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THE INTEGRATION OF PERCEIVED PRIVACY TO UTAUT2: THE MODERATING ROLE OF E-WOM ON BEHAVIOR AND USE INTENTION OF SOCIAL COMMERCE

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Abstract

This study explores the factors influencing behavioral intention and actual usage of social commerce applications by extending the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) with perceived privacy and e-word of mouth. Ten hypotheses were tested using Partial Least Squares (PLS) with a bootstrapping procedure of 5,000 resamples.

Findings indicate that performance expectancy (H1), effort expectancy (H2), social influence (H3), hedonic motivation (H5), and habit (H7) were not supported, showing that low utility, ease of use, social persuasion, enjoyment, and habitual behavior discourage adoption. In contrast, facilitating conditions (H4), price value (H6), perceived privacy (H8), and behavioral intention (H9) were significant predictors. These results highlight the importance of access to smartphones and internet connectivity, the perceived value relative to cost, and the assurance of privacy in shaping adoption decisions. Behavioral intention also strongly influenced actual usage, consistent with prior technology adoption studies.

Moreover, Hypothesis 10 was supported, as e-word of mouth significantly strengthened the relationship between behavioral intention and actual usage (p = 0.000). Overall, the study advances theoretical understanding of social commerce adoption and provides practical insights for developers and marketers to design strategies that enhance trust, value, and user engagement.

INTRODUCTION

Information and communication technology (ICT) has significantly transformed the organizations' strategies and their inside and outside management capabilities. Moreover, now the new products, services, dynamic demands of consumers, delivery methods, and interactive tools are helping businesses to interact with their consumers and build stronger bonds with them (Turban et al., 2011). Moreover, e-commerce has improved the efficiency of businesses and decreased expenses on selling products or services. E-commerce emerged in the 1970s, and since then, it has been considered a new idea (Laudon & Traver, 2012) as every passing day and the technological revolutions are updating the area of e-commerce.

Smartphone use has increased in many ways due to its essential features, which include mobility, affordability, universality, lightweight design, and connectivity at any location at any time (Klopfer et al., 2002). Researchers in numerous sectors are encouraged to leverage new opportunities using smartphones (Aijaz et al., 2019). Mobile technology developments and mobile applications have restructured the consumer buying process (Wagner, et al., 2020), making progress toward the new platform of social commerce (Blaise, et al., 2018). Adam blacker (2022) reports that social networking platforms (such as TikTok, Instagram, and Whatsapp), along with iOS and Google apps, make up the leading three apps adopted by consumers worldwide. For shopping, Shopee, SHEIN, Amazon shopping, AliExpress, Flipkart, and Alibaba are the most adopted apps by consumers. Due to the increasing importance of mobile devices in customers' everyday lives, social commerce and the usage of mobile applications have grown (Vinerean, et al., 2022).

TAM has been used to investigate individual acceptance of technology in a consumer context (Schepers & Wetzels, 2007). Although TAM remained active as a reliable model for technology adoption acceptance, TAM has also been criticized for providing little information on individuals' views about novel technologies and ignoring users' individual characteristics (Agarwal & Prasad, 1999; Mathieson et al., 2001; McMaster & Wastell, 2005). This research has addressed Venkatesh et al. (2012)'s call for more research, which suggested testing the model in various nations, age groups, and technological contexts, as well as expanding it to include other pertinent critical factors to make it applicable to a variety of consumer contexts. Moreover, we used an additional factor of consumer behavior as an extension to the UTAUT2 model, i.e., perceived privacy and electronic word of mouth (e-WOM), to understand consumer attitudes and intentions towards the adoption and acceptance of social commerce apps among Pakistani users. These factors play a significant role in the development of technology acceptance and adoption among the Pakistani consumer segment, given that Pakistan is at the initial stage of the digital economy (Saleem et al., 2022). Thus, research must be done about consumer insights into perceived privacy and e-WOM. Khaskheli et al. (2017) highlighted that technology adoption has become a necessity in today's ultra-competitive environment. However, Liébana-Cabanillas et al. (2017) argued that the use of social commerce in developing nations is still minimal.

LITERATURE REVIEW

Several theories and models from earlier studies were reviewed, examining “use behavior,” “intention to use,” and related terms, which informed the theoretical basis of this study. In addition, several theories and models of behavior intention and use intention can aid in understanding, explaining, and predicting an individual's behavior, including their approval or disapproval of social commerce apps.

The basic definition of technology acceptance is the degree to which people see, accept, and utilize contemporary technology (Dillon & Morris, 1996). The study's theoretical foundation is the expanded Unified Theory of Acceptance and Use of Technology (UTAUT2). Venkatesh et al. (2003) claimed to compile eight models (TRA, TAM, MM, TPB, C-TAM-TPB, MPCU, DIT, and SCT). UTAUT's main constructs and measurement items were derived from each of the mentioned theories, i.e., (TAM, TRA, TPB, MM, SCT, MPCU, DIT, and C-TAM-TPB). The variation described in behavioral intention and technology usage was significantly increased by the UTAUT2 extensions (Chang, 2012). Context of consumer usage is the main emphasis of UTAUT2. Adoption models specifically designed for individual customer assessment can forecast up to 70% of behavioral intention. (Venkatesh et al., 2012). On the other hand, models devoted to organizational settings, when used in a consumer context, predict only 52% of behavior intention (Venkatesh et al, 2012).

It is crucial to state that the moderating effects of age, experience, and gender are irrelevant to this investigation. Consequently, these components were eliminated. This is because there has not been much research done on certain subjects; thus, it is important to have a more comprehensive understanding of Pakistan's technology adoption and usage trends. Furthermore, this study did not employ the moderating influence of age, gender, or experience, which is consistent with earlier research (Mahfuz et al., 2016; Baabdullah, 2018; Al-Azawei & Alowayr, 2020).

Performance Expectancy

Performance expectancy is parallel to the perceived usefulness variable in the Technology Adoption Model (TAM), described by Davis (1989) as "the degree to which a person believes that using a particular system would enhance his or her job performance" (p. 320). Considering that consumers will adopt a technology that yields tangible benefits, this variable has been utilized in consumer contexts such as retail self-service technology (Kaushik & Rahman, 2015), technology-facilitated services (Roy Chowdhury et al., 2014), and mobile payments (Bailey et al., 2017). In general, existing literature suggests that consumers are more likely to adopt emerging technologies if they believe that the new technology will be helpful and useful to them (Alalwan et al., 2017). PE has been proposed based on features that emphasize customer time-saving opportunities, efficiency, and usefulness (Venkatesh et al., 2012). According to studies (i.e., Venkatesh et al., 2003; Lu et al., 2017; Hoque & Sorwar, 2017; Chao, 2019), performance expectancy is a direct determinant of behavioral intention by humans. Lu and Su (2009) observed in China that performance expectations considerably impacted users' use of mobile services. A study by Soni et al. (2019) surveyed fashion mobile shopping apps and found that performance expectancy showed a significant influence on behavior intention and use behavior. Accordingly, the following hypothesis is developed, which postulates that performance expectancy can have a significant impact on customers' behavior intentions toward acceptance and adoption of social commerce apps:

H1. Performance expectancy (PE) has a positive impact on customers' behavior intention (BI) to use social commerce apps.

