MULTIDISCIPLINARY SCIENTIFIC RESEARCH
BJMSR VOL 10 NO 2 (2025) P-ISSN 2687-850X E-ISSN 2687-8518
Available online at https://www.cribfb.com
Journal homepage: https://www.cribfb.com/journal/index.php/BJMSR
Published by CRIBFB, USA

CONSUMERS' ATTITUDE TOWARD AI-DRIVEN E-COMMERCE ADOPTION IN BANGLADESH: AN EXTENSION OF PLANNED BEHAVIOR

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ARTICLE INFO

Article History:

Received: 5th January 2025
Reviewed & Revised: 5th January 2025 to 29th April 2025
Accepted: 30th April 2025
Published: 8th May 2025

Keywords:

Technological adoption, E-commerce, AI-based Personalization, Marketing Strategy, Consumer Behavior, Theory of Planned Behavior

JEL Classification Codes:

O33, L81, M31, M37, D12, D91

Peer-Review Model:

External peer review was done through double-blind method.

ABSTRACT

In recent years, the online shopping sector in Bangladesh has witnessed a tremendous transition driven by technological advancements and changing consumer habits. Artificial intelligence (AI) technologies, including chatbots, AI-enhanced Personalization, and intelligent recommendations, have further developed this sector. However, research indicates that many consumers in Bangladesh still favor offline shopping. This situation highlights the necessity of identifying the factors affecting consumers' AI-driven online shopping behavior. Therefore, this study employs an extended Theory of Planned Behavior (TPB) framework to investigate the factors determining consumer preferences for AI-enabled e-commerce platforms in Bangladesh. Data was gathered using a stratified random sampling method from 384 online shoppers in Rajshahi City Corporation. Structural Equation Modeling (SEM) assessed the affinities between the key variables. The findings reveal that consumers' perceptions of promotional discounts and perceived behavioral control significantly influenced their attitudes toward AI-driven online shopping. Factors such as promotional discounts, perceived benefits, and AI-based Personalization notably influence consumers' purchase intentions. These results underscore the importance of competitive pricing strategies, value-added services, and personalized experiences in encouraging consumer adoption of AI-powered e-commerce platforms, providing valuable insights for improving the online shopping environment nationwide. This research offers actionable strategies for online retailers, suggesting that prioritizing AI integration, promotional offers, and tailored customer experiences can better position e-commerce businesses to meet evolving consumer expectations and sustain long-term market growth in Bangladesh's competitive retail landscape.

INTRODUCTION

The digital transformation of the retail landscape, driven by the integration of artificial intelligence (AI) in e-commerce, is a global phenomenon rapidly reshaping consumer behavior and business practices (Aljarboa, 2024). Despite a slow initial uptake, Bangladesh has recently experienced significant growth in online shopping fueled by increased accessibility through digital banking and online payment systems (Karim et al., 2023). This growth is not merely a trend but a substantial economic force, with Bangladesh's e-commerce sector now supporting thousands of businesses and employees. Furthermore, online platforms have expanded consumer access to diverse product ranges, surpassing the limitations of the customary form of shopping (Ahmed et al., 2020). However, this sector still has many challenges (Fawehinmi et al., 2024). Consumers encounter obstacles during online transactions, underscoring the importance of understanding the factors shaping their shopping experiences (Hossain et al., 2022). To foster sustainable growth and address these challenges, a deeper understanding of consumer preferences for online shopping is crucial despite the sector's rapid expansion and the identified consumer challenges (Sumi & Ahmed, 2022). Research examining consumer behavior in an AI-driven e-commerce context in Bangladesh is notably scarce. This research gap creates a critical need for empirical investigations to illuminate the determinants of consumer adoption and usage of AI-enhanced online platforms. Thus, we aim to address this gap by focusing on consumer preferences for online shopping, employing an extended theory of planned behavior (TPB)

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https://doi.org/10.46281/bjmsr.v10i2.2344

To cite this article: Nourin, S., Rahman, M. A., Hossain, M. E., & Iqbal, M. H. I. (2025). CONSUMERS' ATTITUDE TOWARD AI-DRIVEN E-COMMERCE ADOPTION IN BANGLADESH: AN EXTENSION OF PLANNED BEHAVIOR. *Bangladesh Journal of Multidisciplinary Scientific Research*, *10*(2), 41-52. https://doi.org/10.46281/bjmsr.v10i2.2344

model. To achieve this, we used Structural Equation Modeling (SEM), a widely recognized and robust analytical approach for behavioral research, allowing for the simultaneous evaluation of complex relationships between multiple constructs. By integrating contemporary, technology-driven variables into a traditional behavioral framework, this study will provide valuable insights for online retailers, policymakers, and stakeholders seeking to improve the e-commerce landscape in Bangladesh. Ultimately, this study contributes to a more informed experience of optimizing AI integration in e-commerce to benefit consumers and businesses in a rapidly evolving digital market.

This study is organized into six main sections, each comprising several sub-sections. The Introduction provides a set of the work, sketches the problem statement, and clearly states the objectives. Following this, the Literature review summarizes existing knowledge on consumer online shopping behavior, highlights theoretical foundations, and identifies research gaps the current study aims to address. The Methods section details the research design, data collection procedure, and analytical tool for examining the ' variables' relationships between variables. The Results section presents the empirical findings, indicating which hypotheses were supported and which were not, while the Discussion interprets these results in light of existing literature, offering possible explanations for the findings and situating them within broader behavioral research. Finally, the Conclusion highlights the study's unique contributions, discusses academic and organizational importance, and provides proposals for practice and future research directions.

