UNDERSTANDING CONSUMERS' USAGE INTENTION TO ADOPT E-COMMERCE APPLICATIONS THROUGH AN EXTENDED UTAUT MODEL

Kiran Mishra *
Anupam Karmakar **

Abstract: Recent developments in mobile technology have led to a significant impact on everyday life from mobile commerce, which is also starting to provide novel and beneficial services. In order to improve the convenience and ease of human beings, numerous utility services are being offered. Specifically, the e-commerce (e-com) application has surfaced, facilitating the usage of smartphones by customers to purchase products and services wherever they are. The extended unified theory of acceptance and use of technology (UTAUT) model was applied in this study to examine consumers' usage intention (USI) of e-com applications. Perceived Trust (PVT) is the additional significant factor, along with online rating (ORT) and online review (ORE) as moderating factors that this study introduces and which underpin the UTAUT2 determinants. Data has been collected from e-com website users using an adapted questionnaire, and 300 valid responses were analysed. SmartPLS 3 and partial least squares-structural equation modelling (PLS-SEM) were applied to assess the proposed framework. The findings showed that: (1) USI was favourably and significantly influenced by PVT, performance expectancy (PFE), effort expectancy (EFE), facilitating conditions (FTC) and hedonic motivation (HDM); (2) Use behaviour (UBR) was favourably and significantly impacted by USI; (3) USI was not significantly influenced by social influence (SLI); and (4) ORE significantly and negatively moderated the association between USI and UBR, whereas ORT does not act as a moderator. The study suggests a managerial implication based on test results to assist e-commerce service providers in improving the quality of their services, suggests directions for future development, and approaches suitable tactics for prospective consumer groups.

Keywords: UTAUT Model, Perceived Trust, E-Commerce Applications, Online Rating, Online Review.

* *Research Scholar, University of Calcutta, Kolkata, India ; E-mail: infokiran1994@gmail.com*

** *Associate Professor, New Alipore College, Kolkata, India ; E-mail: anupamkar2016@gmail.com*

Introduction

Mobile applications are growing in popularity and becoming a necessary part of our everyday life in the present day, along with the growth of technological and scientific advancements (Thi My Dung et al., 2024). From making purchases to searching for details about products, smartphone applications are helping users in all facets of their lives. At the present time, a growing number of companies are adopting a consumer-oriented strategy and doing all in their capacity to stay in touch with clients at all times, no matter where they are. Similarly, consumers are increasingly more conscious of the world around them and can quickly access anything they want on their mobile devices by just clicking on it. The use of mobile apps has surpassed that of mobile websites (Malik et al., 2017).

Globally, smartphones and tablets, rather than conventional desktop or laptop PCs, are the main methods for accessing the internet. An online platform that makes it easier to manage, update, purchase, and trade products on a shopping website is known as an e-com application. Many online e-com applications are available on the mobile platform. Customers can purchase through e-com applications offered by well-known organisations as Amazon, Flipkart, Myntra, Ajio, Nykaa etc. (Johri et al., 2023).

Various theories and frameworks are employed to elucidate the behaviour of users and customers concerning technology. After a comprehensive analysis of the literature, (Venkatesh et al., 2003) compared important models and developed UTAUT (Unified Theory of Acceptance and Use of Technology). In terms of explaining users' behaviour connected to technology, UTAUT has been empirically evaluated and shown to be more effective to other models (Venkatesh et al., 2003). UTAUT2 is one of the models that have been designed to assess the acceptability of technology among specific users (Venkatesh et al., 2012). Because UTAUT2 combines the constructs of earlier theories, it is regarded as an extensive framework (Tamilmani et al., 2021). So, the goals for the study are as follows:

i. To assess how different elements like PFE, EFE, FTC, SLI, HDM and PVT affect consumers' USI.

ii. To assess the impact of consumers' USI on consumers' UBR.

iii. To determine the role of ORT & ORE as moderators in establishing an association between consumers' USI and UBR to make purchases through e-commerce applications.

The study is organised in the following manner: the literature is reviewed first, the initial step is the review of the literature, which includes sections on the theoretical foundation of different variables of the modified UTAUT model influencing consumers' acceptance of e-commerce shopping. The second section discusses the research techniques employed for this investigation. The study's results and interpretation are covered in the third section. Lastly, the

conclusion and recommendations for further study are covered in the subsequent section.

Literature Review

UTAUT Model

Venkatesh et al. created the UTAUT in 2003, and they expanded upon it in 2012. In its initial iteration, the theory brought together eight distinct models to describe how technology is accepted and used through four primary determinants: social influence, effort expectancy, performance expectancy, and facilitating condition (Venkatesh et al., 2003). In order to address many scenarios, (Venkatesh et al., 2012) developed UTAUT2, an expansion of the theory. UTAUT2 centres on the customer, in contrast to the initial theory. Hedonic motivation, price, habit, and other factors are added to the four basic UTAUT constructs to describe consumer behaviour in UTAUT2.

Performance Expectancy (PFE), an initial UTAUT2 concept, describes how an individual perceives the performance advantage that a certain technology will provide in an endeavour. As a result, this framework helps to ascertain how interested a customer is in embracing the latest innovations. A scarcity of time is perceived by individuals for a variety of basic reasons. According to (Saksena et al., 2018), any convenience is a strategy to save time on technical and time-consuming work. According to (Lee et al., 2019; Nur & Ria Panggabean, 2021) users of mobile apps provide a greater inclination to continue using this technology and consider it to have significant benefits.