Effort Expectancy

According to Venkatesh et al. (2003), effort expectancy was derived from the perceived 'ease of use' factor proposed by Davis (1989) in the Technology Acceptance Model (TAM); It was discovered that an application that users believe to be simple to use has a higher chance of being approved. Catherine et al. (2017) studied behavioral intention toward fingerprint authentication-based ATMs in Uganda and confirmed that effort expectancy substantially and positively affected BI. Mtebe and Raisamo (2014) highlighted the significant effect of effort expectancy on students' behavioral intention towards mobile learning in higher education in East Africa. Likewise, Fadzil (2018) confirmed the role of effort expectancy for intention behavior to use mobile applications in Malaysia. Murillo-Zegarra et al. (2020) provided empirical evidence that effort expectancy is a major determinant of behavior intention. This research has postulated that customers' behavioral intention toward acceptance and adoption of mobile commerce applications can be strongly influenced by effort expectancy. Thus, the following hypothesis is developed:

H2: The customer's behavior intention (BI) to use the social commerce app is positively impacted by effort expectancy (EE).

Social Influence

Brown and Venkatesh (2005) defined social influence as "the extent to which consumers perceive that important others (e.g., family and friends) believe they should use a particular technology". Existing research confirms that social influence is a strong predictor of behavioral intentions (Chong & Ngai, 2013) across various contexts, including mobile payments (Slade et al., 2015); m-commerce (Chong, 2013), social commerce (Akman and Mishra, 2017), m-banking (Bhatiasevi, 2015), and mobile app usage intentions (Hew at el., 2015). A study by Jaiswal and Singh (2020) with 206 responses found that social influence is an essential factor of behavior intention for mobile wallet services in India, and Leong et al. (2013) stated that social influence is an essential factor of behavior intention. Yang et al. (2012) observed a positive effect of social influence on the adoption intention of mobile payment services in China. In a Malaysian study, Wei et al. (2009) found Social Influence to be significantly and positively correlated to the intention to use social commerce. Colleagues, friends, family, and other seasoned users are therefore assumed to have an impact on users' behavioral intention to use social commerce apps. The study's hypothesis is based on the previous discussion.

H3: Customers' behavior intention (BI) to use social commerce apps is positively impacted by social influence (SI).

Facilitating Conditions

Facilitating conditions reflect the effect of necessary resources (internet connectivity, memory in the smartphone to download an app, online help and support) and the required knowledge necessary to operate social commerce apps. Lewis et al. (2013) and Chong (2013) stated that facilitating conditions have a firm role in technology adoption. A study by Soni et al. (2019) with a sample of 209 participants surveyed fashion mobile shopping apps and found that facilitating conditions showed significant influence on behavior intention and use behavior. Researchers Tak & Panwar (2017) discovered, with a sample of 350 mobile app shoppers in Delhi, India, that facilitating conditions help in the usage of mobile apps for shopping. The study assumes that users' positive opinions of enabling factors, such as assistance, internet access, and/or asking for help, will influence their behavioral intention to download and utilize social commerce applications. Based on the literature, the present researcher believes that this criterion has a favorable impact on Pakistan's acceptability and uptake of social commerce apps.

H4: Customers' behavior intention (BI) to use social commerce apps is positively impacted by facilitating conditions (FC).

Hedonic Motivation

The pleasure a customer experiences from utilizing a particular technology is known as hedonic motivation (Venkatesh et al., 2012). User perceptions about new technology have been found to be significantly influenced by intrinsic characteristics like enjoyment and entertainment (Dabholkar & Bagozzi, 2002). In fact, this measure has been utilized extensively as a predictor of technology usage in the information systems literature (Alalwan et al., 2017). Soni et al. (2019) surveyed 209 participants, conducted a survey for fashion mobile shopping apps, and found that hedonic motivation showed a significant influence on behavior intention and use behavior. The behavioral intention of a user to use a social commerce app will rise in direct proportion to their perceived degree of happiness, according to this study. Thus, the following theories are put forth:

H5: Customers' behavior intention (BI) to use a social commerce app is positively impacted by hedonic motivation (HM).

Price Value

Zeithaml (1988) argued that price value is the complete process through which the evaluation and comparison of the perception of relative rewards and associated costs can be made. If perceived advantages carry more value over the intention to use information technology apps, this will positively impact the use of technology (Deng et al., 2014). Price value is thought to be a predictor of the user's behavioral intention to use the social commerce app in this consumer-use setting, leading to the following hypotheses:

H6: Customers' behavior intention (BI) to use social commerce applications is positively impacted by price value (PV).

Habit

Past experiences lead to Habit or Habitual use (Venkatesh et al., 2012), and consistency in past behavior is one of the principal determinants of present behavior (Ajzen, 2002). Baptista and Oliveira (2015) found Habit as the most important antecedent of use behavior. Kim (2012) reported a direct association between habit and the actual use of mobile applications. Soror et al. (2022) also claimed that habit influences consumers' behavioral intention to use social networking websites. Soni et al. (2019) surveyed 209 participants using fashion mobile shopping apps and highlighted that habit significantly influenced behavior intention and use behavior. Because habit development is assumed to lead to greater behavioral intention and usage behavior, the following hypothesis was developed:

H7: A customer's behavior intention (BI) to utilize social commerce app is favorably impacted by habit (H).

Perceived Privacy

Privacy has become the primary concern in e-commerce (Baek et al., 2016). Users' propensity to provide information to information technology-based services is influenced by their perception of privacy (Joinson et al., 2010). According to Fang et al. (2017), privacy is crucial for users to embrace and utilize mobile applications. Privacy also serves as a significant precondition for the uptake of social commerce (Islam et al., 2011) and users' intent to make purchases (Susanto et al., 2016). Privacy was associated with technology adoption, with 65% of study participants citing privacy concerns as a deterrent to e-commerce use (Harris, 2004). It was confirmed in many studies that perceived privacy, directly and indirectly, influences users' willingness to reveal personal information (e.g., personal data, location, photos) to mobile apps (Xu et al., 2009), intention to pay to mobile apps (Keith et al., 2016), intention to adopt mobile apps (Luo et al, 2010) intention to buy online (Midha, 2012) and online buying behavior (Dinev & Hart, 2005). Based on the past discussion, the current study hypothesized that perceived privacy can significantly influence customers' behavior intentions toward acceptance and adoption of social commerce apps in Pakistan.

H8: Perceived privacy (PP) has a positive and significant influence on behavior intention (BI) to use social commerce apps

Focal Constructs: Behavioral Intention and Actual Use Intention

The main antecedent of use behavior is framed as the behavioral intention in the UTAUT2 model, having a single direct effect on users' actual use of a certain tool. Behavioral intention is seen to be the most accurate predictor of actual behavior of using any new technology (Liébana-Cabanillas et al., 2020). According to Albashrawi et al. (2019), the motivations of American consumers are a significant factor in the explanation of their use of mobile banking based on the replies of 360 m-banking users. Iskandar et al. (2020) indicated and demonstrated that behavioral intention had a significant role in how Indonesians used m-banking. Similarly, this research hypothesized that:

H9: Use intention (UI) to use social commerce applications is positively and significantly influenced by behavior intention (BI).

