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Characteristics of Personalized Recommendation Services and Determinants of User Experience

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Abstract. The rapid growth of e-commerce has intensified competition among platforms to enhance user experience through technological innovations such as personalized recommendation services (PRS). This study investigates the factors influencing the user experience of PRS in Bangladesh, such as Daraz, examining the roles of perceived usefulness, trust, frequency of use, and interface design based on the Technology Acceptance Model (TAM). Data were collected from 445 active Daraz users and analyzed using Exploratory Factor Analysis (EFA), reliability testing, and multiple regression analysis. Results indicate that algorithm design, quality of product information, and intuitive interface design significantly enhance perceived usefulness and trust, leading to improved user experience and engagement. The findings offer valuable implications for enhancing PRS in emerging e-commerce markets. Moreover, this paper discusses theoretical and practical contributions, highlighting strategies for e-commerce platforms aiming to improve customer engagement and satisfaction.

Keywords: Personalized Recommendation Services, User Experience, Technology Acceptance Model, User Trust

1. Introduction

The rise of e-commerce has revolutionized retail markets globally. In Bangladesh, platforms like Daraz have reshaped consumer behavior by offering vast online marketplaces enhanced by personalized recommendation services (PRS). PRS uses machine learning and artificial intelligence to provide tailored product suggestions based on user behavior, improving user satisfaction and loyalty. While PRS has gained popularity in developed countries, emerging economies have received relatively less attention. Despite growing interest, there is limited research on how PRS affects user experience in emerging economies like Bangladesh. Additionally, understanding the mediating effects of trust, perceived usefulness, and usage frequency in such markets remains underexplored. This study seeks to fill that gap and provide valuable insights for both academia and practice. As e-commerce adoption continues to accelerate, businesses are increasingly recognizing the need for personalized strategies to meet diverse consumer expectations. Investigating these dynamics in a localized context like Bangladesh not only enriches academic literature but also offers practical guidance for market players operating in competitive digital ecosystems.

In today's competitive digital marketplace, personalized recommendation services (PRS) have become critical for enhancing customer satisfaction, increasing user engagement, and driving online sales. By offering tailored suggestions, PRS reduces information overload and helps users find relevant products quickly [1]. Studies have shown that personalized experiences not only boost immediate sales but also foster long-term loyalty and brand trust [2]. In emerging markets like Bangladesh, where e-commerce adoption is still growing, the effectiveness of PRS can significantly influence user experience and overall platform success. Moreover, effective personalization strategies can differentiate a platform from its competitors, creating a unique value proposition for users. As digital ecosystems become increasingly crowded, the ability to deliver customized content becomes a key driver of customer retention and platform sustainability.

2. Literature Review

Personalized Recommendation Services (PRS) have become critical tools for enhancing user experience on e-commerce platforms. Rooted in data analytics and machine learning, PRS systems aim to deliver tailored product suggestions that match individual user preferences, thereby improving customer satisfaction, engagement, and loyalty [1]. Early studies, such as Adomavicius and Tuzhilin [2], emphasized the potential of PRS to reduce information overload and streamline decision-making processes, making online shopping more efficient and user-centered.

The Technology Acceptance Model (TAM) proposed by Davis [3] provides the theoretical foundation for understanding how users adopt PRS technologies. According to TAM, perceived usefulness (PU) and perceived ease of use (PEOU) are the primary drivers of user acceptance. Later extensions of TAM have incorporated trust and perceived risk as important variables, especially in e-commerce contexts where privacy and data security are critical concerns [4]. Trust has been consistently identified as a vital mediator in the relationship between personalization and user experience [5]. When users trust that platforms handle their data responsibly and provide accurate recommendations, they are more likely to engage frequently and develop platform loyalty.

Beyond TAM, theories such as the Unified Theory of Acceptance and Use of Technology (UTAUT) have further expanded the understanding of technology adoption by integrating social influence and facilitating conditions [6]. UTAUT emphasizes that social proof—such as reviews and peer recommendations—can significantly influence how users perceive the value of personalized services. In emerging markets like Bangladesh, where online shopping cultures are still evolving, social influence and trust play even stronger roles in shaping consumer behavior [7].