LITERATURE REVIEW

Theoretical Motivation and Existing State of Knowledge

Several theories attempt to explain and predict human behavior, including the TPB, rational choice theory, economic utility analysis, and psychological behavior theories. Among these, Ajzen's (2020) TPB stands out for its robust framework for understanding decision-making. It posits that someone's intention to perform a behavior is driven by three core components: attitude, subjective norms, and perceived behavioral control. The first term, attitude, reflects someone's positive or negative evaluation of a specific manner. In AI-driven e-commerce, attitude captures consumers' feelings toward adopting these practices. As Javadi et al. (2012) demonstrated, positive and negative attitudes significantly influence purchasing behavior. Specifically, trust and perceived usefulness in online shopping shape these attitudes. Essentially, attitude represents the consumer's evaluation of engaging with AI-driven e-commerce. The perceived social pressures that shape conduct are known as subjective norms. Subjective norms in online shopping are influenced by expectations from friends, family, and the community about AI-powered e-commerce. Hasbullah et al. (2016) emphasized the influence of these norms on actual behavior and purchasing intentions. The views of friends, family, and peers frequently impact people (Javadi et al., 2012; Sutisna & Handra, 2022). Subjective norms represent the perceived social pressure to engage with AI-driven e-commerce. Online shopping encompasses their perceived capacity to use AI-driven e-commerce, considering factors like resources, knowledge, and skills. Rhodes and Courneya (2005) defined it as the perception of one's capabilities, while Javadi et al. (2012) emphasized the perceived ease or difficulty of performing the behavior. Customers' perception of their ability to successfully use AI-driven e-commerce is reflected in their perceived behavioral control. By integrating these three components, TPB provides a comprehensive model for predicting and understanding consumers' intentions and actions in AI-driven e-commerce. Therefore, an evidence-based approach, grounded in existing studies and observations, highlights the effectiveness of the TPB in formulating hypotheses and questionnaires for empirical assessment, as explored in the subsequent sections.

AI-Based Personalization and Consumer Online Shopping

The connection between consumer online buying and AI-based personalization marketing, perfectly tailored to each person's tastes, habits, and requirements, is made possible by AI-based Personalization (Babatunde et al., 2024). Big data, behavioral analysis, and prediction algorithms are all used by this technology to provide messages that are specifically personalized to each user. AI-based Personalization has the potential to impact consumers' impulse buying behavior through several methods, such as boosting psychological components like exclusivity and urgency, boosting message relevance, and arousing consumer emotions (Widiatmo, 2024). Therefore, we hypnotize:

H_1: *Personalization powered by AI significantly affects online purchase intention*
H_2: *Personalization powered by AI significantly affects consumer attitudes towards online shopping.*

Attitude and Online Shopping Intention

A person's positive or negative assessment of a specific activity is called their attitude toward conduct in the Theory of Planned Behavior (TPB) (Fawehinmi et al., 2024). Numerous studies have demonstrated a strong link between attitude and online shopping intention. For example, Qi and Ploeger (2019) found that consumer intention to shop online is primarily driven by attitude. Similarly, Alam and Mohamed Sayuti (2011) observed a significant impact of attitude on halal food purchasing behavior. M. C. Lee (2009) also concluded that attitude, perceived benefits, and privacy risk significantly influence intentions of online banking usage. Therefore, we hypothesize:

H_3: *Attitude significantly affects consumers' online shopping intention.*

Subjective Norms and Online Shopping

According to Husna et al. (2024), subjective norm (SN) is a person's sense of social pressure or influence from significant others (such as family, friends, or society) over whether a particular action should be taken. Hasbullah et al. (2016) used the TPB to explore the link between online shopping intention and subjective norms. Ming-Shen et al. (2007) highlighted that subjective norms shape attitudes towards specific behaviors. Studies by Jain (2020) and Lim et al. (2016) further indicate that social pressure and community expectations significantly influence online shopping decisions. Thus, we hypothesize;

H₄: *Subjective norms significantly affect online shopping intention.*

Perceived Behavioral Control and Online Shopping Intention

(PBC) used in the (TPB) model is the degree to which a person believes they can carry out or regulate a specific behavior, depending on perceived resources, abilities, or barriers (Istiasih, 2023). The rise of online shopping has prompted investigations into the factors driving its adoption and continued use. Wu and Song (2021) highlighted the impact of perceived limitations on traditional shopping, finding that a perceived lack of shopping mobility significantly enhances the perceived usefulness of online platforms. Furthermore, their study explored the social dynamics of online shopping, revealing that while perceived social isolation increases subjective norms, it simultaneously diminishes perceived behavioral control. Notably, Wu and Song (2021) and Hoque et al. (2024) found that perceived behavioral control, rather than subjective norms, directly influences online shopping continuance intentions. In alignment with these findings, Islam et al. (2022) demonstrated a direct and substantial relationship between perceived behavioral control and actual online buying activity, underscoring its crucial role in translating intentions into action. We can formulate hypotheses that reflect the key relationships based on the coherent narrative.