Moderation of E-WOM

Arndt (1967) described word of mouth as "oral, person-to-person communication between a receiver and a communicator whom the receiver perceives as non-commercial, regarding a brand, product, or service" (p. 3). The study selected eWOM as a moderation effect due to the growth and significant developments in e-commerce, as well as its ever-increasing need (Verma & Yadav, 2021). E-WOM has become attractive for both practitioners and researchers (Zhang et al., 2022). With the rapid development of social media and the usage of smartphones, eWOM is ubiquitous (Zhang et al., 2017). Filieri et al. (2018) stated that eWOM is considered a vital foundation of information influencing human behavior. In many recent studies, 93% of consumers mentioned that online reviews (an eWOM type) significantly affect their purchase decisions (Tata, et al., 2019). Numerous analytical studies have highlighted the impact on users' intention by eWOM to buy products or services (Plotkina & Munzel , 2016). For example, the purchase intention of cars (Reza & Samiei, 2012), the intention to book hotels (Teng et al., 2017), and laptops (Aerts et al., 2017), as well as the intention to choose tourist destinations (Jalilvand & Samiei, 2012). Therefore, this study assumes that users rely on recommendations from a social group when adopting and using social commerce apps. Thus, the current study hypothesized that eWOM can significantly moderate the influence of customers' behavior intentions toward acceptance and adoption of social commerce apps in Pakistan.

H10: E-word of mouth (EWOM) positively and significantly moderates the relationship between behavior intention (BI) and use intention (UI) to adopt social commerce apps

Based on the literature given above, the following theoretical framework is developed (See Figure 1).

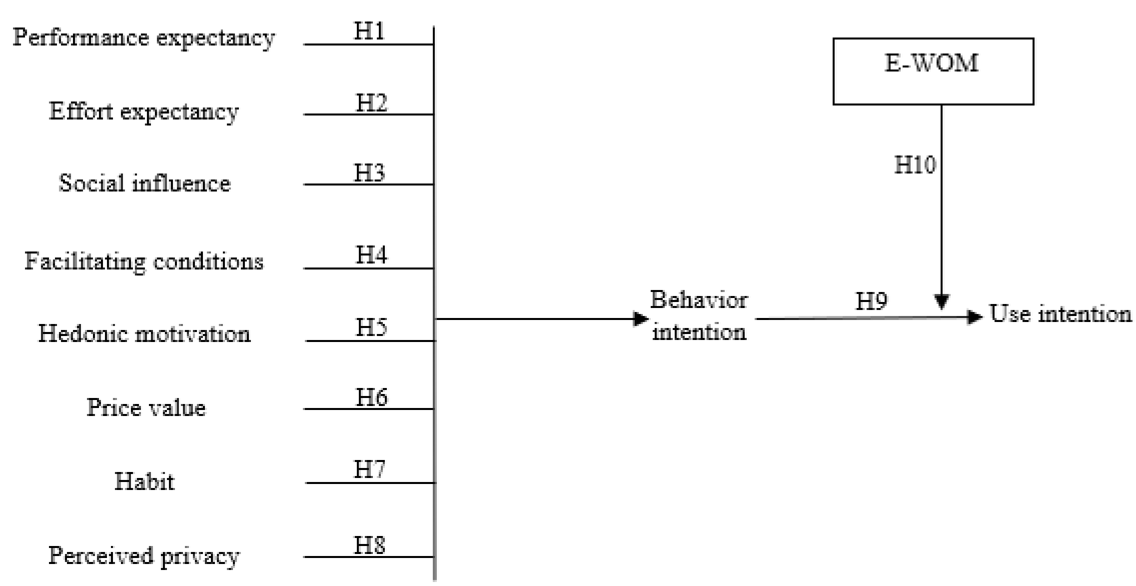

Fig. 1 Theoretical framework for social commerce apps adoption

METHODOLOGY

The research has employed a quantitative research technique to examine the expected hypotheses' strength and to investigate the adopted and expanded theoretical viewpoint of UTAUT2 to obtain a more comprehensive approach to data gathering and analysis. Male and female smartphone users who have used social commerce apps in Pakistan were the study's target subjects.

Active users of social commerce apps were chosen as the study's target audience. Internet-connected smartphone users made up the population of inference. Chuan and Penyelidikan (2006) stated that Krejcie and Morgan's criterion is a commonly employed method for estimation of sample size in research, which supports an appropriate sample size with a minimum of 384 for a population of more than 1 million. Thus, this research has followed the same.

The PLS-SEM method can highlight the complicated relationship between the constructs and identify path coefficients' relative values (Hair et al., 2011). PLS-SEM enables researchers to process the model, which has constructs, indicators, and paths (Hair et al., 2019). For all results involving testing the measurement (validity) and structural models (hypotheses), results were obtained through Smart PLS version 3.8. The P-value should be less than 0.05, which has been recognized by several social sciences (Saunders et al., 2012).

Results

The current study has a total of 434 respondents. Most of the respondents were young Pakistanis who are engaged with social commerce. 29.96% were between 18-25 years old, 24.19% were between 26-33 years old, 25.12% were between 34-41 years old, and the rest 20.73% were above 41 years old. The next aspect is the gender of the respondents, with 227 males (52.30%) and 207 females (47.70%) in the data set. This difference is justifiable in the male-dominated society of Pakistan. The measurement model consisted of 10 constructs, where each construct consisted of items ranging from 3 to 4. Table 1 shows that Cronbach's alpha is above the 0.7 threshold for all constructs (Hardy & Bryman, 2009). Bagozzi and Yi (1988) recommended that the threshold value of composite reliability be set at 0.6. Table 2 presents the factor loading (FL) and average value extracted (AVE). The threshold values for AVE and factor loading are 0.5 (Kline, 2023) and 0.6 (Hair et al., 2016), respectively, as presented in Table 2.