The design and presentation of PRS also impact user experience. Research highlights that user interface (UI) design, clarity of product information, and transparency of recommendation algorithms significantly affect user satisfaction [8]. A well-organized interface reduces cognitive load, while clear product information improves decision-making confidence [9]. Studies have shown that platforms providing high-quality, relevant, and diverse product recommendations achieve higher user engagement rates compared to those offering generic suggestions [10].

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While the effectiveness of PRS has been widely studied in developed markets, limited research addresses their impact in emerging economies. Platforms such as Daraz Bangladesh provide a unique case where PRS adoption is growing amidst a digitally maturing user base. Factors like low digital literacy, price sensitivity, and cultural attitudes toward online privacy can influence the success of personalized services differently than in Western contexts [11].

In addition, the frequency of user interaction with PRS systems has emerged as a significant variable. Regular engagement allows recommendation algorithms to learn more accurately from user behavior, enhancing personalization and strengthening platform loyalty over time [12]. However, frequent interaction is contingent upon user trust, perceived system usefulness, and seamless user experiences, underlining the interconnectedness of these factors.

Despite the growing body of literature, gaps remain regarding the holistic evaluation of PRS effectiveness by incorporating system design, trust, perceived usefulness, frequency of use, and user experience into a unified framework. This study addresses these gaps by empirically investigating how these elements collectively influence the user experience on Daraz's platform in Bangladesh, offering new insights into PRS optimization strategies in emerging e-commerce markets.

3. Research model and hypotheses development

3.1. Concept model

The study proposes a conceptual model based on the Technology Acceptance Model (TAM) and Trust Theory, where the design of PRS, quality of product information, and user interface design influence trust, frequency of use, and perceived usefulness, ultimately shaping User Experience.

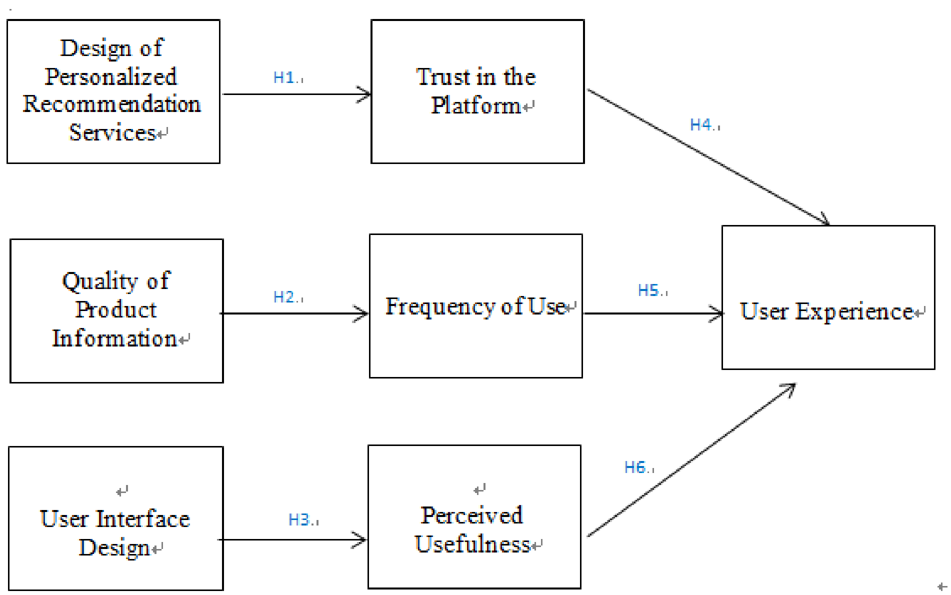

Figure 1: Concept model

3.2. Research hypotheses

The design quality of personalized recommendation services plays a significant role in building trust among users. A well-designed recommendation system that accurately predicts user preferences leads to increased user trust. According to Adomavicius and Tuzhilin [1], effective recommendation designs enhance perceived reliability and satisfaction, encouraging users to revisit the platform. Thus we propose the following hypothesis H1.

H1: Design of personalized recommendation services is positively associated with trust in the platform.
The quality and accuracy of product information provided through recommendations directly impact users' willingness to frequently interact with the platform. High-quality information reduces uncertainty and enhances decision-making efficiency [4]. When users find the recommended products reliable and informative, their frequency of use increases. As a result, we propose the following hypothesis H2.