H_5: *Behavioral Control significantly affects consumers' attitudes toward online shopping*
H_6: *Behavioral control significantly affects online shopping intention.*

Perceived Benefits and Attitudes

Perceived benefits significantly shape consumers' attitudes towards online shopping. These benefits include technological characteristics like download speed, website navigation, data security, and product attributes such as diagnostic and value. Furthermore, consumer-specific elements, such as digital skills, time and monetary resources, and the convenience of information access, play crucial roles. As highlighted by Ruiz-Herrera et al. (2023), a positive attitude towards website usage, driven by perceived usefulness and trust, directly fosters usage intention by facilitating easier and safer transactions. This aligns with Bhatti and Rehman (2019), who linked perceived benefits to consumer satisfaction, and Akroush and Al-Debei (2015), who emphasized the significant impact of time-saving and convenience on e-shopping attitudes. In essence, the confluence of these perceived benefits cultivates a positive consumer attitude, which drives usage intention and satisfaction.

H_7: *Perceived benefits influence attitude toward online shopping behavior*
H_8: *Perceived benefits influence consumers' online shopping intentions*

Promotional Discounts and Attitude

Promotional discounts can enhance perceived benefits and alleviate perceived risks, positively impacting attitudes. Zhu et al. (2019) found that discounts enhance perceived cost savings. Kim and Krishnan (2019) suggested that discounts reduce perceived risk. L. Lee and Charles (2021) highlighted that discounts can motivate online shopping and positively influence attitudes. Therefore, we hypothesize:

H_9: *Promotional discounts significantly affect attitudes towards online shopping.*
H_{10}: *Promotional discounts significantly affect consumers' online shopping intentions.*

The proposed hypotheses, derived from the TPB and existing literature, require empirical validation within the Bangladeshi context to accurately assess and understand the factors influencing consumer behavior in online shopping.

It is possible to infer from the current research that several indicators influence consumers' online purchasing habits. According to observational studies like Javadi et al. (2012), a customer's attitude can influence their purchase intentions again. Istiasih (2023) showed that subjective norms are another significant component that might affect consumer behavior. Additionally, some researchers discovered compelling evidence that a consumer's control over their behavior can affect their behavior. TPB model consists of all three components. Once more, when we extend this model, we discover that other factors can affect attitude. According to an observational study, risk and benefit can affect attitude (Ruiz-Herrera et al., 2023). Artificial intelligence, such as chatbots and AI-based customization, can also affect attitudes (Babatunde et al., 2024). Thus, combining all of these variables with the notion of planned behavior can create a conceptual framework for comprehending consumer AI-driven online buying behavior. The study's conceptual framework is depicted in Figure 1 below.

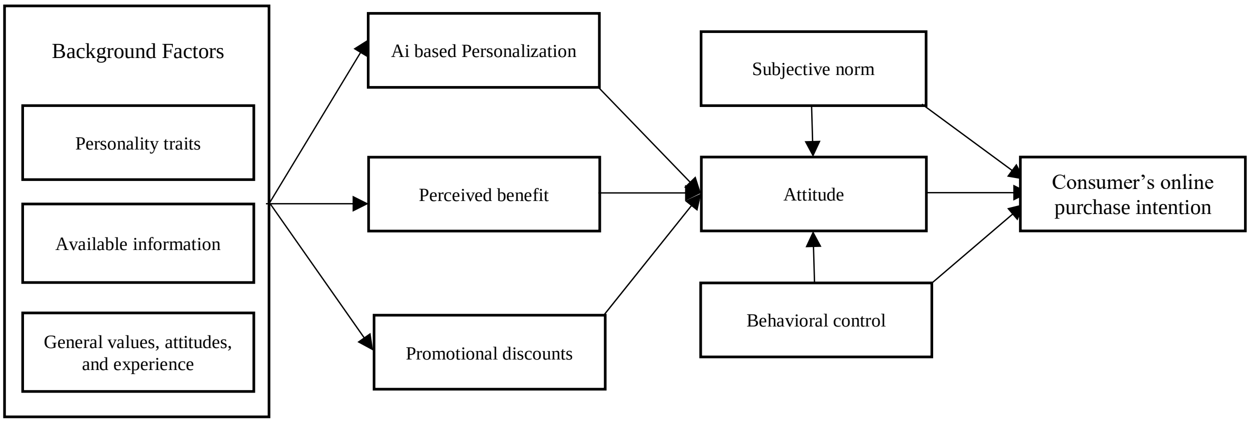

Figure 1. Conceptual framework
Source: Prepared by the authors based on Ajzen, 1991

MATERIALS AND METHODS

Study Area

For several reasons, we selected Rajshahi City Corporation (RCC) as our study area. First, RCC is one of the most digitally advanced regions in the country. Second, relatively easy internet access is crucial for this study. Finally, RCC is a significant urban, commercial, and educational hub in Bangladesh, and it serves as the administrative headquarters for its division and surrounding regions.