Table 1. Construct Reliability Analysis

Variable	Cronbach's Alpha	CR
Behavior Intention	0.815	0.890
Effort Expectancy	0.879	0.913
Facilitating Conditions	0.813	0.877
Habit	0.815	0.890
Hedonic Motivation	0.847	0.908
Performance Expectancy	0.807	0.870
Perceived Privacy	0.753	0.886
Price Value	0.812	0.889
Social Influence	0.836	0.896
Use Intention	0.856	0.912

E-Word of Mouth	0.789	0.904

Table 2. Factor Loadings (FL) and Average Variance Extracted (AVE)

Constructs	FL	AVE	Constructs	FL	AVE
Behavior Intention		0.730	**Perceived Privacy**		0.795
BI1	0.833		PP1	0.845	
BI2	0.878		PP2	0.936	
BI3	0.851		PP3	*	
Effort Expectancy		0.725	**Performance Expectancy**		0.697
EE1	0.873		PE1	0.947	
EE2	0.920		PE2	0.903	
EE3	0.748		PE3	0.716	
EE4	0.854		**Use Intention**		0.777
Facilitating Conditions		0.642	UI1	0.866	
FC1	0.829		UI2	0.908	
FC2	0.837		UI3	0.869	
FC3	0.831		**Price Value**		0.727
FC4	0.700		PV1	0.823	
Hedonic Motivation		0.766	PV2	0.874	
HM1	0.846		PV3	0.860	
HM2	0.918		**Habit**		0.729
HM3	0.860		H1	0.838	
Social Influence		0.741	H2	0.846	
SI1	0.846		H3	0.876	
SI2	0.921		**E-Word of Mouth**		0.825
SI3	0.813		EWOM1	0.918	
			EWOM2	0.899	
			EWOM3	*	

**NOTE:* *Items less than 0.500 were deleted from the original analysis*

The Fornell and Larcker method states that the square root value of AVE of constructs should be greater than the variance of the variables with each other. The results, presented in Table 3, indicate that all values exceed the shared variance. Heterotrait-Monotrait Ratio (HTMT) Criterion is developed by Henseler et al. (2015); "HTMT criterion measures the average correlations of the indicators across constructs". The acceptable level of the HTMT criterion is <0.90 (Henseler et al., 2015). Each of the values is under the cut-off value, according to the output displayed in the table below. The HTMT criterion is presented in Table 4.

Table 3. Fornell-Larcker Criterion

	BI	EE	FC	H	HM	PE	PP	PV	SI	UI	ewom
BI	0.855										
EE	-0.083	0.851									
FC	0.34	-0.01	0.801								
H	0.202	-0.077	0.308	0.854							
HM	0.321	-0.028	0.358	0.344	0.875						
PE	-0.08	0.579	-0.039	-0.063	-0.074	0.835					
PP	0.271	0.098	0.13	0.181	0.279	0.045	0.892				
PV	0.388	-0.02	0.382	0.336	0.371	0.08	0.347	0.853			
SI	-0.09	0.47	0.003	-0.043	0.022	0.462	0.023	-0.017	0.861		
UI	0.462	-0.003	0.151	0.144	0.231	0.006	0.359	0.397	-0.035	0.881	
ewom	-0.410	0.026	-0.194	-0.136	-0.335	0.034	-0.322	-0.404	-0.017	-0.393	0.909

Table 4. HTMT criterion

	BI	EE	FC	H	HM	PE	PP	PV	SI	UI	ewom	ewom x BI
BI												
EE	0.094											
FC	0.414	0.054										
H	0.245	0.077	0.37									
HM	0.386	0.086	0.43	0.417								
PE	0.092	0.695	0.061	0.088	0.087							
PP	0.334	0.142	0.158	0.211	0.348	0.078						
PV	0.476	0.051	0.474	0.411	0.449	0.105	0.443					
SI	0.100	0.602	0.046	0.058	0.051	0.691	0.063	0.038				
UI	0.552	0.034	0.182	0.172	0.271	0.051	0.445	0.477	0.034			
ewom	0.510	0.054	0.244	0.165	0.414	0.049	0.415	0.506	0.044	0.476		
ewom x BI	0.077	0.085	0.353	0.011	0.116	0.058	0.09	0.207	0.108	0.331	0.269	

The VIF value can range between 3.3 and 10; however, it should be less than 3.3 (Hair et al., 2017). The VIF values are shown in Table 5 and are all found to be less than 3.3. Thus, the study has no issue of multicollinearity. The Path Analysis is presented in Table 6.

Table 5. Values of VIF

Sr.#	Items/Construct	VIF	Sr.#	Items/Construct	VIF
00	BI * EWOM	1.000	17	HM3	1.994
01	BI1	1.659	18	PE1	2.315
02	BI2	2.024	19	PE2	2.226
03	BI3	1.838	20	PE3	1.428
04	EE1	2.604	21	PP1	1.572
05	EE2	2.51	22	PP2	1.572
06	EE3	1.803	23	PV1	1.667
07	EE4	2.644	24	PV2	1.951
08	FC1	1.899	25	PV3	1.806
09	FC2	2.078	26	SI1	1.981
10	FC3	1.864	27	SI2	1.901
11	FC4	1.381	28	SI3	1.968
12	H1	1.679	29	UI1	1.986
13	H2	1.92	30	UI2	2.449
14	H3	1.853	31	UI3	2.122
15	HM1	1.952	32	eWOM1	1.737
16	HM2	2.609	33	eWOM2	1.737

Table 6. The Path Analysis

	Original Sample (O)	T Statistics (|O/STDEV|)	P Values	Result
BI -> UI	0.370	5.832	0.000	Accepted
EE -> BI	-0.037	0.679	0.497	Rejected
FC -> BI	0.191	2.574	0.01	Accepted

H -> BI	-0.010	0.145	0.885	Rejected
HM -> BI	0.132	1.793	0.073	Rejected
PE -> BI	-0.039	0.673	0.501	Rejected
PP -> BI	0.141	2.33	0.02	Accepted
PV -> BI	0.222	2.868	0.004	Accepted
SI -> BI	-0.058	0.995	0.320	Rejected
EWOM -> UI	-0.185	3.09	0.002	Accepted
EWOM * BI -> UI	0.172	4.147	0.000	Accepted

The SmartPLS (i.e., structural model) was used to measure the study's path analysis. Every value satisfies the bootstrapping value of 1.96 or the minimal requirement of a 0.095% interval. The path analysis findings are shown in Table 6. H1 indicates relationship between PE and BI. Statistics show that PE has non-significant influence on BI. Hence H1 is rejected (p=0.501). H2 indicates relationship between EE and BI. Statistical shows that EE makes no influence of BI (p=0.497). H3 is rejected (p=0.320), H3 indicates relationship between SI and BI. H4 indicates relationship between FC and BI, demonstrating a positive significant influence of BI, so H4 is accepted (β=0.191). H5 indicates relationship between HM and BI, statistics show non-significant effect on BI, therefore, H5 is rejected (p=0.073). H6 is accepted (β=0.222). H6 indicates relationship between PV and BI. H7 indicates relationship between H and BI. H7 is rejected (p=0.885). H8 indicates relationship between PP and BI, so H8 is accepted (β=0.141). H9 indicates relationship between BI and UI, statistics show that BI has significant positive influence on UI, hence H9 is accepted (β=0.370). H10 indicates moderating relationship of e-WOM between BI and UI. H10 is accepted (β=0.172). Measurement model is shown in figure 2.