Effort Expectancy (EFE) measures how much a person (consumer) believes using technology, such as online purchasing, doesn't require much work (Venkatesh et al., 2003). (Hansen, 2017) noted that ease of use and hassle-free transactions are the main reasons why consumers engage in online purchasing (physical and mental). According to (Fang et al., 2016), this construct seems to be essential while using mobile applications. The EFE and USI towards mobile apps have been found to be positively and significantly correlated in earlier studies (Lee et al., 2019; Nur & Ria Panggabean, 2021).

As stated by (Venkatesh et al., 2003) Facilitating Conditions (FTC) is the level of belief that an individual has in the existence of sufficient managerial and technological resources to facilitate the utilisation of technology., It describes a group of circumstances that enable a consumer to intend to utilise technology more. The availability of funds, time, connectivity to the internet, and mental and physical skills can therefore influence the intention to continue using technology (Nur & Ria Panggabean, 2021; Yang, 2010).

The Social Influence (SLI) construct is defined as a change in other people's desire to utilise a specific technology (e.g., relatives, acquaintances, and peers) (Venkatesh et al., 2003). The use of specific technologies might impact social integration (Chopdar & Sivakumar, 2019), which means that SLI appears to impact the intention to continue using apps. The SLI and behavioural intention to use mobile apps are positively and

significantly correlated in earlier studies (Garg, 2021; Yang, 2010).

HDM is used to assess the pleasure or satisfaction that comes from employing technology. These characteristics, in the opinion of (Brown & Venkatesh, 2005) are critical to the adoption of technology. HDM has a strong and significant influence on UI (Jasim et al., 2022; Maizatul Akmar Mohd Rasli et al., 2020). Nevertheless, HDM has a stronger effect on consumers at the beginning of their experience, according to (Venkatesh et al., 2012).

In light of the preceding discussions and the earlier literature review, we have thus developed the direct hypotheses listed below:

H_1: PFE has a positive and significant influence on consumers' USI.

H_2: EFE has a positive and significant influence on consumers' USI.

H_3: FTC has a positive and significant influence on consumers' USI.

H_4: SLI has a positive and significant influence on consumers' USI.

H_5: HDM has a positive and significant influence on consumers' USI.

H_7: USI has a positive and significant influence on consumers' UBR.

Perceived Trust (PVT): According to (Mayer et al., 1995), trust is defined as the customer's readiness to be prepared for sensitivity based on a favourable anticipation of the actions of another party in the foreseeable future. This would be the customer's readiness to engage in e-commerce transactions and their anticipation that an e-commerce provider will satisfy its responsibilities in the setting of e-commerce (Cao et al., 2018). (Jasim et al., 2022; Wang et al., 2022) discovered that PVT had a major impact on future buying decisions while examining the determinants of consumers' desire to utilise online shopping.

H_6: PVT has a positive and significant influence on consumers' USI.

Bandwagon Effect: Bandwagoning is the practice of complying with indications from prior consumers of a product or service, such as ratings, reviews, suggestions, and hashtags put digitally. These indications assist consumers in forming opinions and preferences as well as in making selections about what goods or services to buy (Sundar et al., 2008). OREs and ORTs have been labelled bandwagoning indicators by (Sundar & Limperos, 2013) because of their psychological impact on consumers and tendency to encourage them to adopt styles, patterns, or recommendations made by others. Even experienced or satisfied consumers consult ORTs and OREs prior to making a purchase choice, so it is a significant factor for influencing consumers' intention to use (Kuo et al., 2013). According to (Agarwal & Sahu, 2022) the ORT and ORE demonstrate a negative moderating influence on the link between e-satisfaction and recommendation to use.

- **Online Rating (ORT):** According to (Filieri, 2015), ORT is a distinct kind of crowd assessment that shows an average

evaluation of certain product or service qualities by consumers. Consumers evaluate goods and services using a numerical rating system (e.g., a 5-star rating system) that is applied to the attributes (e.g., experience, cost, or reliability) provided by previous customers. In light of this, (Tran, 2020) explored the influence of ORTs on the continuation intent of satisfied hotel consumers and discovered that ORT functioned as a moderator, with higher ratings causing a sharp rise in the continuation intent.

- **Online Review (ORE):** (Singh et al., 2017) state that online reviews and feedback from consumers are frequently regarded as quite trustworthy and reputable. (Filieri, 2015; Saumya et al., 2018) contend that as a result, consumers regularly examine the sources of information they want to investigate further. Moreover, (Thi My Dung et al., 2024) have highlighted the vital function that online reviews play in interaction between consumers within the virtual community. Customers now appreciate and consider these reviews as trustworthy sources of information when making decisions or considering choices (Filieri, 2015).

In light of the preceding discussions and the earlier literature review, we have thus developed the moderating hypotheses listed below:

H_{8a}: The relationship between USI and UBR is significantly moderated by ORT.

H_{8b}: The relationship between USI and UBR is significantly moderated by ORE.

Research Gap

The UTAUT2 model has been applied by various academicians earlier in multiple technological contexts. Still, no such research that we are familiar with has been conducted to determine the variables influencing usage intention as well as the use behaviour towards e-commerce shopping apps in India, which makes the study unique. As in the e-com sector, trust as well as online ratings and reviews perform a vital role in building consumers' opinions to affect their usage patterns. Our study has tried to fill the gap by incorporating trust perception as a fresh exogenous factor and online rating and online review (Bandwagon Effect) as moderators to the UTAUT2 in this study.

Research Methodology

Sample: This study applied a convenience (non-probability) sampling approach within a quantitative design. To gather information, a systematic, closed-ended questionnaire was employed. Through various social media websites, we reached out to potential respondents who had previously utilised e-com apps for shopping purposes. Although data from 336 respondents was gathered, the study only included data from 300 respondents (the final sample), which was obtained after outliers and missing data were removed.