Sampling Process

This study targeted individuals within Rajshahi City Corporation who have reliable internet access and engage in online shopping. According to the BBS (2022), this City Corporation has a population of 552,791, with approximately 19.7% of the Rajshahi Division population using the internet. Applying this percentage, we estimated our target population to be roughly 108,900 individuals. Therefore, to determine the required sample size, we used a 5% margin of error, resulting in a total of 384. To collect this data, we utilized stratified random sampling, dividing Rajshahi City Corporation into four strata based on its four thanas (police stations): Boalia, Motihar, Rajpara, and Shah Makhdum. We then allocated the sample size equally across these strata, aiming for approximately 96 individuals per thana. Recognizing that not all internet users have experience with online shopping, our questionnaire included a screening question to identify eligible respondents. To achieve our target of 384 valid responses, we conducted surveys with 587 individuals. The final distribution of respondents across the thanas was as follows: 136 from Boalia, 149 from Motihar, 163 from Rajpara, and 139 from Shah Makhdum.

Questionnaire Design for a Survey

We structured our questionnaire into four sections designed to capture specific information. In the first section, we keep a screening question to ensure respondents met the study's inclusion criteria. In the Second section, we asked questions about their socio-economic characteristics. After that, in the Third section, the questionnaire explored basic details related to respondents' online shopping experiences. Finally, we keep a concluding section to understand respondents' intentions toward future online shopping. The careful design of the questionnaire reflects our respect for the respondents' time and the value we place on their responses.

Piloting

Before collecting full-scale data, we conducted pilot research with 30 respondents to improve the questionnaire. We carefully observed and recorded respondents' feedback during these pilot interviews. This pre-test was crucial in identifying and addressing potential issues, such as misleading questions, grammatical errors, or insufficient information, ensuring the quality of our data. On average, each pilot interview took approximately 15 minutes. After gathering data from all 30 respondents and analyzing their feedback, we finalized the questionnaire for the primary survey.

Data Analysis Technique

We employed SEM to analyze consumer intentions towards online shopping. SEM is a statistical technique widely used in behavioral science that combines path and factor analysis (Byrne, B. M., 2016). As Sathyanarayana and Mohanasundaram (2024) noted, SEM utilizes latent variables to represent theoretical constructs, with path coefficients illustrating the relationships between these constructs. Path analysis, a specific form of SEM, describes the structural connections between observable variables, as highlighted by (Lei & Wu, 2007). In this research, hypotheses were formulated to examine the impacts, directions, and interrelationships between various variables. These structural relations reveal how independent variables influence the dependent variable, providing a comprehensive understanding of consumer intentions.

RESULTS

Respondent's Characteristics

In the final survey, the 384 respondents exhibited a near-even gender distribution, with 54% male (207 respondents) and 46% female (177 respondents), as presented in Table 1.

Table 1. Participants' demographic characteristics (n = 384)

Attributes/Variables	Value	Frequency	Percentage
Gender	Male	207	54%
	Female	177	46%
Marital status	Married	264	68.7
	Unmarried	120	31.3
Education	Higher secondary level	74	19.3
	Undergraduate level	36	9.4
	Graduate level	164	42.7
	Postgraduate level	110	28.7
Hours of Internet usage	Less than 3 hours	64	16.67
	4 to 7 hours	151	39.33
	8 to 11 hours	118	30.67
	More than 11 hours	51	13.33
Online shopping pattern	Multiple times per week	38	10.0
	Once a week	113	29.3
	2-3 times per month	174	45.3
	Once a month	49	15.3
Expenditure on online shopping	5,000 ≤	77	20
	5,001-10,000	95	24.67
	10,000-15,000	74	19.33
	15,001-20,000	107	28
	20,001≥	31	8

Source: Survey data, 2024

Table 1 shows that most participants were married (68.7%, n = 264), and the remaining 31.3% (n = 120) were unmarried. Educational attainment was diverse, reflecting a range of academic backgrounds: 19.3% (n = 74) had completed higher secondary education, 9.4% (n = 36) held an undergraduate degree, 42.7% (n = 164) possessed a graduate degree, and 28.7% (n = 110) had a postgraduate qualification. Internet usage patterns varied significantly, indicating a broad spectrum of engagement. A substantial portion of the respondents (39.33%, n = 151) reported using the internet for 4 to 7 hours daily, while 30.67% (n = 118) used it for 8 to 11 hours. Smaller segments of the sample reported less than 3 hours (16.67%, n = 64) or more than 11 hours (13.33%, n = 51) of daily internet usage. This varied internet usage likely influences online shopping behaviors, demonstrating variability. Specifically, 45.3% (n = 174) of respondents shopped online 2-3 times per month, 29.3% (n = 113) shopped once a week, 15.3% (n = 49) shopped once a month, and 10% (n = 38) shopped multiple times per week. Regarding online shopping expenditures over the past six months, a significant portion (28%, n = 107) spent between 15,001 and 20,000, while other spending ranges included 5,000 or less (20%, n = 77), 5,001 to 10,000 (24.67%, n = 95), 10,001 to 15,000 (19.33%, n = 74), and more than 20,001 (8%, n = 31).

Confirmatory Factor Analysis (CFA)

CFA was performed to understand the factors influencing online shopping behaviors. This analysis aimed to validate the measurement model by examining the constructs of the TPB model, AI-based Personalization, perceived benefit, and product discount. Using SPSS AMOS, the CFA assessed the fit of these constructs to the observed data. Model fit was evaluated using established criteria, including a chi-square to degrees of freedom ratio below 3 (Sathyanarayana & Mohanasundaram, 2024) and (GFI) above 0.90 (Hair et al., 2019). Figure 1 presents the CFA measurement model, while Table 2 summarizes the model's overall fit indices.