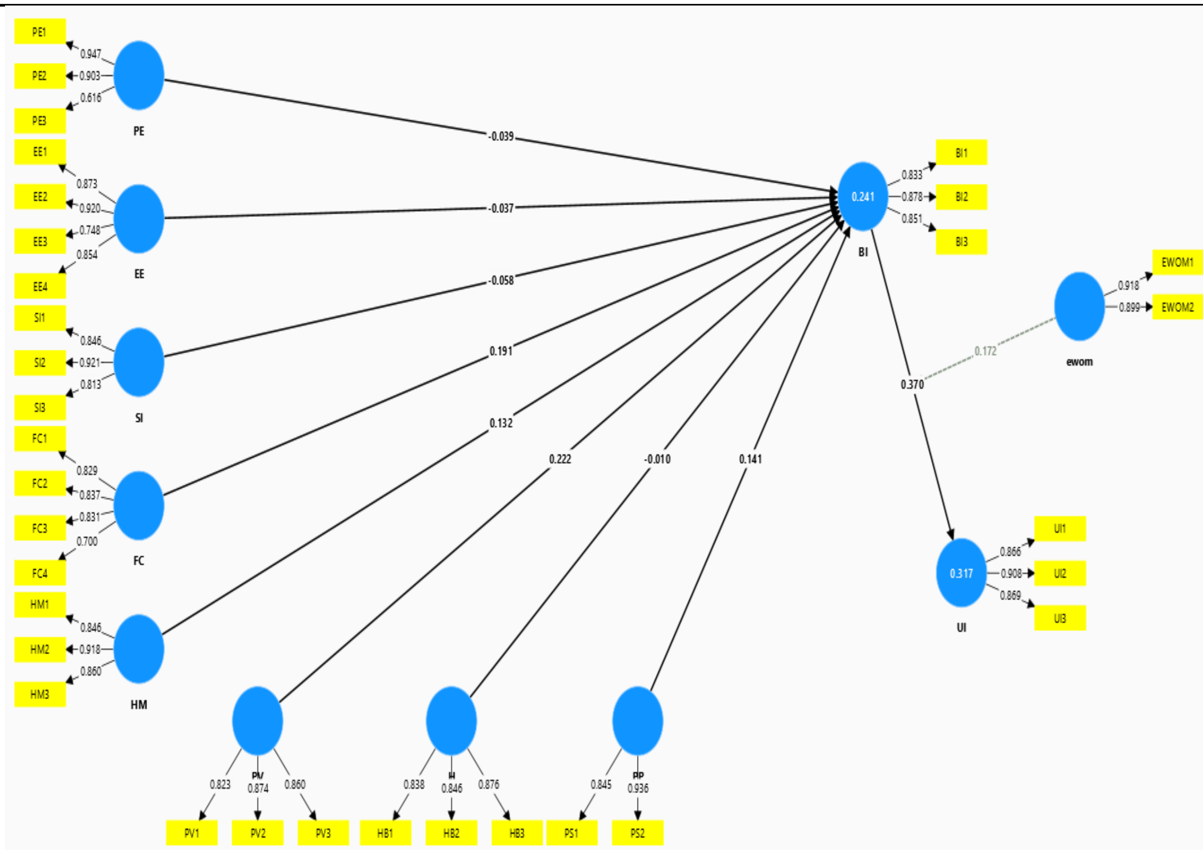

Fig. 2 Measurement Model

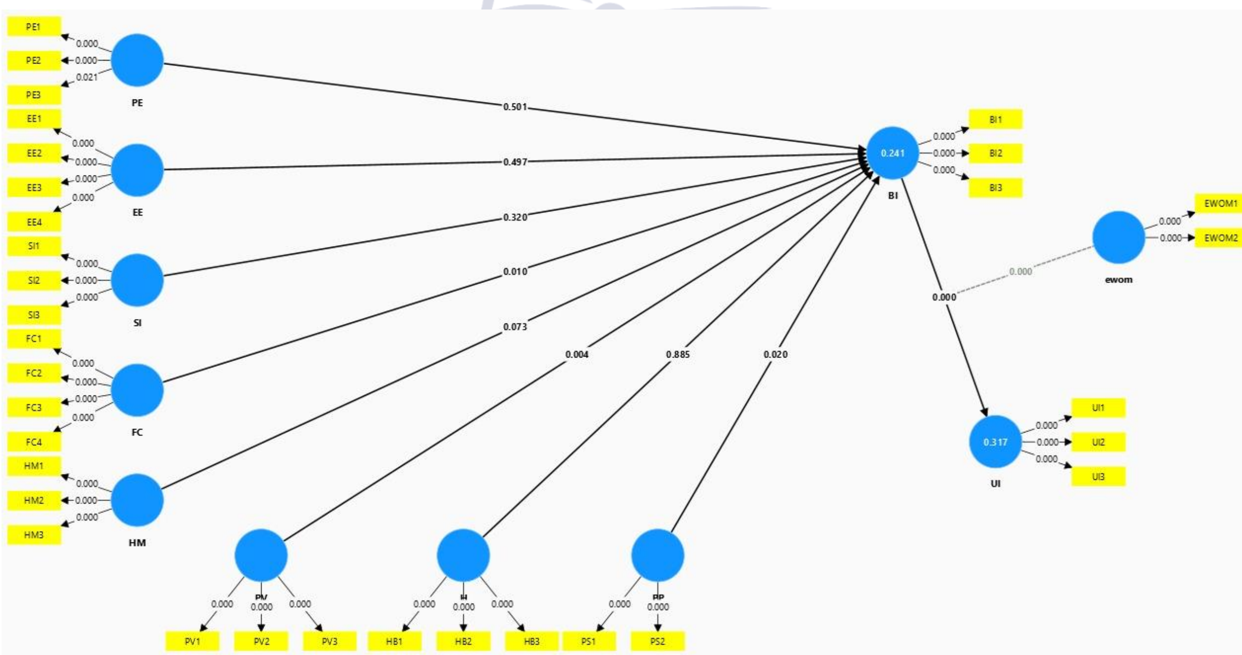

Fig. 3 Structural Model

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DISCUSSION

H1 was not supported. Performance expectancy in this study refers to the tendency of users to inhibit behavioral intention when they perceive low levels of perceived utility, extrinsic incentive, relative advantage, job-fit, and result expectations. Current findings differ greatly from those of previous studies, including e-wallet behavior intention in Indonesia (Tusyanah, et al., 2021). H2 was not supported. Effort expectancy, in this study, consists of two sub-constructs namely complexity, and perceived ease of use. This means that users who perceive a low level of complexity, and perceived ease of use tend to discourage behavioral intention. The result of this relationship was also supported by various studies, for example, e-wallet behavior intention in Indonesia (Tusyanah, et al., 2021), e-commerce user acceptance of technology-based loan application features (Pramudito et al., 2023). There was no support for H3. Social influence: Users who place less significance on the advice of friends and family are more likely to H6 was approved. Since the advantages of utilizing social commerce applications are thought to outweigh the costs, pricing value was considered in the current study. Accordingly, individuals who place a high value on something are more likely to support behavioral intention. Numerous research also confirmed the relationship's findings, such as behavior intention towards mobile app shopping (Kapoor, & Singh, 2020). There was no support for H7. Because consumers thought using social commerce applications would become second nature to them, the habit was assumed in this study. This implies that those who use cellphones less frequently behave less when it comes to using social commerce apps. The findings of this connection were also supported by other studies, including as visual e-banking systems (Fajar et al., 2018). H8 was supported. In this study, perceived privacy was assumed as the individual's perception that their personal information is safe from potential compromise. This means that users who discourage behavioral intention. Current findings differ greatly from those of previous studies, including e-commerce for beauty products (Vallerie et al., 2021). H4 was supported in this study. This means that users with smartphones and internet connectivity tend to develop behavioral intentions. The result of this relationship was also supported by various empirical pieces of research, for example, the adoption of fashion mobile shopping applications (Soni et al., 2019) and e-wallet behavior intention in Indonesia (Tusyanah et al., 2021). H5 was not supported. In the current study, hedonic motivation consists of the user's enjoyment in using social commerce apps. This means that users who perceive a low level of enjoyment or fun tend to discourage behavioral intention. The result of this relationship was also supported by various studies, for example, mobile banking in Indonesia (Susilowati, 2021).