H2: Quality of product information is positively associated with frequency of use.
An intuitive and user-friendly interface simplifies the user journey and improves perceived usefulness. As Davis proposed in the TAM [2], the ease of navigating the platform and understanding the recommendations strengthens users’ belief that the platform is beneficial. Thus, we propose the following hypothesis H3.

H3: User interface design is positively associated with perceived usefulness.
Trust serves as a fundamental factor that impacts user experience directly. A trustworthy recommendation system fosters a positive attitude towards the platform and enhances overall satisfaction [5]. Therefore, we propose the following hypothesis H4.

H4: Trust in the platform is positively associated with user experience.
Frequent interaction with personalized recommendation services reinforces familiarity and loyalty, leading to a richer user experience. Venkatesh et al. argue that increased engagement promotes positive evaluations of platform utility [3]. So we have the H5.

H5: Frequency of use is positively associated with user experience.
Perceived usefulness remains a core determinant in TAM, strongly influencing user satisfaction and loyalty. Users who find recommendation services helpful are more likely to have a positive overall experience [2]. As a result, we propose the following hypothesis H6.

H6: Perceived usefulness is positively associated with user experience.

4. Research methodology

4.1 Research variables and measurements

Our research model has six explanatory variables and one dependent variable. We measure each research variable using traditional measurements proposed by existing literature. The measurement table is shown in Table 1.

Table 1: Variables and Measurements

Variables	Items
Design of PRS (PRS)	Q1: The personalized recommendation services on Daraz are well-designed and easy to use.
	Q2: The recommendations provided align with my preferences and needs.
	Q3: The recommendation system enhances my trust in the platform.
Quality of Product Information (QPI)	Q4: The product descriptions on Daraz are accurate and detailed.
	Q5: The product images provided accurately represent the actual products.
	Q6: Customer reviews and ratings on Daraz are reliable and helpful.
User Interface Design (UID)	Q7: The Daraz platform has an intuitive and user-friendly interface.
	Q8: The platform's layout and features make navigation easy and efficient.
	Q9: The design of the interface enhances the perceived usefulness of the platform.
Trust in Platform (TR)	Q10: I trust that Daraz secures my personal information and transaction data.
	Q11: The platform's transparency strengthens my confidence in using it.
	Q12: Trust in Daraz enhances my overall shopping experience.
Frequency of Use (FU)	Q13: I frequently engage with the platform due to the reliable product information.
	Q14: Regular use of Daraz improves my familiarity with its features.
	Q15: Frequent interaction with the platform enhances my shopping experience.
Perceived Usefulness (PU)	Q16: The personalized recommendations on Daraz help me discover relevant products efficiently.
	Q17: Using Daraz saves me time in finding the products I need.
	Q18: The platform's usefulness positively impacts my shopping satisfaction.
User Experience (UX)	Q19: I am satisfied with my overall shopping experience on Daraz.
	Q20: The platform provides an enjoyable and engaging shopping journey.
	Q21: I am likely to recommend Daraz to others based on my experience.

4.2. Questionnaire design and testing

The questionnaire consisted of two sections: demographic information and measurement scales for key constructs. Measurement items were adapted from established literature and modified to fit the context of Daraz. A five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree) was used. Pre-tests and reliability analyses ensured internal consistency (Cronbach's Alpha > 0.7 for all constructs). In addition, expert feedback was incorporated during questionnaire development to enhance content validity and ensure clarity and relevance to the study objectives.

The questionnaire was collected through several channels, including the social media platform of Facebook and personal relationships such as friends and work colleagues. More than 445 questionnaires were distributed to the aforementioned sources, and 466 was finally feedback. After quality insurance checking, 445 qualified questionnaires were finally adopted.

5. Research results

5.1. Sample descriptions

For the qualified sample adopted to do hypotheses testing, its characteristics are described in Table 2.

