE	0.459	0.524	0.622	0.543	0.642	0.514	0.666	0.48	0.507	0.679	0.619
CR	0.718	0.813	0.868	0.826	0.843	0.841	0.923	0.786	0.755	0.894	0.89

The results show good internal consistency for all constructs, with Cronbach's alpha values between 0.715 and 0.923, all above the recommended 0.70. Attitude had the highest reliability ($\alpha = 0.923$), followed by Behavioral Intention ($\alpha = 0.893$) and Consumer Buying Intention ($\alpha = 0.890$). Composite Reliability values ranged from 0.718 to 0.923, which confirms the constructs are reliable. Most Average Variance Extracted (AVE) values were above the recommended 0.50, showing good convergent validity. While Performance Expectancy (0.459) and Perceived Risk (0.480) had AVE values just below 0.50, their Composite Reliability values were above 0.70, which is considered acceptable in SEM literature. Overall, these results confirm that the measurement scales are reliable and valid for further analysis.

4.3 Measurement Model Validation

To test the proposed measurement framework, Confirmatory Factor Analysis (CFA) was performed on the baseline UTAUT model, which included the original constructs: Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, Behavioral Intention, and Consumer Buying Intention. While the baseline model showed an acceptable fit, it did not consider AI-specific psychological factors that are important for understanding consumer behavior in AI-enabled shopping. To address this, we added Perceived Ease of Use, Attitude, Perceived Risk, and Trust in AI to create the Extended UTAUT model. Figure 4 shows the CFA results for both models. To see if adding these new constructs improved the measurement model, we compared the goodness-of-fit indices for both models. The results are shown in Table 3. It shows that both models met the recommended criteria for goodness-of-fit in covariance-based Structural Equation Modeling. The Extended UTAUT model performed slightly better than the baseline model. For example, the Tucker–Lewis Index (TLI) rose from 0.915 to 0.921, and the Root Mean Square Error of Approximation (RMSEA) dropped from 0.081 to 0.072, which means the model fit improved. While the Goodness-of-Fit Index (GFI) and Normed Fit Index (NFI) decreased a little, both stayed above the recommended 0.90 threshold, and the Comparative Fit Index (CFI) did not change. These results show that adding Perceived Ease of Use, Attitude, Perceived Risk, and Trust in AI made the original UTAUT framework more effective without reducing the overall model fit. Therefore, the Extended UTAUT model was used for further analysis and hypothesis testing.



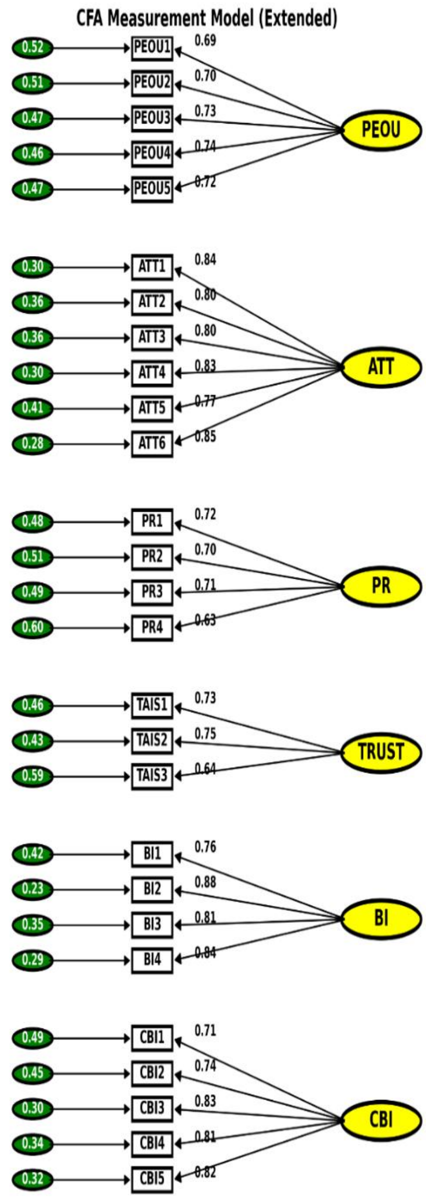


Figure 4.Confirmatory Factor Analysis (CFA) measurement model

Table 3.Comparison of goodness-of-fit indices between the baseline UTAUT model and the proposed Extended UTAUT model.