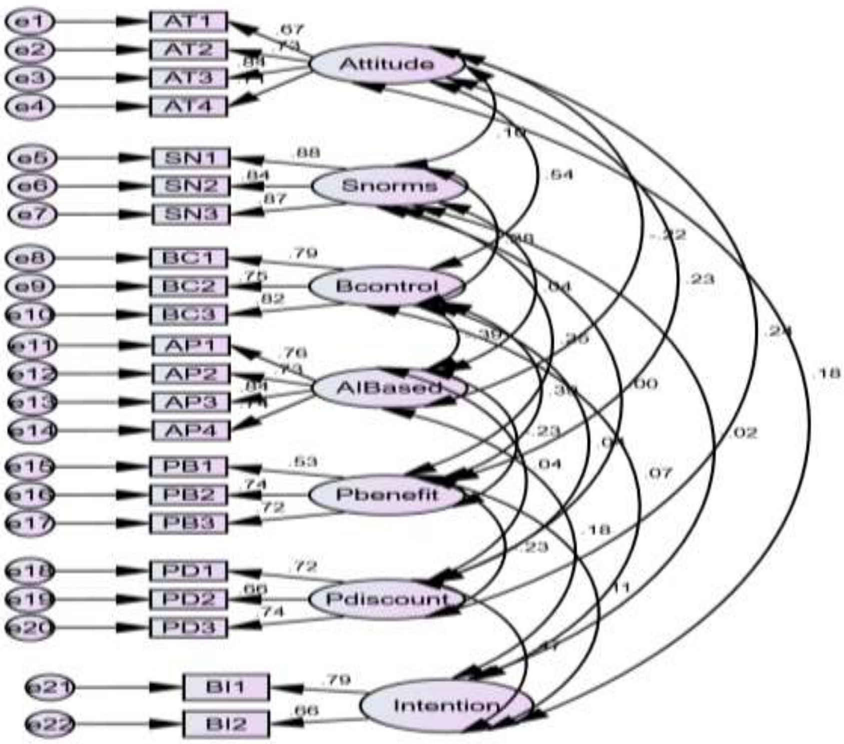

Figure 2. Structure of CFA
Source: Survey data, 2024

Table 2 details the measurement model's fitness indices, using multiple fit indicators to assess its overall adequacy.

Table 2. Fitness indices by CFA

Fit Indices	Criteria	Value
(χ2)	> 0.050	459.759
(χ^2/d.f)	< 5.00	2.44
(RMSEA)	< 0.08	0.061
GFI	> 0.90	0.915
(AGFI)	> 0.90	0.905
(IFI)	> 0.90	0.923
(TLI)	> 0.90	0.904
(CFI)	> 0.90	0.922

Source: Survey data, 2024

Table 2 displays the primary fit indices used to evaluate the measurement model's validity. While the χ^2 = 459.759 is significant, sample size often influences this. Therefore, we considered additional fit indices to provide a more comprehensive assessment. The normed χ^2/d.f = 2.44 fell within the acceptable range of less than 5.0, indicating a good fit. Similarly, the RMSEA is 0.061, below the recommended threshold of 0.08, further supporting a well-fitting model. The GFI = 0.915 and the AGFI = 0.905 exceeded the 0.90 criterion, confirming model adequacy. Furthermore, the IFI = 0.923, TLI = 0.904, and CFI = 0.922 surpassed the 0.90 cutoff. These results demonstrate that the measurement model exhibits a strong fit to the data and is thus valid and suitable for subsequent analyses.

Reliability & Validity of the Constructs

To further establish the model's overall validity and reliability, we assessed discriminant and convergent validity, adhering to the guidelines outlined by Campbell and Fiske (1959). The results of these analyses and the measurement model fit indices are presented in Tables 2 and 3.

This study evaluated the reliability and validity of seven key constructs: AI-based Personalization, attitudes, perceived benefit, subjective norms, behavioral control, product discount, and buying intention. Each construct was measured using multiple items, demonstrating strong factor loadings ranging from 0.765 to 0.996, indicating a robust relationship between the items and their respective constructs. Internal consistency was evaluated using (CR) values, and all constructs had values more than 0.848, indicating strong reliability. Convergent validity was established by calculating the (AVE). All constructs surpassed the 0.50 threshold, confirming adequate convergent validity, with buying intention exhibiting the highest AVE at 0.958. Furthermore, Cronbach's alpha (CA) values were above 0.90, demonstrating excellent reliability and consistency.

Table 3. Reliability & validity of the constructs

Construct	Items	Loadings	CR	AVE	CA
Attitude	AT1	0.765	0.886	0.662	0.901
	AT2	0.804			
	AT3	0.874			
	AT4	0.807			
Subjective Norms	SN1	0.910	0.929	0.814	0.926
	SN2	0.857			
	SN3	0.938			
Behavioral Control	BC1	0.851	0.891	0.731	0.904
	BC2	0.837			
	BC3	0.877			
AI-based Personalization	AP1	0.858	0.928	0.764	0.920
	AP2	0.847			
	AP3	0.904			
	AP4	0.886			
Perceived Benefit	PB1	0.765	0.848	0.650	0.901
	PB2	0.790			
	PB3	0.861			
Product Discount	PD1	0.830	0.867	0.685	0.904
	PD2	0.807			
	PD3	0.845			
Buying Intention	BI1	0.996	0.978	0.958	0.911
	BI2	0.961			

Source: Survey data, 2024

These results confirm that the measurement model exhibits strong fitness, with reliable and valid constructs suitable for further analysis.