Instrument: Five-point Likert scales, "ranging from 1 = Strongly Disagree to 5 = Strongly Agree", are the tools utilised in the study to evaluate respondent replies. To conform to the current research's perspective, all measuring

items for the components were modified from earlier, validated studies. The questionnaire had the following dimensions, as well as the total number of items for each measure:

1. Five-item PFE scale (Soni et al., 2019; Yang, 2010)

2. Four-item EFE scale (Palos-Sanchez et al., 2019; Puriwat & Tripopsakul, 2021)

3. Four-item FTC scale (Palau-Saumell et al., 2019; Zanetta et al., 2021)

4. Four-item SLI scale (Chotigo & Kadono, 2021; Zanetta et al., 2021)

5. Three-item HDM scale (Tak & Panwar, 2017; Zanetta et al., 2021)

6. Four-item PVT scale (Chotigo & Kadono, 2021; Nur & Ria Panggabean, 2021)

7. Four-item USI scale (Palos-Sanchez et al., 2019; Puriwat & Tripopsakul, 2021)

8. Three-item ORT scale and four-item ORE scale (Agarwal & Sahu, 2022)

9. Three-item UBR scale (Palos-Sanchez et al., 2019; Tak & Panwar, 2017)

Data Analysis & Interpretation

Measurement Model: Convergent validity is a step in confirming the validity of constructs. (Hair et al., 2019) identified three methods of estimations that quantify convergent validity: factor loadings, AVE (average variance extracted), and discriminant validity. The basis for proving this validity is found in the multivariate data analysis literature and is based on (Fornell & Larcker, 1981) and (Hair et al., 2019). All the indicator loadings shown in Table 1 are greater than 0.50, and the composite reliability, which describes the latent construct of the items, is examined. According to (Fornell & Larcker, 1981), if the composite reliability value is greater than 0.7, it meets the criteria. The following table's values range from 0.898 to 0.940. (Hair et al., 2009) state that the AVE threshold needs to be more than 0.5. The allowed range for the AVEs in the research was between 0.721 and 0.771. Lastly, multicollinearity between the components was assessed using VIF. As can be seen in Table 1, no multicollinearity issue was found because all values are below the permissible threshold of 5 (Ringle & Sarstedt, 2016).

Table 1: Factor Loading, Composite Reliability, rho_A, AVE, VIF and Cronbach's alpha

Factor	Item	Factor Loading	CR	rho_A	AVE	VIF	Cronbach's α
PFE	PFE1	.874	0.940	0.922	0.760	3.029	0.921
	PFE2	.869				3.007	
	PFE3	.903				3.570	
	PFE4	.829				2.346	
	PFE5	.881				3.263	

Factor	Item	Factor Loading	CR	rho_A	AVE	VIF	Cronbach's α
EFE	EFE1	.872	0.930	0.900	0.768	2.804	0.899
	EFE2	.863				2.380	
	EFE3	.893				3.065	
	EFE4	.877				2.570	
FTC	FTC1	.866	0.929	0.902	0.767	2.898	0.899
	FTC2	.862				2.546	
	FTC3	.903				3.233	
	FTC4	.871				2.830	
SLI	SLI1	.837	0.912	0.873	0.721	2.182	0.871
	SLI2	.857				2.359	
	SLI3	.857				2.371	
	SLI4	.846				2.307	
HDM	HDM1	.838	0.898	0.832	0.745	1.774	0.829
	HDM2	.869				1.893	
	HDM3	.882				2.132	
PVT	PVT1	.848	0.918	0.886	0.738	2.559	0.882
	PVT2	.839				2.019	
	PVT3	.882				2.642	
	PVT4	.866				2.536	
USI	USI1	.853	0.915	0.879	0.728	2.844	0.876
	USI2	.833				2.125	
	USI3	.884				2.785	
	USI4	.843				2.448	
UBR	UBR1	.854	0.910	0.858	0.771	2.147	0.851
	UBR2	.868				1.891	
	UBR3	.910				2.673	

(Henseler et al., 2015) suggested a method to assess discriminant validity: the Heterotrait-Monotrait (HTMT) ratio of correlations. They employ a Monte Carlo simulation study to show off the capacity of HTMT. The present research used the same methodology to evaluate for discriminant validity because it was such an effective power strategy. According to (Henseler et al., 2015), there is evidence for discriminant validity between the two reflective conceptions when the HTMT values are less than 0.85. The HTMT test outcomes are presented in Table 2, and the values shown satisfy the $HTMT_{0.90}$ criteria (Gold et al., 2001; Kline, 2011), demonstrating the discriminant validity of the measurement model.

Table 2: HTMT Ratio

EFE	FTC	HDM	PFE	PVT	SLI	UBR	USI
EFE							
FTC	0.654						
HDM	0.626	0.748					
PFE	0.785	0.637	0.586				
PVT	0.574	0.601	0.620	0.573			
SLI	0.758	0.661	0.674	0.807	0.602		
UBR	0.539	0.557	0.568	0.502	0.754	0.500	
USI	0.742	0.778	0.756	0.724	0.825	0.731	0.810

Regarding the endogenous (dependent) factors in the structural model, Table 3 displays the following set of values: coefficient of determination (R^2), effect size (f^2), and predictive relevance (Q^2). According to (Cohen, 1988), the range of values for the coefficient of determination (R^2) is 0.26, 0.13, and 0.02 for strong, moderate, and low. With R^2 values for USI and UBR both exceeding 0.25, the proposed framework is regarded as having a substantial explanatory ability. Considering the PLS-SEM variables, the model's prediction ability was assessed using a blindfolding technique (Chin, 1998). The Q^2 value method was used to gauge the PLS path model's capacity for prediction. (Fornell & Cha, 1994) state that in both generation-based and overall models, predictive significance is present when the Q^2 result is greater than 0. Since the Q^2 values of both USI and UBR are higher than 0, the model is thought to have a significant capacity for prediction.