perceive a high level of privacy tend to have a stronger intention to behave. Current findings are significantly changed from existing research, such as online travel purchases (Dogra & Adil, 2022). H9 has been supported. In this study, behavior intention was defined as an individual's perceived likelihood of engaging in a certain activity. This indicates that users who believe there is a high degree of behavior intent are more likely to promote real use behavior. The study's findings are consistent with previous research, such as the adoption of mobile health applications (Garavand et al., 2019). This study used the PLS approach to assess the moderating effect, as suggested by (Chin et al., 2003). A bootstrapping test (bootstrap sample size = 5000) was applied, and it was observed that when e-word of mouth is present, the association between behavior intention and the actual use intent is significant ($p = 0.000$). Thus, Hypothesis 10 is supported.

REFERENCES

1) Adam blacker. (2022) *Worldwide Leaders*. *[Internet]*. Available at: https://blog.apptopia.com/worldwide-and-us-download-leaders-2021#Shopping (Accessed 10 November 2022)
2) Aerts, G., Smits, T., & Verlegh, P. W. (2017). How online consumer reviews are influenced by the language and valence of prior reviews: A construal level perspective. *Computers in Human Behavior*, *75*, 855-864.
3) Agarwal, R., & Prasad, J. (1999). Are individual differences germane to the acceptance of new information technologies?. *Decision sciences*, *30*(2), 361-391.
4) Aijaz, A., Stanoev, A., & Sooriyabandara, M. (2019). Toward real-time wireless control of mobile platforms for future industrial systems. *arXiv preprint arXiv:1907.01979*.
5) Ajzen, I. (2002). Residual effects of past on later behavior: Habituation and reasoned action perspectives. *Personality and social psychology review*, *6*(2), 107-122.
6) Akman, I., & Mishra, A. (2017). Factors influencing consumer intention in social commerce adoption. *Information Technology & People*, *30*(2), 356-370.
7) Alalwan, A. A., Dwivedi, Y. K., & Rana, N. P. (2017). Factors influencing adoption of mobile banking by Jordanian bank customers: Extending UTAUT2 with trust. *International Journal of Information Management*, *37*(3), 99-110.
8) Alalwan, A. A., Dwivedi, Y. K., & Rana, N. P. (2017). Factors influencing adoption of mobile banking by Jordanian bank customers: Extending UTAUT2 with trust. *International Journal of Information Management*, *37*(3), 99-110.
9) Al-Azawei, A., & Alowayr, A. (2020). Predicting the intention to use and hedonic motivation for mobile learning: A comparative study in two Middle Eastern countries. *Technology in Society*, *62*, 101325.
10) Albashrawi, M., Kartal, H., Oztekin, A., & Motiwalla, L. (2019). Self-reported and computer-recorded experience in mobile banking: A multi-phase path analytic approach. *Information Systems Frontiers*, *21*, 773-790.
11) Arndt, J. (1967). "Role of Product-Related Conversations in the Diffusion of a New Product", *Journal of Marketing Research*, 4 (August), pp. 291-295.
12) Baabdullah, A. M. (2018). Consumer adoption of Mobile Social Network Games (M-SNGs) in Saudi Arabia: The role of social influence, hedonic motivation and trust. *Technology in society*, *53*, 91-102.
13) Baek, S., Seo, S. H., & Kim, S. (2016). Preserving patient's anonymity for mobile healthcare system in IoT environment. *International Journal of Distributed Sensor Networks*, *12*(7), 2171642.
14) Bailey, A.A., Pentina, I., Mishra, A.S. and Ben Mimoun, M.S. (2017), "Mobile payments adoption by US consumers: an extended TAM", International Journal of Retail & Distribution Management, Vol. 45 No. 6, pp. 626-640
15) Baptista, G., & Oliveira, T. (2015). Understanding mobile banking: The unified theory of acceptance and use of technology combined with cultural moderators. *Computers in Human Behavior*, *50*, 418-430.
16) Bhatiasevi, V. (2016). An extended UTAUT model to explain the adoption of mobile banking. *Information Development*, *32*(4), 799-814.
17) Blaise, R., Halloran, M., & Muchnick, M. (2018). Mobile commerce competitive advantage: A quantitative study of variables that predict m-commerce purchase intentions. *Journal of Internet Commerce*, *17*(2), 96-114.
18) Brown, S. A., & Venkatesh, V. (2005). Model of adoption of technology in households: A baseline model test and extension

incorporating household life cycle. *MIS quarterly*, 399-426.

19) Catherine, N., Geofrey, K. M., & Aballo, G. (2017). Effort expectancy, performance expectancy, social influence and facilitating conditions as predictors of behavioural intentions to use ATMs with fingerprint authentication in Ugandan banks. *Global Journal of Computer Science and Technology*, *17*(E5), 9-25.
20) Chang, A. (2012). UTAUT and UTAUT 2: A review and agenda for future research. *The Winners*, *13*(2), 10-114.
21) Chao, C. M. (2019). Factors determining the behavioral intention to use mobile learning: An application and extension of the UTAUT model. *Frontiers in psychology*, *10*, 1652.
22) Chin, W. W., Marcolin, B. L., & Newsted, P. R. (2003). A partial least squares latent variable modeling approach for measuring interaction effects: Results from a Monte Carlo simulation study and an electronic-mail emotion/adoption study. *Information systems research*, *14*(2), 189-217.
23) Chong, A. Y. L. (2013). Predicting m-commerce adoption determinants: A neural network
24) Chong, A. Y. L., & Ngai, E. T. (2013). What influences travellers' adoption of a location-based social media service for their travel planning?.
25) Chuan, C. L., & Penyelidikan, J. (2006). Sample size estimation using Krejcie and Morgan and Cohen statistical power analysis: A comparison. *Jurnal Penyelidikan IPBL*, *7*(1), 78-86.
26) Clement, J., (2019). Most concerning issues about data privacy according to mobile users in the United States as of April 2019 Harvard Bus. Rev., available at: https://www.statista.com/statistics/248488/frequency-with-which-us-internet-users-worry-about-online-privacy/#statisticContainer, (Accessed 5 April 2023)
27) Dabholkar, P. A., & Bagozzi, R. P. (2002). An attitudinal model of technology-based self-service: moderating effects of consumer traits and situational factors. *Journal of the academy of marketing science*, *30*, 184-201.
28) Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS quarterly*, 319-340.
29) Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS quarterly*, 319-340.
30) Deng, Z., Mo, X., & Liu, S. (2014). Comparison of the middle-aged and older users' adoption of mobile health services in China. *International journal of medical informatics*, *83*(3), 210-224.
31) Dillon, A., & Morris, M. G. (1996). User acceptance of new information technology: theories and models.
32) Dinev, T., & Hart, P. (2005). Internet privacy concerns and social awareness as determinants of intention to transact. *International Journal of Electronic Commerce*, *10*(2), 7-29.
33) Dogra, N., & Adil, M. (2022). Should we or should we not? Examining travelers' perceived privacy, perceived security and actual behavior in online travel purchases. *Journal of Vacation Marketing*, 13567667221122103.
34) Fadzil, F. (2017). A study on factors affecting the behavioral intention to use mobile apps in Malaysia. *Available at SSRN 3090753*.
35) Fajar, A. N., Johanes, F. S., Girsang, A. S., & Wang, G. (2018, September). Evaluation of the used of visual electronic banking system application using UTAUT 2 in Bank Central Asia corporation. In *IOP Conference Series: Materials Science and Engineering* (Vol. 420, No. 1, p. 012096). IOP Publishing.
36) Fang, J., Zhao, Z., Wen, C., & Wang, R. (2017). Design and performance attributes driving mobile travel application engagement. *International Journal of Information Management*, *37*(4), 269-283.