Table 2: Sample characteristics

Demographic variables	Categories	Frequency	Percentage
Gender	Male	162	36.4%
	Female	283	63.6%
Age	Below 18	57	12.8%
	18-30	236	53.0%
	30-40	125	28.1%
	40-50	19	4.3%
	Above 50	8	1.8%
Education	High School	17	3.8%
	Bachelor	387	87.0%
	Graduate	41	9.2%
Monthly Salary (BDT)	Below 10,000	175	39.3%
	15,000-20,000	67	15.1%
	20,000-25,000	111	24.9%
	25,000-30,000	88	19.8%
	Above 30,000	4	0.9%
Total	-	N=445	100%

5.2. Reliability statistics

The reliability of each construct was assessed using Cronbach's α value. The scale mean and scale variance were examined when each item was deleted. Additionally, the corrected item-total correlation and Cronbach's α value were calculated when each item was removed. A construct is considered credible if the α value exceeds 0.60 according to existed references. The results revealed that Design of personalized recommendation services (DPRS), scale with three items (α = 0.643), Quality of product information (QPI), scale with three items (α = 0.825) and User interface design (UID), scale with three items (α = 0.87) were found reliable. Similarly, Trust in the platform (TP), scale with three items (α = 0.685), Frequency of use (FU), scale with three items (α = 0.843), Perceived usefulness (PU), scale with three items (α = 0.754) and User experience (UE), scale with three items (α = 0.836) were also found to be reliable. The variables in the study generally exhibit good to high internal consistency, indicating that the measurement items reliably measure the intended constructs. The Reliability results are shown in Table 3 below.

Table 3: Results of the reliability test

Variables	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's α if Item Deleted
Design of personalized recommendation services (DPRS): Cronbach Alpha: 0.643				
DPRS1	8.02	1.585	.437	.569
DPRS2	7.86	1.438	.498	.484
DPRS3	7.96	1.307	.434	.584
Quality of product information (QPI): Cronbach Alpha: 0.825				
QPI1	7.68	2.735	.703	.738
QPI2	7.64	2.767	.726	.715
QPI3	7.78	2.962	.619	.820
User interface design (UID): Cronbach Alpha: 0.871				
UID1	6.94	2.767	.826	.754
UID2	6.65	2.755	.729	.842
UID3	6.68	2.920	.709	.857
Trust in the platform (TP): Cronbach Alpha: 0.685				
TP1	7.48	2.462	.486	.626
TP2	7.07	2.963	.491	.605
TP3	7.17	2.906	.538	.551
Frequency of use (FU): Cronbach Alpha: 0.843				
FU1	7.00	3.063	.712	.780
FU2	7.05	2.729	.725	.767

FU3	7.34	3.032	.692	.797
Perceived usefulness (PU): Cronbach Alpha: 0.754				
PU1	6.77	3.040	.627	.619
PU2	6.82	3.508	.562	.695
PU3	6.84	3.340	.562	.695
User experience (UE): Cronbach Alpha: 0.836				
UE1	7.27	3.147	.659	.811
UE2	7.16	2.681	.703	.768
UE3	7.15	2.564	.740	.729

5.3. Validity analysis

5.3.1. KMO and Barlett's test

According to Garson (2003), the standard of factor analysis method, Kaiser-Meyer- Olkin (KMO) Measure of Sampling Adequacy must be greater than 0.5 and the Significance of Barlett's Test is less than 0.05, which proves that the data for factors analysis is accepted, see table 4. The result shows the KMO value is 0.747. Therefore, it is evident that the data which is used for factors analysis is totally accepted.

Table 4: KMO and Bartlett's test

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.747
Bartlett's Test of Sphericity	Approx. Chi-Square	3532.661
	Df	210
	Sig.	.000

5.3.2. Total variance explained

The results in Table 5 show that observed variables (Initial Eigenvalues) are divided into seven iterations by conducting the component analysis according to the Principal Components Analysis method with Varimax Rotation Method. The value of Total Variance Explained is 71.578% (>50%), which means that these iterations explain 71.578% of the data variation, with the eigenvalues of all components being higher than 1. The smallest value is 1.097>1. In conclusion, the EFA test results are accepted. The designed items validly measure the variables.