Table 3: R^2 and Q^2

	R Square	Q^2 Predict
UBR	0.503	0.381
USI	0.724	0.516

The results of (Hair et al., 2013)'s analysis of the hypothesised variable's impacts using the effect size f^2 is shown in Table 4. (Cohen, 1988) proposed this criterion to determine the magnitude of the relationship among the model's latent variables. According to the study, values of 0.35, 0.15, and 0.02 have been identified for high, moderate, and weak associations, respectively. In this study only one variable i.e. perceived trust has moderate to high predictive power. The comparatively low to moderate magnitude of this index is apparent.

Table 4: Effect Size

	f^2	Effect
PFE	0.021	Weak
EFE	0.031	Weak
FTC	0.078	Weak
SLI	0.003	None
HDM	0.029	Weak
PVT	0.310	Moderate to High

(Tenenhaus et al., 2004) state that the average communality index is multiplied by the square root of the model's average R^2 value to determine the GoF value. GoF values are taken into account as follows: 0.25 for moderate GoF, 0.36 for substantial GoF, and 0.1 for low GoF. The range of GoF values is 0 to 1. It is evident from Table 5 and the preceding formula calculation that the study model fulfils the substantial GoF criteria, with a GoF value of 0.679. This suggests that the model could be capable of a good job of explaining actual data, hence bolstering the validity of the proposed model as a whole.

Table 5: Goodness of Fit Index

Factor	AVE	R^2
PFE	0.760	-
EFE	0.768	-
FTC	0.767	-
SLI	0.721	-
HDM	0.745	-
PVT	0.738	-
UBR	0.771	0.503
USI	0.728	0.724
Average Scores	0.750	0.614
(GoF = square root of AVE×R^2)		**0.679**

Path Analysis

Using a bootstrapping method in smart PLS 3, the structural model, path coefficient, and corresponding t-value for the direct and moderated relationship have been identified in the conclusion. According to (Hair et al., 2011), a path coefficient is considered significant if its t-value is more than 1.96. This shows that the path coefficient passed the test at the 5% level of significance. The testing of the suggested correlations is further illustrated by path coefficients, displayed in Fig. 1 and Table 6.

Figure 1: Structural Model

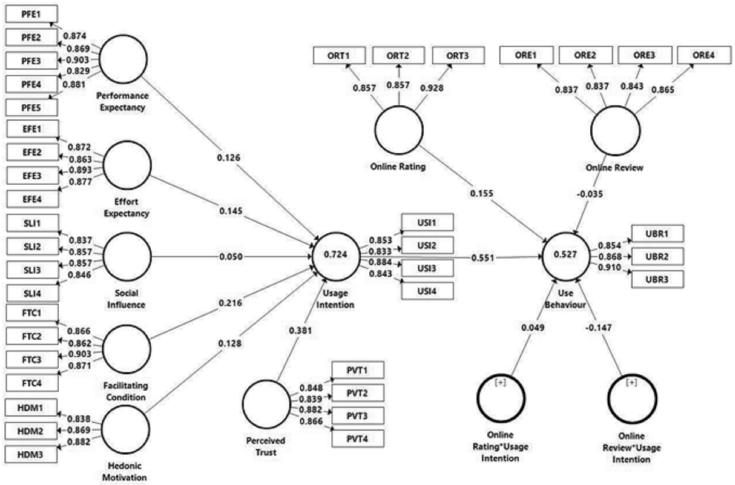


Table 6: Hypothesis Testing

	Original Sample	Sample Mean	Standard Deviation	T Statistics	P Values	Decision
PFE -> USI	0.126	0.123	0.060	2.090	0.037	Supported
EFE -> USI	0.145	0.144	0.060	2.401	0.016	Supported
FTC -> USI	0.216	0.218	0.058	3.736	0.000	Supported
SLI -> USI	0.050	0.054	0.061	0.815	0.415	Rejected
HDM -> USI	0.128	0.127	0.060	2.133	0.033	Supported
PVT -> USI	0.381	0.379	0.061	6.259	0.000	Supported
USI -> UBR	0.551	0.547	0.072	7.666	0.000	Supported
ORT*USI -> UBR	0.049	0.052	0.071	0.693	0.488	Rejected
ORE*USI -> UBR	-0.147	-0.151	0.064	2.300	0.021	Supported

Two indirect relationships and seven direct relationships make up the nine hypotheses presented within the present research. The smart PLS analysis findings indicated that factors like PFE (Beta score = 0.126, t-score = 2.090, sig. value < 0.05), EFE (Beta score = 0.145, t-score = 2.401, sig. value < 0.05), FTC (Beta score = 0.216, t-score = 3.736, sig. value = 0.000), HDM (Beta score = 0.128, t-score = 2.133, sig. value < 0.05) and PVT (Beta score = 0.381, t-score = 6.259, sig. value = 0.000) have a direct, positive, and significant influence on the USI towards e-com shopping apps. Consequently, H_1, H_2, H_3, H_5 and H_6 were validated respectively. There is a significant influence of consumers' USI on consumers' UBR towards e-commerce apps (Beta score = 0.551, t-score = 7.666, sig. value = 0.000), so H_7 is also supported. However, there is no significant influence of SLI on consumers' USI (Beta score = 0.050, t-score = 0.815, sig. value > 0.05). H_4 is thus rejected.