37) Filieri, R., Raguseo, E., & Vitari, C. (2018). When are extreme ratings more helpful? Empirical evidence on the moderating effects of review characteristics and product type. Computers in Human Behavior, 88, 134–142.
38) Garavand, A., Samadbeik, M., Nadri, H., Rahimi, B., & Asadi, H. (2019). Effective factors in adoption of mobile health applications between medical sciences students using the UTAUT model. *Methods of information in medicine*, *58*(04/05), 131-139.
39) Hair Jr, J. F., Matthews, L. M., Matthews, R. L., & Sarstedt, M. (2017). PLS-SEM or CB-SEM: updated guidelines on which method to use. *International Journal of Multivariate Data Analysis*, *1*(2), 107-123.
40) 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.
41) Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European business review*, *31*(1), 2-24.
42) Hair, Jr, J. F., Sarstedt, M., Matthews, L. M., & Ringle, C. M. (2016). Identifying and treating unobserved heterogeneity with FIMIX-PLS: part I–method. *European business review*, *28*(1), 63-76.
43) Hardy. M., and Bryman, A. (2009). The Handbook of Data Analysis. London: Sage Publications
44) 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*, 115-135.
45) Hew, J. J., Lee, V. H., Ooi, K. B., & Wei, J. (2015). What catalyses mobile apps usage intention:
46) Hoque, R., & Sorwar, G. (2017). Understanding factors influencing the adoption of mHealth by the elderly: An extension of the UTAUT model. *International journal of medical informatics*, *101*, 75-84.
47) Iskandar, M., Hartoyo, H., & Hermadi, I. (2020). Analysis of factors affecting behavioral intention and use of behavioral of mobile banking using unified theory of acceptance and use of technology 2 model approach. *International Review of Management and Marketing*, *10*(2), 41.
48) Islam, M. A., Khan, M. A., Ramayah, T., & Hossain, M. M. (2011). The adoption of mobile commerce service among employed mobile phone users in Bangladesh: self-efficacy as a moderator. *International Business Research*, *4*(2), 80.
49) Jaiswal, S., & Singh, A. (2020). Influence of the determinants of online customer experience on online customer satisfaction. *Paradigm*, *24*(1), 41-55.
50) Jalilvand, M. R., & Samiei, N. (2012). The impact of electronic word of mouth on a tourism destination choice: Testing the theory of planned behavior (TPB). *Internet research*, *22*(5), 591-612.
51) Joinson, A. N., Reips, U. D., Buchanan, T., & Schofield, C. B. P. (2010). Privacy, trust, and self-disclosure online. *Human–Computer Interaction*, *25*(1), 1-24.
52) Kapoor, N., & Singh, C. K. (2020). EFFECT OF PERFORMANCE EXPECTANCY, EFFORT EXPECTANCY AND PRICE VALUE ON CONSUMER'S BEHAVIOURAL INTENTION TOWARDS MOBILE APPBASED SHOPPING. *Prestige International Journal of Management & IT-Sanchayan*, *9*(2), 45-63.
53) Kaushik, A. K., & Rahman, Z. (2015). An alternative model of self-service retail technology adoption. *Journal of Services Marketing*, *29*(5), 406-420.
54) Keith, M. J., Babb, J., Furner, C., Abdullat, A., & Lowry, P. B. (2016). Limited information and quick decisions: consumer privacy calculus for mobile applications. *AIS Transactions on Human-Computer Interaction (THCI)*, *8*(3), 88-130.

55) Khaskheli, A., Jun, Y., & Bhuiyan, M. A. (2017). M-commerce and mobile apps: opportunities for MSMEs in developing countries. *Marketing*, *2*(2), 20-23.
56) Kline, R. B. (2023). *Principles and practice of structural equation modeling*. Guilford publications.
57) Klopfer, E., Squire, K., & Jenkins, H. (2002, August). Environmental detectives: PDAs as a window into a virtual simulated world. In *Proceedings. IEEE international workshop on wireless and mobile technologies in education* (pp. 95-98). IEEE.
58) Krejcie, R.V. and Morgan, D.W. (1970) 'Determining sample size for research activities', Educational and psychological measurement, 30(3), 607-610.
59) Laudon, K., and Traver, C. (2012). *E-Commerce: Business, Technology, Society*. New York: Person
60) Leong, L. Y., Hew, T. S., Tan, G. W. H., & Ooi, K. B. (2013). Predicting the determinants of the NFC-enabled mobile credit card acceptance: A neural networks approach. *Expert Systems with Applications*, *40*(14), 5604-5620.
61) Lewis, C. C., Fretwell, C. E., Ryan, J., & Parham, J. B. (2013). Faculty use of established and emerging technologies in higher education: A unified theory of acceptance and use of technology perspective. *International Journal of Higher Education*, *2*(2), 22-34.
62) Liébana-Cabanillas, F., Japutra, A., Molinillo, S., Singh, N., & Sinha, N. (2020). Assessment of mobile technology use in the emerging market: Analyzing intention to use m-payment services in India. *Telecommunications Policy*, *44*(9), 102009.
63) Liébana-Cabanillas, F., Marinković, V., & Kalinić, Z. (2017). A SEM-neural network approach for predicting antecedents of m-commerce acceptance. *International Journal of Information Management*, *37*(2), 14-24.
64) Lu, H. P., & Su, P. Y. J. (2009). Factors affecting purchase intention on mobile shopping web sites. *Internet research*, *19*(4), 442-458.
65) Lu, J., Yu, C. S., Liu, C., & Wei, J. (2017). Comparison of mobile shopping continuance intention between China and USA from an espoused cultural perspective. *Computers in Human Behavior*, *75*, 130-146.
66) Luo, X., Li, H., Zhang, J., & Shim, J. P. (2010). Examining multi-dimensional trust and multi-faceted risk in initial acceptance of emerging technologies: An empirical study of mobile banking services. *Decision support systems*, *49*(2), 222-234.
67) Mahfuz, M. A., Khanam, L., & Mutharasu, S. A. (2016, March). The influence of website quality on m-banking services adoption in Bangladesh: Applying the UTAUT2 model using PLS. In *2016 International Conference on Electrical, Electronics, and Optimization Techniques (ICEEOT)* (pp. 2329-2335). IEEE.
68) Mathieson, K., Peacock, E., & Chin, W. W. (2001). Extending the technology acceptance model: the influence of perceived user resources. *ACM SIGMIS Database: the DATABASE for Advances in Information Systems*, *32*(3), 86-112.
69) McMaster, T., & Wastell, D. (2005). Diffusion–or delusion? Challenging an IS research tradition. *Information Technology & People*, *18*(4), 383-404.
70) Midha, V. (2012). Impact of consumer empowerment on online trust: An examination across genders. *Decision Support Systems*, *54*(1), 198-205.
71) Mtebe, J., & Raisamo, R. (2014). Investigating students' behavioural intention to adopt and use mobile learning in higher education in East Africa. *International Journal of Education and Development using ICT*, *10*(3).
72) Murillo-Zegarra, M., Ruiz-Mafe, C., & Sanz-Blas, S. (2020). The effects of mobile advertising alerts and perceived value on