Table 5: Total variance explained

Total Variance Explained						
Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3.802	18.102	18.102	3.802	18.102	18.102
2	2.935	13.974	32.077	2.935	13.974	32.077
3	2.385	11.355	43.432	2.385	11.355	43.432
4	1.983	9.441	52.873	1.983	9.441	52.873

5	1.557	7.414	60.287	1.557	7.414	60.287
6	1.275	6.070	66.357	1.275	6.070	66.357
7	1.097	5.222	71.578	1.097	5.222	71.578
8	.702	3.343	74.921			
9	.647	3.082	78.003			
10	.571	2.718	80.721			
11	.534	2.545	83.265			
12	.517	2.463	85.728			
13	.445	2.117	87.845			
14	.426	2.030	89.875			
15	.404	1.923	91.798			
16	.351	1.670	93.468			
17	.341	1.624	95.092			
18	.321	1.530	96.621			
19	.283	1.348	97.969			
20	.246	1.172	99.141			
21	.180	.859	100.000			

In the context of factor analysis or principal components analysis, a scree plot helps the analyst visualize the relative importance of the factors, a sharp drop in the plot signals that subsequent factors are ignorable. According to figure 2, we can see that 7 components are extracted on the steep slope.

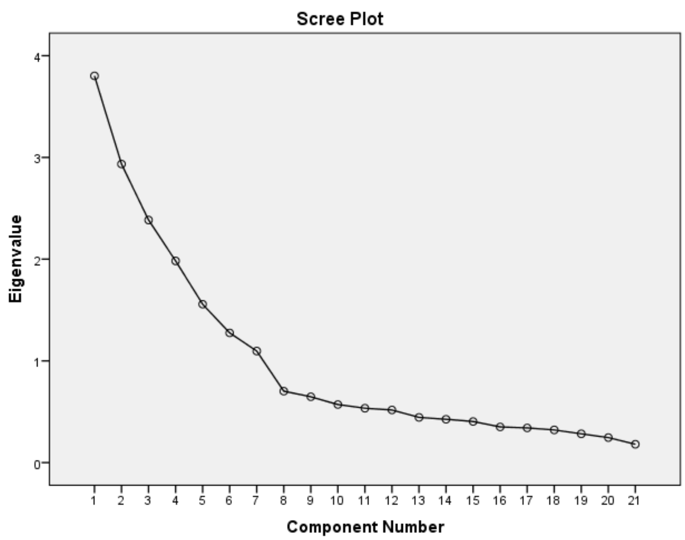

Figure 2: The scree plot

5.3.3. Rotated component matrix

More importantly, with the rotated component matrix, 21 items were rotated using the Varimax rotation with Kaiser Normalization. The results displayed by Table 6 indicated that all 21 items loaded onto seven factors, with loading coefficients greater than 0.5, and there was no cross-loading on any factor.

Table 6: Rotated component matrix

Rotated Component Matrix[a]							
	Component						
	1	2	3	4	5	6	7
DPRS1	.812						
DPRS2	.778						
DPRS3	.628	.					
QPI1		.855			.		
QPI2		.874					
QPI3		.809					
UID1			.905				
UID2			.867				
UID3			.867				
TP1				.786			
TP2				.742			
TP3				.779			
FU1					.843		
FU2					.852		
FU3					.826		
PU1						.815	
PU2						.792	
PU3						.792	
UE1							.803
UE2							.840
UE3							.878

5.4. Pearson correlation analysis

Table 7 shows the results of Pearson correlations of all the variables. According to this, the Sig. value of all independent variables FV, HV, PU, PR, PK, SN and the dependent variable ITU in Pearson correlations are all 0.000<0.05. Hence, the linear relationship is significant between observed variables and dependent variables.

Table 7: Correlations result

		DPRS	QPI	UID	TP	FU	PU	UE
DPRS	Pearson Correlation	1	.251**	-.029	.269**	-.173**	-.097*	-.010
	Sig. (2-tailed)		.000	.548	.000	.000	.041	.830
	N	445	445	445	445	445	445	445
QPI	Pearson Correlation	.251**	1	-.010	.171**	.110*	-.056	-.044
	Sig. (2-tailed)	.000		.837	.000	.020	.238	.357
	N	445	445	445	445	445	445	445
UID	Pearson Correlation	-.029	-.010	1	-.029	.106*	.279**	.105*
	Sig. (2-tailed)	.548	.837		.539	.025	.000	.026