As per the analysis of the data, Hypothesis 8a was rejected, indicating that there was no significant effect of consumers' USI on UBR due to the moderating role of ORT (Beta score = 0.049, t-score = 0.693, and sig. value > 0.05). Hypothesis 8b is supported, which states that there is a significant effect of consumers' USI on UBR due to the interaction effect, providing an explanation for the moderation impact of ORE (Beta score = -0.147, t-score = 2.300, sig. value < 0.05). Fig. 2 & 3 illustrate the interaction effects.

Figure 2: Interaction Effect of Online Rating

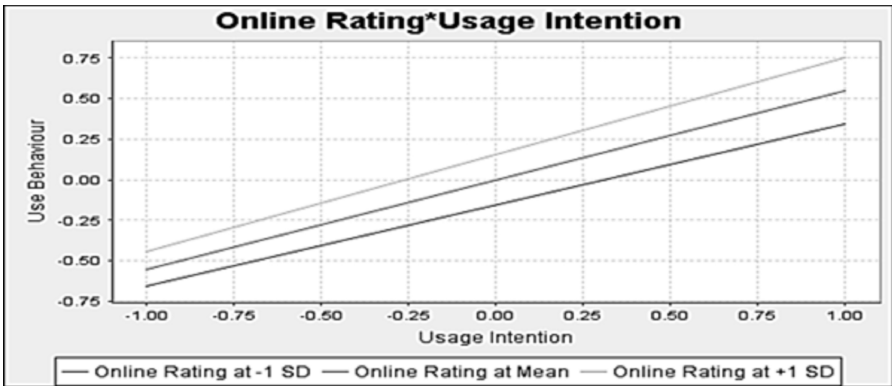
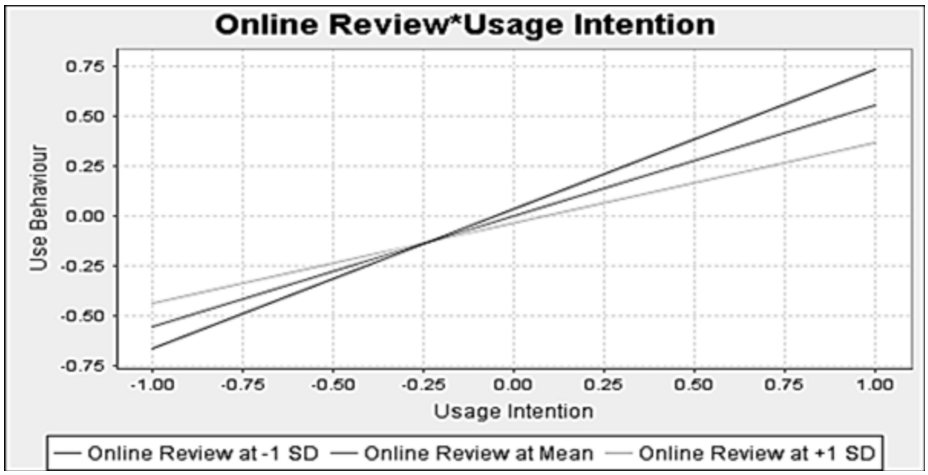


Figure 3: Interaction Effect of Online Review



Importance-Performance Map Analysis (IPMA)

Lastly, an IPMA was used to assess the constructs' importance and performance. (Ringle & Sarstedt, 2016) state that the purpose of importance-performance map analysis is to pinpoint the elements that performed poorly yet are crucial to the target constructs. The IPMA in PLS-SEM is an accurate and beneficial analysis that goes beyond the typical route coefficient estimations in a more significant way. This study found that the following elements impact customers' usage intention towards e-com shopping apps: PFE, EFE, FTC, SLI and PVT.

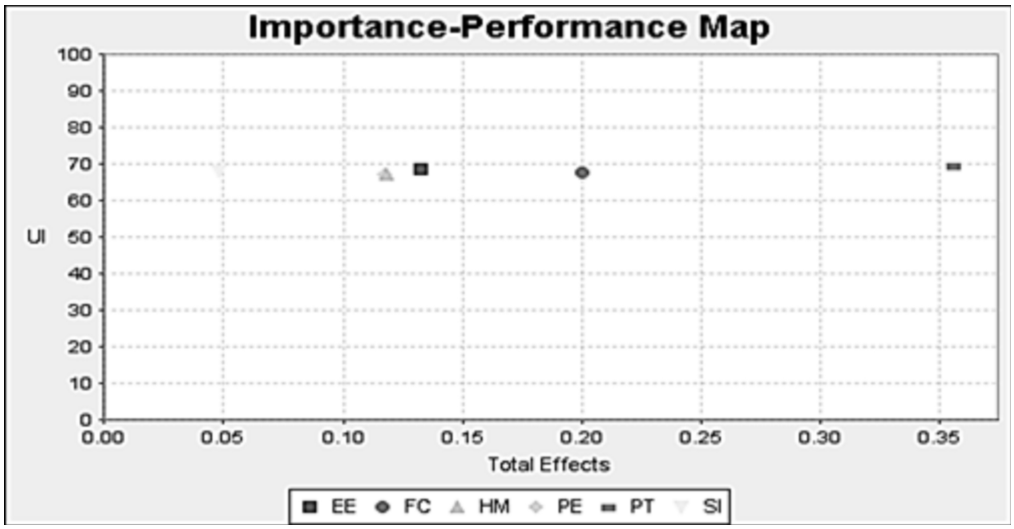
Taking into account the elements depicted in Figure 4, not a single one of them falls into the category of low importance-low performance or potential stress categories.