continuance intention for branded mobile apps. *Sustainability*, *12*(17), 6753.

73) Plotkina, D., & Munzel, A. (2016). Delight the experts, but never dissatisfy your customers! A multi-category study on the effects of online review source on intention to buy a new product. *Journal of Retailing and Consumer Services*, *29*, 1-11.

74) Pramudito, D. K., Ginting, R. U. B., Sekianti, A., & Baresi, I. S. (2023). Analysis of E-Commerce User Acceptance of Technology-Based Loan Application Features Using The UTAUT Model. *Jurnal Informasi dan Teknologi*, *5*(3), 36-42.

75) Roy Chowdhury, I., Patro, S., Venugopal, P., & Israel, D. (2014). A study on consumer adoption of technology-facilitated services. *Journal of Services Marketing*, *28*(6), 471-483.

76) S.C. Harris, Position Privacy in an Electronic Device, Prantice Hall, 2004.

77) Saleem, A., Aslam, J., Kim, Y. B., Nauman, S., & Khan, N. T. (2022). Motives towards e-Shopping Adoption among Pakistani Consumers: An Application of the Technology Acceptance Model and Theory of Reasoned Action. *Sustainability*, *14*(7), 4180.

78) Saunders, M., Lewis, P. and Thornhill, A. (2012) Research Methods for Business Students. England, Pearson.

79) Schepers, J., & Wetzels, M. (2007). A meta-analysis of the technology acceptance model: Investigating subjective norm and moderation effects. *Information & management*, *44*(1), 90-103.

80) 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.

81) 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.

82) Soror, A., Steelman, Z. R., & Turel, O. (2022). Exhaustion and dependency: a habituation–sensitization perspective on the duality of habit in social media use. *Information Technology & People*, *35*(1), 67-95.

83) Susanto, A., Chang, Y., & Ha, Y. (2016). Determinants of continuance intention to use the smartphone banking services: An extension to the expectation-confirmation model. *Industrial Management & Data Systems*, *116*(3), 508-525.

84) Susilowati, A. (2021). Effects of UTAUT 2 model on the use of BCA mobile banking in Indonesia. *Turkish Journal of Computer and Mathematics Education (TURCOMAT)*, *12*(10), 686-694.

85) 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.

86) Tata, S. V., Prashar, S., & Gupta, S. (2019). An examination of the role of review valence and review source in varying consumption contexts on purchase decision. Journal of Retailing and Consumer Services. https://doi.org/10.1016/j.jretconser.2019.01.003

87) Turban, E., King, D. & and Lang, J. (2011). *Introduction to Electronic Commerce*. United Kingdom: Person

88) Tusyanah, T., Wahyudin, A., & Khafid, M. (2021). Analyzing factors affecting the behavioral intention to use e-wallet with the UTAUT model with experience as moderating variable. *Journal of Economic Education*, *10*(1), 113-123.

89) Vallerie, K., Fahira, N. I., Sebastian, V., & Limantara, N. (2021, August). Usage Evaluation of Beauty E-Commerce with Unified Theory of Acceptance and Use of Technology (UTAUT). In *2021 International Conference on Information Management and Technology (ICIMTech)* (Vol. 1, pp. 429-433). IEEE.

90) Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of

information technology: Toward a unified view. *MIS quarterly*, 425-478.

91) Venkatesh, V., Thong, J. Y., & Xu, X. (2012). Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology. *MIS quarterly*, 157-178.
92) Verma, S., & Yadav, N. (2021). Past, present, and future of electronic word of mouth (EWOM). *Journal of Interactive Marketing*, *53*(1), 111-128.
93) Vinerean, S., Budac, C., Baltador, L. A., & Dabija, D. C. (2022). Assessing the effects of the COVID-19 pandemic on M-commerce adoption: an adapted UTAUT2 approach. *Electronics*, *11*(8), 1269.
94) Wagner, G., Schramm-Klein, H., & Steinmann, S. (2020). Online retailing across e-channels and e-channel touchpoints: Empirical studies of consumer behavior in the multichannel e-commerce environment. *Journal of Business Research*, *107*, 256-270.
95) Wei, T. T., Marthandan, G., Chong, A. Y. L., Ooi, K. B., & Arumugam, S. (2009). What drives Malaysian m-commerce adoption? An empirical analysis. *Industrial management & data systems*, *109*(3), 370-388.
96) Xu, H., Teo, H. H., Tan, B. C., & Agarwal, R. (2009). The role of push-pull technology in privacy calculus: the case of location-based services. *Journal of management information systems*, *26*(3), 135-174.
97) Yang, S., Lu, Y., Gupta, S., Cao, Y., & Zhang, R. (2012). Mobile payment services adoption across time: An empirical study of the effects of behavioral beliefs, social influences, and personal traits. *Computers in Human Behavior*, *28*(1), 129-142.
98) Zeithaml, V. A., Berry, L. L., & Parasuraman, A. (1988). Communication and control processes in the delivery of service quality. *Journal of marketing*, *52*(2), 35-48.
99) Zhang, L., Zheng, L., & Peng, T. Q. (2017). Structurally embedded news consumption on mobile news applications. *Information Processing & Management*, *53*(5), 1242-1253.
100) Zhang, Y., Zhang, J., & Liu, C. (2022). Motives for employees communicate positive electronic word of mouth (eWOM) on social network sites: Exploring moderating mechanisms. *Australasian Marketing Journal*, *30*(1), 60-73.