	N	445	445	445	445	445	445	445
TP	Pearson Correlation	.269**	.171**	-.029	1	-.012	.041	.134**
	Sig. (2-tailed)	.000	.000	.539		.794	.389	.005
	N	445	445	445	445	445	445	445
FU	Pearson Correlation	-.173**	.110*	.106*	-.012	1	.212**	.407**
	Sig. (2-tailed)	.000	.020	.025	.794		.000	.000
	N	445	445	445	445	445	445	445
PU	Pearson Correlation	-.097*	-.056	.279**	.041	.212**	1	.214**
	Sig. (2-tailed)	.041	.238	.000	.389	.000		.000
	N	445	445	445	445	445	445	445
UE	Pearson Correlation	-.010	-.044	.105*	.134**	.407**	.214**	1
	Sig. (2-tailed)	.830	.357	.026	.005	.000	.000	
	N	445	445	445	445	445	445	445

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

5.5. Regression results

To test the hypotheses, regression analysis was performed to study the effects of independent variables on user experience after controlling for demographic characteristics. Regression will allow us to make statements about how well one or more independent variables will predict the value of a dependent variable. In this section, the software of SPSS 23 is used to obtain the regression results.

5.5.1. Relationship between the design of PRS and TR

The regression model was tested to explore the influence of design of personalize recommendation services on users' trust in the platform. The result is shown in Table 8. Multicollinearity, measured by the variance inflation factor (VIF) index, was less than 10 in all. Therefore, there is no problem relating to Multicollinearity.

It demonstrates that, in Model 1, which is without control variables, the design of personalize recommendation services (β =.377, sig < .001) was found to be a significant predictor. When demographic control variables were included in Model 2, the design of personalize recommendation services still remained significant (β = .369, p < .001). The result reveals that hypotheses H1 is supported in the concept model by empirical data. It suggests that increased design of personalised recommendation services can positively impact users' trust in the platform.

Table 8: Results of regression analysis

Variable	**Model 1**					**Model 2**				
	B	Beta	t	sig	VIF	B	Beta	t	sig	VIF
(Constant)	2.122		8.255	.000		2.033		5.749	.000	

DPRS	.377	.269	5.886	.000	1.000	.369	.264	5.720	.000	1.012
Gender						.080	.050	1.053	.293	1.063
Age						-.060	-.063	-1.082	.280	1.614
Income						.041	.064	1.090	.276	1.652
Education						.016	.007	.157	.875	1.015

5.5.2 Relationship between QPI and FU

The regression results are shown in table 9. It demonstrates that, in Model 1 which is without control variables, quality of product information (β =.113, sig < .005) was found to be significantly influence on frequency of use. When demographic control variables were included in Model 2, the quality of product information still remained a significant (β = .111, p < .005) impact on frequency of use. The result reveals that hypotheses H2 is supported in the concept model by empirical data. It suggests that increased quality of product information can positively impact user's frequency of use.

Table 9: Regression analysis results

Variable	Model 1					Model 2				
	B	Beta	t	sig	VIF	B	Beta	t	sig	VIF
Constant)	3.133		16.472	.000		2.941		8.728	.000	
QPI	.113	.110	2.328	.020	1.000	.111	.108	2.237	.026	1.046
Gender						.037	.022	.445	.656	1.055
Age						.050	.049	.816	.415	1.616
Income						-.009	-.013	-.217	.828	1.700
Education						.021	.009	.192	.848	1.014

5.5.3. Relationship between UID and PU

The regression results are shown in Table 10. It demonstrates that, in Model 1, which is without control variables, user interface design (β =.377, sig < .001) was found to be significantly influential on users' perceived usefulness of the platform. When demographic control variables were included in Model 2, the user interface design still remained a significant (β = .369, p < .001) impact on users' perceived usefulness. The result reveals that hypothesis H3 is supported in the concept model by empirical data. It suggests that increased quality of product information on the platform can positively impact users' perceived usefulness.