The Importance-Performance Map Analysis of usage intention suggests that e-commerce service providers should do better on facilitating conditions and perceived trust. In terms of importance, the values reported are relatively small. The performance index figures, however, are remarkable. In order to strengthen their place in the marketplace, e-commerce marketers merely need to bolster their marketing and promotion strategies. A thorough summary of the Importance Performance Map Analysis outcomes is demonstrated in Table 7.

Table 7: Importance & Performance Value

Construct	Importance (Total Effect)	Performance (Index Value)
PFE	0.118	66.890
EFE	0.132	68.339
SLI	0.048	68.217
FTC	0.200	67.697
HDM	0.118	67.218
PVT	0.356	69.127

Figure 4: Importance-Performance Map Analysis



Conclusion

In the present study, the UTAUT framework was utilised to identify the elements that influence consumers to use e-com apps. The results showed that PVT and FTC are the factors that have the strongest effects on usage intention, followed by EFF, PFF and HDM.

It was demonstrated that the most significant determinant in the suggested model is the effect of trust on usage intention. E-commerce organisations should enhance their transparency about data protection, confidentiality, and reimbursement policies, as well as their data safety and security technologies, to boost consumer perception of trust. They need to employ trustworthy safety features like fingerprint recognition to guard against unauthorised access to customer data. Since confidential financial and personal data is exchanged during e-commerce transactions, highly secure encryption techniques must be used to safeguard data. The usage intention of e-com applications is strongly affected by facilitating conditions. This can be understood that the infrastructural developments in the telecom sector over the past few years have improved and high-speed internet is accessible at affordable rates. As a result, consumers continue to easily obtain high-quality smartphones and quick internet connections, which facilitates the usage of e-com apps for their shopping experiences.

USI towards e-com websites for shopping is positively influenced by effort and performance expectancies. Due to its ability to boost their effectiveness when purchasing, respondents found e-commerce shopping to be beneficial. Consumers think e-com apps are simple to use and learn. The respondents believe that their shopping speed has significantly increased. The adoption of e-com apps is also significantly predicted by hedonic motivation. This demonstrates how the characteristics and functionalities of shopping apps may make users feel satisfied. This suggests that their motivation stems from their love of the shopping experience and their involvement in this task. The findings of this research also indicated that SLI does not have a significant impact on USI towards e-commerce services, suggesting that consumer adoption of these services was not influenced by other people's perceptions towards their use. The results show that users have their own opinions, which are not impacted by the advice, ideas, and endorsements of significant persons (colleagues, relatives, and close friends).

Finally, this paper makes a contribution by investigating the moderating function of ORT and ORE in the onset of USI among e-commerce consumers. The key finding is that customers' use behaviour is negatively moderated by ORE whereas ORT does not act as a moderator, indicating that even users who have the intention to use the app become puzzled prior to use the app if the reviews are negative. The e-com app providers should take into account of poor reviews and these errors could undermine all of their marketing initiatives. If there are unfavourable reviews, e-commerce

collaborators, delivery management, and consumer assistance facilities will be accountable.

Limitations

This research is associated with a number of constraints. Firstly, this study was carried out in a brief timeframe and was cross-sectional in design. With the accumulation of new information and experiences, users' opinions of various factors towards e-com apps are subject to alter throughout the years. Thus, a longitudinal study might be used in later research to get more precise data. Furthermore, even though surveys conducted online are frequently employed in consumer studies, biases in sampling may still arise. Thus, in order to lessen these biases, future research must include a variety of techniques for gathering data. Future research may be done to evaluate the significance of the risk construct for the role of mediator/ moderator, particularly the danger of losing private information. Finally, the influence of cultural variables (such as eating patterns, size of household, and lifestyles) was not taken into account in this study. Subsequent research endeavours consider these cultural dimensions and aim to extrapolate the results to a broader geographic context.

Conflict of Interests

The authors declare that there is no conflict of interests that are directly or indirectly related to this research work.

Funding

The authors declare that they did not receive any financial support from any organization to undertake this study.

References

- Agarwal, V., & Sahu, R. (2022). Predicting repeat usage intention towards O2O food delivery: extending UTAUT2 with user gratifications and bandwagoning. *Journal of Foodservice Business Research*, *25*(4), 434–474. https://doi.org/10.1080/15378020.2021.1951074
- Brown, S. A., & Venkatesh, V. (2005). Model of adoption of technology in households: A baseline model test and extension incorporating household life cycle. In *MIS Quarterly: Management Information Systems* (Vol. 29, Issue 3, pp. 399–426). Management Information Systems Research Center. https://doi.org/10.2307/25148690
- Cao, Y., Ajjan, H., & Hong, P. (2018). Post-Purchase Shipping and Customer Service Experiences in Online Shopping and Their Impact on Customer Satisfaction: An Empirical Study with Comparison. *Asia Pacific Journal of Marketing and Logistics*, *30*, 400–416. https://doi.org/https://doi.org/10.1108/APJML-04-2017-0071
- Chin, W. W. (1998). The Partial Least Squares Approach to Structural Equation Modeling. *Modern Method for Business Research*, 295–336. https://www.researchgate.net/publication/311766005
- Chopdar, P., & Sivakumar, V. J. (2019). Impulsiveness and its impact on behavioural intention and use of mobile shopping apps: a mediation model. *International-Journal-of-Business-Innovation-and-Research*, *19*(1), 29.
- Chotigo, J., & Kadono, Y. (2021). Comparative analysis of key factors

encouraging food delivery app adoption before and during the covid-19 pandemic in thailand. *Sustainability (Switzerland)*, *13*(8). https://doi.org/10.3390/su13084088