Table 4. Discriminant validity test

	Intention	Attitude	SN	BC	AP	PB	PD
Intention	0.979						
Attitude	0.261	0.813					
SN	0.058	0.185	0.902				
BC	0.192	0.530	0.327	0.855			
AP	0.052	-0.077	0.084	-0.254	0.874		
PB	0.216	0.203	0.337	0.318	-0.130	0.806	
PD	0.653	0.273	0.088	0.048	-0.003	-0.106	0.827

Source: Survey data, 2024

The validity of the constructs was rigorously evaluated. First, we use Cronbach's alpha, which, according to Hair et al. (2019), should be greater than 0.7. In our study, Cronbach α coefficients ranged from 0.901 to 0.926, significantly exceeding the 0.700 threshold and indicating strong internal consistency for all constructs. Furthermore, factor loadings, which should surpass 0.700 according to Hair et al. (2019), ranged from 0.765 to 0.996, meeting this criterion and demonstrating robust item-construct relationships.

Next, convergent validity was examined using CR and AVE, adhering to the guidelines of Ab Hamid et al. (2017). These measures assess the degree to which items within a construct converge on the latent variable. Consistent with Inthong et al. (2022), CR values should be above 0.700 and AVE values above 0.500 for adequate convergent validity. In this study, CR values ranged from 0.848 to 0.978, and AVE values ranged from 0.662 to 0.958, all exceeding the established thresholds, as detailed in Table 2. These findings provide compelling evidence for the convergent validity of the CFA results.

Result of Hypothetical SEM

Utilizing SPSS AMOS 24, we proceed with our analysis in two key stages. First, the overall fitness of the hypothesized model was evaluated to determine how well it represented the observed data. Subsequently, the hypothesized relationships between exogenous (predictor) variables and endogenous (outcome) variables were tested. The overall model fit assessment results are presented in Figure 3 and Table 5.

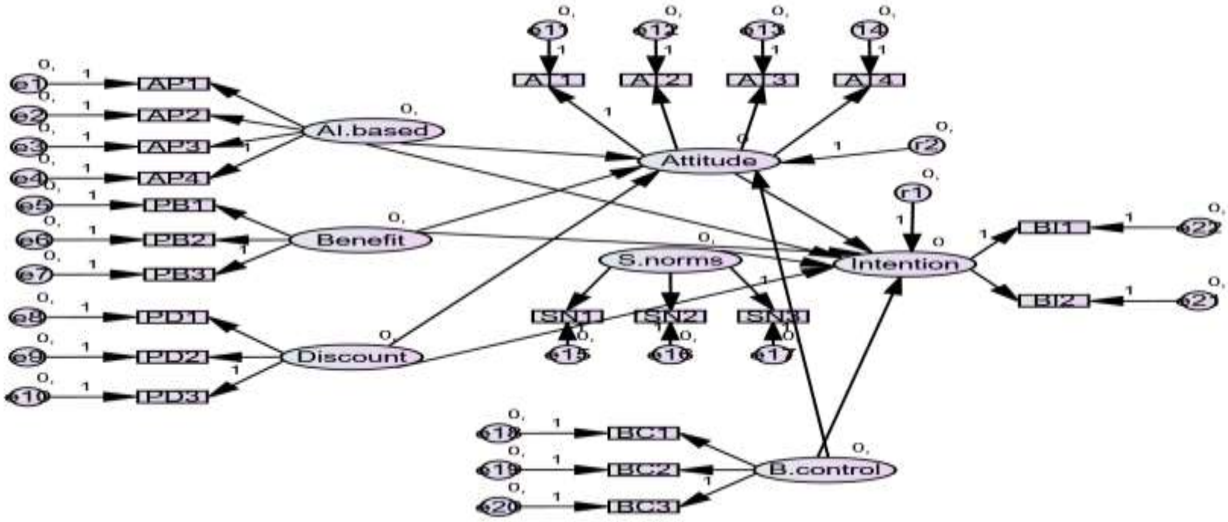

Figure 3. Hypothetical SEM
Source: Survey data, 2024

Table 5. Fitness Indices of Conceptual Structural Model

Fit index	Required criteria	Value
χ2	> 0.050	593.6
Normed χ²/d.f	< 5.00	2.98
RMSEA	< 0.08	0.072
GFI	> 0.90	0.853
AGFI	> 0.90	0.845
IFI	> 0.90	0.887
TLI	> 0.90	0.867
CFI	> 0.90	0.868

Source: Survey data, 2024

The above hypothetical model does not demonstrate an adequate fit, as some key indices fall short of the recommended thresholds. The RMSEA of 0.077 slightly exceeds the upper limit for a good fit, and the GFI (0.853) and AGFI (0.845) are below the desired value of 0.90. Similarly, the IFI (0.887), TLI (0.867), and CFI (0.868) don't meet the > 0.90 threshold, suggesting that the model lacks adequate incremental and comparative fit.