Table 10: Regression analysis results

Variable	Model 1					Model 2				
	B	Beta	t	sig	VIF	B	Beta	t	Sig	VIF
(Constant)	2.398		14.158	.000		2.446		7.580	.000	
UID	.298	0.279	6.109	.000	1.000	.314	.294	6.384	.000	1.025
Gender						.080	.045	.953	.341	1.057
Age						.025	.023	.400	.689	1.615
Income						-.086	-.118	-2.020	.044	1.663
Education						-.047	-.019	-.418	.676	1.015

5.5.4. Relationship between determinants and UX

The following multi-regression model was tested to explore the influence of factors on users' experience of the platform, applying multi-regression method. The result is shown in Table 11. Multicollinearity measured by the variance inflation factor (VIF) index was less than 10 in all. Therefore, there is not any problem relating Multicollinearity. According to the result of VIF coefficients of all independent variables from the table 5.10, we can see that all of them are less than 2. This result reveals that the problem of Multicollinearity does not exist in this regression model. Therefore, this model formulation is acceptable and can be proceed both trust in platform ($\beta = .463$, $p < 0.001$), frequency of use ($\beta = 374$, $p < 0.001$), and perceived usefulness ($\beta = 374$, $p < 0.001$) were all found to be significant predictors of user experience. These results reveal that hypothesis H4, H5, and H6 of the concept model are all supported by the empirical data.

Table 11: Regression analysis results

Variable	**Model 1**					**Model 2**				
	B	Beta	t	Sig	VIF	B	Beta	t	sig	VIF
Constant)	1.363		5.618	.000		1.365		4.041	.000	
TP	.139	.134	3.137	.002	1.002	.142	.137	3.226	.001	1.011
FU	.372	.382	8.763	.000	1.047	.366	.375	8.656	.000	1.052
PU	.119	.128	2.939	.003	1.049	.128	.138	3.172	.002	1.060
Gender						-.096	-.057	-1.317	.188	1.064
Age						.075	.075	1.399	.162	1.621
Income						.029	.043	.782	.434	1.659
Education						-.051	-.023	-.528	.598	1.015

Based on the above hypothesis tests, we obtain all the results of the hypotheses proposed in the concept model. A summary of these results is shown in the following Table 12. It illustrates that all the relationships stated in the concept model are supported by empirical data.

Table 12: Summary Results of Hypothesis Test

Hypothesis	Statement	Result
H1	The design of personalized recommendation services significantly and positively influences trust in the platform	Supported
H2	The quality of product information significantly and positively influences the frequency of use	Supported
H3	User interface design significantly and positively influences perceived usefulness	Supported
H4	Trust in the platform significantly and positively influences user experience	Supported
H5	Frequency of use significantly and positively influences user experience	Supported
H6	Perceived usefulness significantly and positively influences user experience	Supported

6. Conclusions and discussion

The findings support that personalized recommendations significantly influence user trust, perceived usefulness, and engagement frequency. These mediating factors strongly contribute to an enhanced user experience. Trust emerged as a crucial factor in facilitating continued platform use, aligning with previous research emphasizing the role of trust in online shopping behavior. The quality of product information and intuitive user interface design also contribute substantially to the perceived value of PRS. These results validate the TAM framework in the emerging market context of Bangladesh, demonstrating that both technological and psychological factors play pivotal roles in user satisfaction and engagement.

This research sheds light on how personalized recommendation services enhance user experience in the context of an emerging e-commerce market. By empirically validating the roles of trust, perceived usefulness, and frequency of use, the study reinforces the importance of a user-centered approach to digital retail. E-commerce platforms that effectively leverage personalization while ensuring ease of use and user trust can significantly improve customer satisfaction and loyalty. As e-commerce continues to evolve, understanding the nuanced impact of personalization technologies will be essential for achieving sustained competitive advantage. The findings offer strategic insights for platform designers, marketers, and policymakers aiming to optimize digital consumer engagement and foster long-term growth in the digital economy.

Moving forward, future research can explore additional moderating factors such as cultural influences, privacy concerns, and user demographics that may further shape the effectiveness of personalized recommendation services. Longitudinal studies could also offer more profound insights into how user experience evolves over time with sustained interactions on personalized platforms. By broadening the scope of inquiry, researchers and practitioners can better anticipate changing consumer behaviors and design more adaptive, inclusive, and resilient digital ecosystems that cater to diverse market needs.

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