- Cohen, J. (1988). *Statistical Power Analysis for the Behavioral Sciences Second Edition*.
- Fang, J., Cao, Y., Matsuzaki, M., & Suzuki, H. (2016). Effects of apple pomace proportion levels on the fermentation quality of total mixed ration silage and its digestibility, preference and ruminal fermentation in beef cows. *Animal Science Journal*, *87*(2), 217–223. https://doi.org/10.1111/asj.12410
- Filieri, R. (2015). What makes online reviews helpful? A diagnosticity-adoption framework to explain informational and normative influences in e-WOM. *Journal of Business Research*, *68*(6), 1261–1270. https://doi.org/10.1016/j.jbusres.2014.11.006
- Fornell, C., & Cha, J. (1994). Partial Least Squares. *Advanced Methods of Marketing Research*, *407*, 52–78.
- Fornell, C., & Larcker, D. F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *Journal of Marketing Research*, *18*(1), 39. https://doi.org/10.2307/3151312
- Garg, A. (2021). The Technology Acceptance and use of Tablet Menu among Young Adults: An Empirical Study based on UTAUT 2 Model. *International Journal of Hospitality & Tourism Systems*, *14*(1). https://ssrn.com/abstract=3809622
- Gold, A. H., Malhotra, A., & Segars, A. H. (2001). Knowledge Management: An Organizational Capabilities Perspective. *Journal of Management Information System*, *18*(1), 185–214. https://www.researchgate.net/publication/220591588
- Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2009). *Multivariate data analysis* (Pearson New International, Ed.; seventh).
- Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed a silver bullet. *Journal of Marketing Theory and Practice*, *19*(2), 139–152. https://doi.org/10.2753/MTP1069-6679190202
- Hair, J. F., Ringle, C. M., & Sarstedt, M. (2013). Partial Least Squares Structural Equation Modeling: Rigorous Applications, Better Results and Higher Acceptance. In *Long Range Planning* (Vol. 46, Issues 1–2, pp. 1–12). Elsevier Ltd. https://doi.org/10.1016/j.lrp.2013.01.001
- Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. In *European Business Review* (Vol. 31, Issue 1, pp. 2–24). Emerald Group Publishing Ltd. https://doi.org/10.1108/EBR-11-2018-0203
- Hansen, L., Saridakis, G., Benson, V. (2017). Risk, Trust, and the Interaction of Perceived Ease of Use and Behavioural Control in Predicting Consumers' Use of Social Media for Transactions. Computers in Human Behaviour, 80(1).
- Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8
- Jasim, N. I., Kasim, H., & Mahmoud, M. A. (2022). Towards the Development of Smart and Sustainable Transportation System for Foodservice Industry: Modelling Factors

Influencing Customer's Intention to Adopt Drone Food Delivery (DFD) Services. *Sustainability (Switzerland)*, *14*(5). https://doi.org/10.3390/su14052852

- Johri, A., Wasiq, M., Kaur, H., & Asif, M. (2023). Assessment of users' adoption behaviour for stock market investment through online applications. *Heliyon*, *9*(9). https://doi.org/10.1016/j.heliyon.2023.e19524
- Kline, R. B. (2011). *Principles and Practice of Structural Equation Modeling*. THE GUILFORD PRESS New York London.
- Kuo, Y.-C., Walker, A. E., Belland, B. R., & Schroder, K. E. E. (2013). *A Predictive Study of Student Satisfaction in Online Education Programs A in Online Courses*.
- Lee, S. W., Sung, H. J., & Jeon, H. M. (2019). Determinants of continuous intention on food delivery apps: Extending UTAUT2 with information quality. *Sustainability (Switzerland)*, *11*(11). https://doi.org/10.3390/su11113141
- Maizatul Akmar Mohd Rasli, Nurfariza Hanim Zulkefli, Nor Sofiza Abu Salleh, & Fadhilah Abdul Ghani. (2020). Determinants of Behavioural Intention on Online Food Delivery (OFD) APPS: Extending UTAUT2 with Information Quality. *An International Journal*, *12*(4).
- Malik, A., Suresh, S., & Sharma, S. (2017). Factors influencing consumers' attitude towards adoption and continuous use of mobile applications: A conceptual model. *Procedia Computer Science*, *122*, 106–113. https://doi.org/10.1016/j.procs.2017.11.348
- Mayer, R. C., Davis, J. H., & David Schoorman, F. (1995). An Integrative Model of Organizational Trust. *The Academy of Management Review*, *20*(3), 709–734. https://www.jstor.org/stable/258792?seq=1&cid=pdf-
- Nur, T., & Ria Panggabean, R. (2021). Factors Influencing the Adoption of Mobile Payment Method among Generation Z: the Extended UTAUT Approach. *Journal of Accounting Research*, *4*(1), 14–28. www/http/jurnal.unsyiah.ac.id/JAROE
- Palau-Saumell, R., Forgas-Coll, S., Sánchez-García, J., & Robres, E. (2019). User acceptance of mobile apps for restaurants: An expanded and extended UTAUT-2. *Sustainability (Switzerland)*, *11*(4). https://doi.org/10.3390/su11041210
- Palos-Sanchez, P. R., Correia, M. B., & Saura, J. R. (2019). An empirical examination of adoption of mobile applications in Spain and Portugal, based in UTAUT. In *Int. J. Mobile Communications* (Vol. 17, Issue 5).
- Puriwat, W., & Tripopsakul, S. (2021). Understanding food delivery mobile application technology adoption: A utaut model integrating perceived fear of covid-19. *Emerging Science Journal*, *5*(Special issue), 94–104. https://doi.org/10.28991/esj-2021-SPER-08
- Ringle, C. M., & Sarstedt, M. (2016). Gain more insight from your PLS-SEM results the importance-performance map analysis. In *Industrial Management and Data Systems* (Vol. 116, Issue 9, pp. 1865–1886). Emerald Group Publishing Ltd. https://doi.org/10.1108/IMDS-10-2015-0449
- Saksena, M. J., Okrent, A. M., Anekwe, T. D., Cho, C., Dicken, C., Effland, A., Elitzak, H., Guthrie, J., Hamrick, K. S., Hyman, J., Jo, Y., Lin, B.-H., Mancino, L., Mclaughlin, P. W., Rahkovsky, I., Ralston, K., Smith, T. A., Stewart, H., Todd, J., & Tuttle, C. (2018).