Modified Structural Model

Our hypothetical model shows inadequate fitness; therefore, we introduced a modified structural model following the guidance of modification indices provided by SPSS AMOS. The model with its corresponding fit index is presented below:

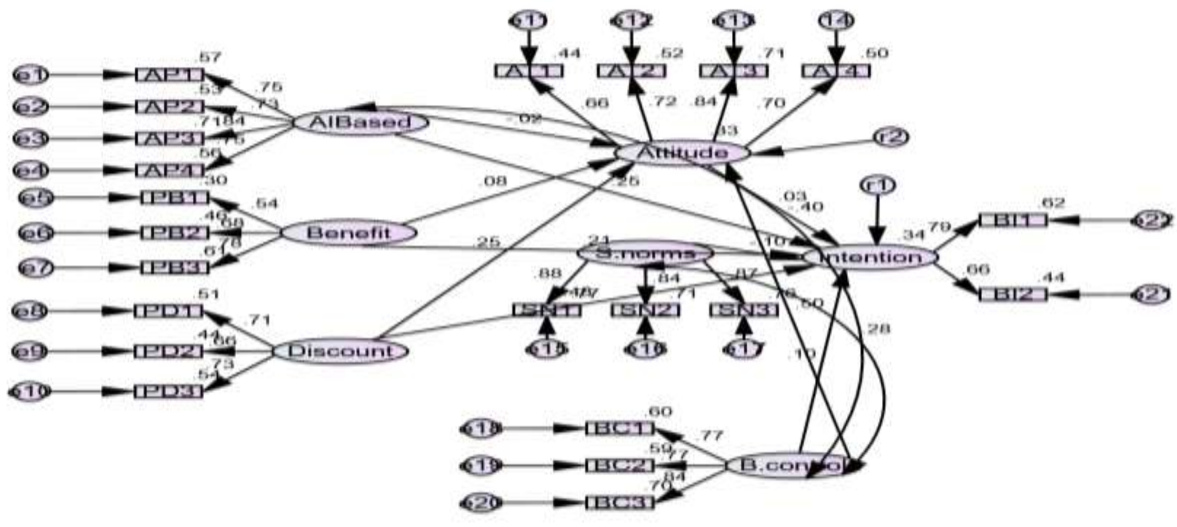

Figure 4. Modified structural model
Source: Survey data, 2024

Table 6. Fitness Indices of Modified Structural Model

Fit Index	Required criteria	Value
CMIN		523.61
d.f		197
Normed χ²/d.f	< 5.00	2.65
RMSEA	< 0.08	0.066
GFI	> 0.90	0.902
AGFI	> 0.90	0.904
IFI	> 0.90	0.910
TLI	> 0.90	0.901
CFI	> 0.90	0.913

Source: Survey data, 2024

Based on the table, the Modified structural model demonstrates a desirable good fit, as the ratio of the Chi-square & the degrees of freedom is 2.65, showing the below required threshold of 5.00 (Anderson & Gerbing, 1988). According to Hair et al. (2012), the value of RMSEA (0.066) is under the 0.08 benchmark, which confirms that the model is a good fit. For a model to be considered a good fit, the GFI should exceed 0.90, and in this modified model, the GFI is approximately 0.902, indicating a good fit. Moreover, George (2018) suggests that the AGFI should have 0.90 or above, and in this study, the AGFI value of 0.907 also indicates a well-fitting model. Furthermore, the (IFI), (NFI), (TLI), and (CFI) values in this research are (NFI = 0.90), (IFI = 0.940), (TLI = 0.910) (CFI = 0.913), all of which are above 0.90, confirming that this model indicating good fit.

Path Analysis

As our modified structural equation model shows a good fit, we can now perform hypothesis testing. The below table 7 shows the result of the hypothesis testing:

Table 7. Hypothesis testing

Hypotheses	Path	Estimate	P value	Results
H_1	Intention <--- AI-Based	0.213^{***}	0.001	Supported
H_2	Attitude <--- AI-Based	-0.0118	0.683	Not supported
H_3	Intention <--- Attitude	0.034	0.717	Not supported
H_4	Intention <--- S.Norms	-0.065	0.118	Not supported
H_5	Intention <--- B. Control	0.080	0.222	Not supported
H_6	Attitude <--- B. Control	0.327^{***}	0.000	Supported
H_7	Intention <-- P. Discount	0.499^{***}	0.000	Supported
H_8	Intention <--- P. Benefit	0.230^{***}	0.001	Supported
H_9	Attitude <--- P. Discount	0.218^{***}	0.001	Supported
H_{10}	Attitude <--- P. Benefit	0.075	0.143	Not supported

Note. *** shows significant at 1% level

Table 7 reveals that five of our 10 hypotheses were supported, and five were rejected. All five supported hypotheses demonstrated a 1% significance level ($p < 0.01$), indicating strong statistical evidence. Specifically, H_1 confirmed a significant positive impact of AI-based Personalization on online shopping intentions. Again, H_6 demonstrated that behavioral control significantly affects consumers' attitudes toward online shopping. After that, H_7 further validated that promotional discounts significantly and positively influence online buying intentions. Additionally, H_8 revealed that perceived benefits positively impact online purchase intentions. The remaining supported hypothesis, H_9, revealed that perceived benefit strongly influences consumers' attitudes towards online shopping.