Fit Index	**Baseline Model**	**Extended Model**
CFI	0.934	0.934
TLI	0.915	0.921
RMSEA	0.081	0.072
GFI	0.914	0.907
AGFI	0.888	0.89

NFI	0.914	0.907

4.4 Structural Model Assessment

After confirming the measurement model, we estimated the structural model to test the hypothesized relationships between the latent constructs. Figure 5 shows the standardized Structural Equation Model (SEM) for the proposed Extended UTAUT framework.

Final Extended UTAUT SEM Model

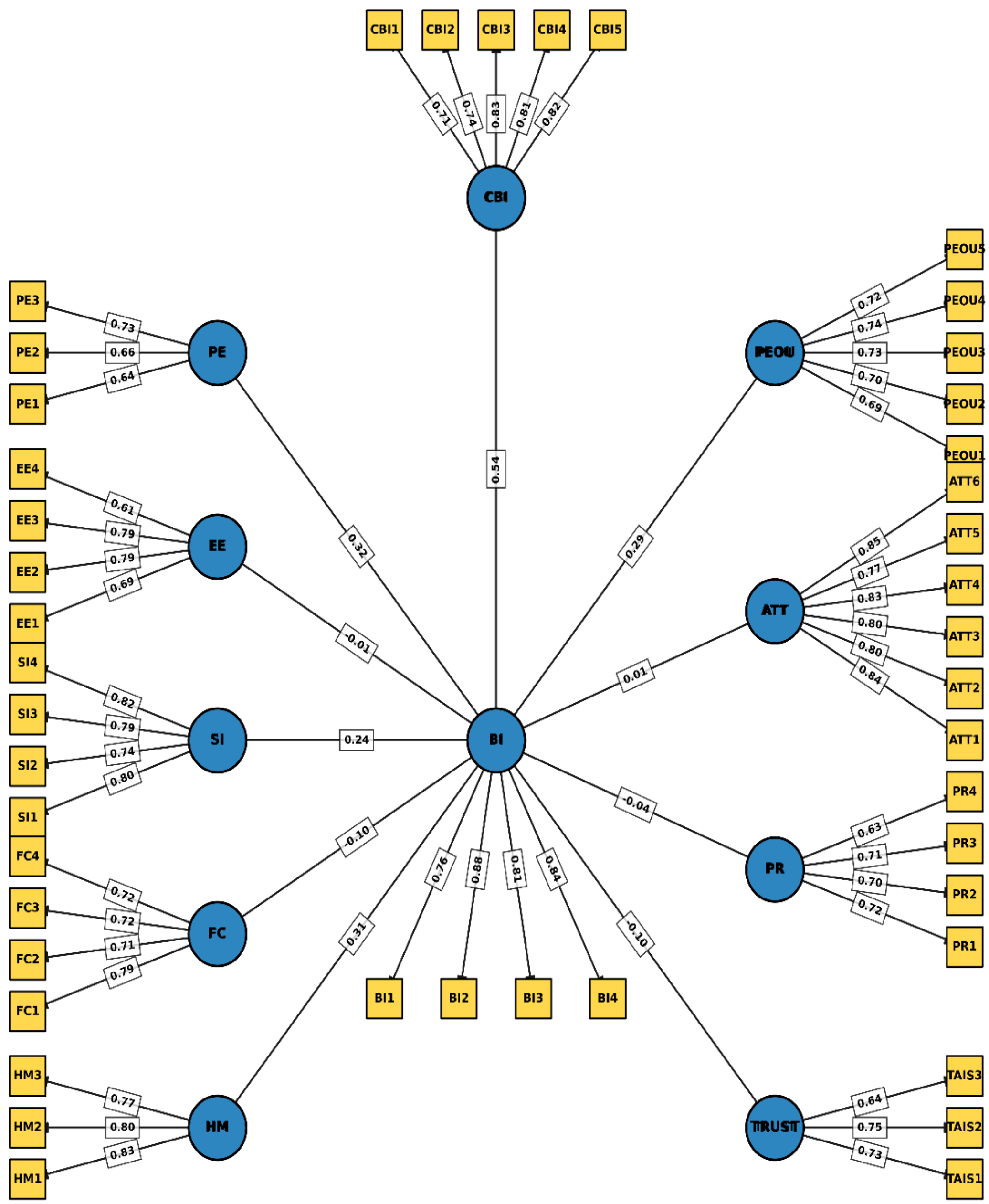


Figure 5.Structural Equation Model (SEM) of the proposed Extended UTAUT model

The structural model measures how the proposed factors directly affect Behavioral Intention, and how Behavioral Intention then influences Consumer Buying Intention. Table 4 summarizes the standardized path coefficients, critical ratios, and significance levels for each hypothesis.