United States Department of Agriculture America's Eating Habits: Food Away From Home United States Department of Agriculture. www.ers.usda.gov

- Saumya, S., Singh, J. P., Baabdullah, A. M., Rana, N. P., & Dwivedi, Y. K. (2018). Ranking online consumer reviews. *Electronic Commerce Research and Applications*, *29*, 78–89. https://doi.org/10.1016/j.elerap.2018.03.008
- Singh, J. P., Irani, S., Rana, N. P., Dwivedi, Y. K., Saumya, S., & Kumar Roy, P. (2017). Predicting the "helpfulness" of online consumer reviews. *Journal of Business Research*, *70*, 346–355. https://doi.org/10.1016/j.jbusres.2016.08.008
- Soni, M., Jain, K., & Kumar, B. (2019). Factors affecting the adoption of fashion mobile shopping applications. *Journal of Global Fashion Marketing*, *10*(4), 358–376. https://doi.org/10.1080/20932685.2019.1649165
- Sundar, S. S., & Limperos, A. M. (2013). Uses and Grats 2.0: New Gratifications for New Media. *Journal of Broadcasting and Electronic Media*, *57*(4), 504–525. https://doi.org/10.1080/08838151.2013.845827
- Sundar, S. S., Shyam Sundar, S., Oeldorf-Hirsch, A., & Garga, A. K. (2008). *A cognitive-heuristics approach to understanding presence in virtual environments*. https://www.researchgate.net/publication/228831557
- Tak, P., & Panwar, S. (2017). Using UTAUT 2 model to predict mobile app based shopping: evidences from India. *Journal of Indian Business Research*, *9*(3), 248–264. https://doi.org/10.1108/JIBR-11-2016-0132
- Tamilmani, K., Rana, N. P., Wamba, S. F., & Dwivedi, R. (2021). The extended Unified Theory of Acceptance and Use of Technology (UTAUT2): A systematic literature review and theory evaluation. *International Journal of Information Management*, *57*. https://doi.org/10.1016/j.ijinfomgt.2020.102269
- Tenenhaus, M., Paris, H., Vinzi, V. E., & Amato, S. (2004). *A global goodness-of-fit index for PLS structural equation modelling A global Goodness-of-Fit index for PLS structural equation modelling 1 Un indice di validazione globale per i modelli ad equazioni strutturali con il metodo PLS*. https://www.researchgate.net/publication/284462849
- Thi My Dung, D., Quoc Chi, V., Thi Hong My, N., & Trang Bao Ngoc, L. (2024). *FACTORS INFLUENCING THE STUDENTS' INTENTION OF USING ONLINE FOOD ORDERING APPS: A CASE STUDY IN HO CHI MINH CITY*. https://doi.org/10.37550/tdmu.EJS/2024.02.541
- Tran, L. T. T. (2020). Online reviews and purchase intention: A cosmopolitanism perspective. *Tourism Management Perspectives*, *35*. https://doi.org/10.1016/j.tmp.2020.100722
- Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly: Management Information Systems*, *27*(3), 425–478. https://doi.org/10.2307/30036540
- Venkatesh, V., Walton, S. M., Thong, J. Y. L., & Xu, X. (2012). CONSUMER ACCEPTANCE AND USE OF INFORMATION TECHNOLOGY: EXTENDING THE UNIFIED THEORY OF ACCEPTANCE AND USE OF TECHNOLOGY. In *MIS Quarterly* (Vol. 36, Issue 1). http://ssrn.com/abstract=2002388

- Wang, X., Zhang, W., Zhang, T., Wang, Y., & Na, S. (2022). A Study of Chinese Consumers' Consistent Use of Mobile Food Ordering Apps. *Sustainability (Switzerland)*, *14*(19). https://doi.org/10.3390/su141912589
- Yang, K. (2010). Determinants of US consumer mobile shopping services adoption: Implications for designing mobile shopping services. *Journal of Consumer Marketing*, *27*(3), 262–270. https://doi.org/10.1108/07363761011038338
- Zanetta, L. D. A., Hakim, M. P., Gastaldi, G. B., Seabra, L. M. A. J., Rolim, P. M., Nascimento, L. G. P., Medeiros, C. O., & da Cunha, D. T. (2021). The use of food delivery apps during the COVID-19 pandemic in Brazil: The role of solidarity, perceived risk, and regional aspects. *Food Research International*, *149*. https://doi.org/10.1016/j.foodres.2021.110671