DISCUSSIONS

This study examined the factors influencing online shopping intention through an extended (TPB) model, incorporating AI-based Personalization, promotional discounts, and perceived benefits. The findings partially support our proposed hypotheses, with both expected and surprising outcomes. To begin with, H_1 was supported, indicating a significant positive effect of AI-based Personalization on online shopping intention ($p < 0.001$).

Conversely, H_2 was not supported, as AI-based Personalization did not significantly influence consumers' attitudes toward online shopping ($p = 0.683$). One possible post hoc explanation is that Personalization can directly drive purchase intent through immediate utility. However, it may not fundamentally shift underlying attitudes unless combined with trust-building factors or consistent positive experiences. Similarly, H_3 through H_5 did not yield significant results. Neither attitude (H_3: $p = 0.717$), subjective norms (H_4: $p = 0.118$), nor behavioral control (H_5: $p = 0.222$) significantly influenced online shopping intention. These findings diverge from classical TPB expectations (Ajzen, 1991), where these constructs typically emerge as central predictors of behavioral intention. One explanation may be that in online shopping, particularly among digital-native consumers, situational variables such as promotional discounts and technological affordances overshadow traditional psychological predictors. Though our study findings diverge from classical TPB expectations (Ajzen, 1991), we cannot invalidate our study as many researchers have found this result. For example, studies by Shin et al. (2016) found subjective norms to have an insignificant influence on food purchase intention, while Irianto (2015) and Nguyen and Drakou (2021) reported attitude's lack of significant impact on online organic food and general purchase intentions, respectively. Similarly, Mohammed et al. (2017) indicated behavioral control's insignificant effect on intention. Conversely, using structural equation modeling, Lim et al. (2016) found significant positive impacts of subjective norms and perceived usefulness, noting an insignificant negative influence of subjective norms on shopping behavior.

However, H_6 was supported, revealing that behavioral control significantly impacts attitudes toward online shopping ($p < 0.001$). Similarly, H_7 showed that promotional discounts significantly affect intention ($p < 0.001$). Again, H_8 was also supported, with perceived benefit positively influencing intention ($p < 0.001$). It aligns with the notion that when consumers perceive tangible advantages like convenience, variety, and time savings, they are more likely to intend to shop online. Finally, both H_9 ($p < 0.001$) and H_{10} ($p = 0.143$) examined predictors of attitude. While promotional discounts positively influenced attitudes (H_9 supported), perceived benefits did not significantly affect attitudes (H_{10} not supported). Monetary incentives play a more immediate role in shaping attitudes than generally perceived benefits, which may act indirectly through satisfaction or loyalty rather than initial attitude formation.

CONCLUSIONS

This study examines the factors influencing online shopping behavior by extending the Theory of Planned Behavior (TPB) with AI-based Personalization, promotional discounts, and perceived benefits. This study offers unique insights into how AI-driven personalization and incentive strategies influence online shopping intentions by integrating these contemporary variables into a well-established theoretical framework. One of the key contributions of this paper is the empirical validation of AI-based Personalization as a significant driver of consumers' online shopping intention, providing evidence for its growing relevance in consumer decision-making processes while also highlighting the limitations of traditional TPB constructs like attitude, subjective norms, and behavioral control in online retail contexts. The findings contribute to behavioral theory by suggesting that consumer behavior models must evolve to accommodate emerging technological influences and shifting consumer priorities in the digital economy. This study provided valuable recommendations for online retailers to invest in AI-driven personalization tools and promotional offers to enhance consumer engagement and conversion. Additionally, the mixed significance of traditional TPB predictors suggests that marketing strategies should prioritize situational and transactional factors over purely psychological predictors when targeting online consumers. Future research is encouraged to explore the moderating roles of consumer trust, perceived privacy risks, and habitual technology use, as well as to examine these dynamics across different cultural and market settings to enhance the generalizability of these findings.

Author Contributions: Conceptualization, S.N. and M.A.R.; Methodology, M.A.R.; Software, S.N. and M.A.R.; Validation, M.H.I. and M.E.H.; Formal Analysis, S.N. and M.A.R.; Investigation, M.E.H.; Resources, M.E.H.; Data Curation, S.N. and M.A.R.; Writing – Original Draft Preparation, S.N. and M.A.R.; Writing – Review & Editing, S.N.; Visualization, S.N. and M.H.I.; Supervision, M.E.H.; Project Administration, S.N.; Funding, S.N. and M.A.R. Authors have read and agreed to the published version of the manuscript.

Institutional Review Board Statement: Ethical review and approval were waived for this study because the research does not deal with vulnerable groups or sensitive issues.

Funding: This study was conducted with the authors' funding. However, Southeast University, Dhaka, Bangladesh, provided APC.

Acknowledgments: We sincerely express our deepest gratitude to the respondents who participated in the data collection for this study. Their willingness to share valuable insights and cooperate was essential to the successful completion of this study. Again, we would like to thank the entire data enumerator team for their significant efforts in ensuring the accuracy of the data. Additionally, we are profoundly grateful to the library staff for their continuous support throughout the study.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The data presented in this study are available on request from the corresponding author. The data are not publicly available due to restrictions.

Conflicts of Interest: The authors declare no conflict of interest.

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