Table 4.Structural path coefficients and hypothesis testing

Hypothesis	**Path**	**Standardized β**	**S.E.**	**C.R. (z)**	**p-value**	**Decision**
H1	PE → BI	0.318	0.046	7.586	<0.001	Supported
H2	EE → BI	-0.006	0.046	-0.151	0.880	Not Supported
H3	SI → BI	0.238	0.045	5.401	<0.001	Supported
H4	FC → BI	-0.1	0.045	-2.376	0.017	Not Supported*
H5	HM → BI	0.306	0.045	6.801	<0.001	Supported
H6	PEOU → BI	0.294	0.047	6.908	<0.001	Supported
H7	ATT → BI	0.013	0.047	0.273	0.785	Not Supported
H8	PR → BI	-0.045	0.053	-0.958	0.338	Not Supported
H9	TRUST → BI	-0.099	0.046	-2.281	0.023	Not Supported*
H10	BI → CBI	0.535	0.039	13.157	<0.001	Supported

The covariance-based Structural Equation Modeling (CB-SEM) was used to examine the relationships among the main factors. The results show that Performance Expectancy had a significant positive effect on Behavioral Intention ($\beta = 0.318$, $p < 0.001$), supporting H1. This means consumers are more likely to use AI-powered shopping if they believe it helps them shop more efficiently and make better decisions. Social Influence also had a significant positive effect on Behavioral Intention ($\beta = 0.238$, $p < 0.001$), supporting H3. This suggests that recommendations from family, friends, and social networks encourage consumers to try AI-powered shopping technologies. The results also show that Hedonic Motivation had a significant positive effect on Behavioral Intention ($\beta = 0.306$, $p < 0.001$), supporting H5. This means consumers are more likely to use AI-powered shopping when they find the experience enjoyable and engaging. Perceived Ease of Use also had a significant positive relationship with Behavioral Intention ($\beta = 0.294$, $p < 0.001$), supporting H6. This suggests that easy-to-use AI interfaces and simple interactions make consumers more willing to use AI shopping platforms. On the other hand, Effort Expectancy did not have a significant effect on Behavioral Intention ($\beta = –0.006$, $p = 0.880$), so H2 was not supported. Attitude ($\beta = 0.013$, $p = 0.785$) and Perceived Risk ($\beta = –0.045$, $p = 0.338$) also did not show significant effects, so H7 and H8 were not supported either. These results suggest that consumers are more influenced by the benefits and experience of AI-powered shopping than by their general attitudes or concerns about risk. Facilitating Conditions had a significant but negative relationship with Behavioral Intention ($\beta = –0.100$, $p = 0.017$), which was the opposite of what we expected, so H4 was not supported. This suggests that just having access to technology and support does not always make people more likely to use AI-powered shopping. Trust in AI also had a significant negative relationship with Behavioral Intention ($\beta = –0.099$, $p = 0.023$), so H9 was not supported. This result suggests that even if consumers say they trust AI, they may still be cautious about using AI shopping systems, possibly because of concerns about transparency, privacy, or less human involvement in buying decisions.

5. Conclusion

This study looked at what affects consumers' intentions to buy through AI-powered shopping. The researchers expanded the Unified Theory of Acceptance and Use of Technology (UTAUT) by adding Perceived Ease of Use, Attitude, Perceived Risk, and Trust in AI. They used covariance-based Structural Equation Modeling (CB-SEM) to analyze data from 432 respondents and explored how technological, psychological, and behavioral factors influence consumers' adoption of AI-powered shopping. The results showed that Performance Expectancy, Social Influence, Hedonic Motivation, and Perceived Ease of Use all had a strong positive effect on Behavioral Intention. Behavioral Intention was also the strongest factor predicting whether consumers would buy. On the other hand, Effort Expectancy, Attitude, and Perceived Risk did not have a significant impact on Behavioral Intention. Facilitating Conditions and Trust in AI were significant but had negative effects, which was unexpected. This suggests that more research is needed to understand how these factors influence AI-powered shopping. This study adds to research on how consumers use AI by showing that expanding the UTAUT framework helps explain why people choose AI-powered shopping. For managers, the results suggest that retailers and e-commerce platforms should focus on making AI shopping tools more useful, easier to use, and enjoyable to encourage consumers to use them and make purchases. However, this study has some limitations. Its cross-sectional design and the specific group of respondents may limit how widely the findings can be applied. Future research could use longitudinal studies, look at more AI-related factors, and test the framework in different regions, among various demographic groups, and on other e-commerce platforms to better understand how people adopt AI-powered shopping.

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