Generation X's Shopping Behavior in the Electronic Marketplace Through Mobile Applications During the COVID-19 Pandemic

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Abstract Thanks to the prevalence of mobile applications (mobile apps), consumer behavior is shifting from conventional to online. Globally, mobile commerce has taken precedence over other forms of transaction due to the impact of the COVID-19 pandemic except for Generation X (Gen X) customers. They have restricted access to modern technologies and are critically impacted by the COVID-19 pandemic. Hence, this chapter applied the Theory of Acceptance and Use of Technology model (UTAUT), and Task-technology fit models (TTF) to determine how the pandemic and Gen X characteristics affect buying behaviors in the electronic marketplace. The primary research method was the quantitative approach, in which data was collected from 467 respondents through a structured questionnaire. The findings indicate that Gen X consumers' mobile commerce buying intentions are influenced favorably by mobile shopping (m-shopping) efficiency, effort expectancy, and the perceived severity of COVID-19. Generation X's shopping behavior in the e-marketplace through mobile apps was also affected by the usability of mobile applications and their desire to purchase online. Additionally, the Gen X consumers' expectation of effort was negatively impacted by the usability of mobile apps.

1 Introduction

Technology changes consumer behavior from traditional to online through mobile applications (apps). Mobile commerce (m-commerce) has become a prior transaction form worldwide. Also, various elements may influence how people use and interact with technology, especially their ages, classifying customers into generational cohorts. Cohorts of people born simultaneously have similar views, goals, values, and behaviors. These differences create a generational identity that can influence how people use technology, interact with it, and behave [1]. There are significant differences in how different generations utilize technology; as a result, the generational cohort may influence how individuals use and interact with technology. In

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cohort-based categorization, people are often divided into younger members like the millennials (Gen Y) or who?—Generation Z (Gen Z) and older members like those in Baby Boomer and Generation X (Gen X) [2]. As "digital natives" and technologically aware, Gen Y and Gen Z have been proven to be different from previous generations; hence, the bulk of study has focused on perceptions of technology of Gen Y and Gen Z. Research on the motives of previous cohorts, such as Gen X and Baby Boomer, to use and interact with technology is lacking. Gen X is the group of people born between 1965 and 1980 known for their scepticism, pragmatism, and a desire to avoid taking risks [3]. This generation was not exposed to the internet or digital technology from an early age and has recently become proficient users. As personal computers became more common in schools and the internet expanded, Gen X had little trouble integrating new technology into their everyday routines. Gen X, as opposed to Millennials or Gen Z, was not born into the digital age but has embraced many, if not all, of its new features of it as they have progressed through life; as a result, Gen X might be referred to as "digital immigrants," because they were not born into a technologically advanced society but have instead learned to live with it [4].

As the primary method of preventing the pandemic, people have been advised to stay at home while social distance is applied across the globe. The elderly is unquestionably one of the most vulnerable populations throughout this unprecedented pandemic, putting them in danger of bodily and mental harm. Along with the chronic illnesses group, they are dealing with the most significant risk of mortality because of the most severe symptoms, with a mortality rate of 3.6% among those 60–69 years old, rising to 18.6% for those over 80 [5].

In light of the continuing COVID-19 pandemic, mobile apps solutions are now more critical than ever to minimize the danger of cross-contamination from close contact. COVID-19's proliferation has been slowed by various strategies using mobile technologies. Mobile devices, which may help with social isolation, are widely available, accepted, and easy to use. Due to the COVID-19 pandemic, additional evidence suggested the risk and perceived difficulty of utilizing Gen X apps on m-commerce [6]. Hence, Gen X customers have reexamined their purchasing patterns or have developed new ones entirely. As a result of stringent containment procedures and safeguards, customers have been forced to explore alternatives such as internet shopping, home delivery, and cashless payments. In the wake of the COVID-19 issue, Gen X customers have become more reliant on apps in m-commerce to communicate, get information, and cope with the COVID-19 pandemic. The perceived severity of COVID-19 is developing not only in health [7] but also in education [8], and economics [9]. Most Chinese individuals engage in health-protective behaviors such as remaining at home, severely limiting their social life due to the perceived severity of COVID-19 [10]. While individual health-protective activities have effectively prevented the spread of Coronavirus, they have also resulted in a major increase in psychological strain, resulting in varying degrees of mental stress [11]. If COVID-19 spreads extensively across the population, nobody knows what will happen, especially among those who feel they are susceptible or believe the risks are substantial [12]. Evidence supports the hypothesis that social norms contradicting behavior might prevent the implementation of preventive measures. As a result, there are strong arguments for merging the Unified Theory of Acceptance and Use of Technology model (UTAUT) and the Task-technology fit model (TTF) and adding m-commerce characteristics, mobile app characteristics, and COVID-19's perceived severity to study Gen X's buying behavior in the e-marketplace through applications in COVID-19.

Based on UTAUT and TTF, this chapter explored the impact of COVID-19 and the Gen X characteristics on consumers' shopping behavior in the electronic marketplace (e-marketplace) through mobile apps. The research results have theoretical and practical contributions as combining UTAUT and TTF to assess Gen X consumers' shopping behavior. In addition, the study also pointed out the influence of the perceived severity of COVID-19 on shopping intention in m-commerce. Finally, some managerial implications were proposed for businesses in the e-marketplaces to enhance Gen X consumers' shopping behavior.

2 Literature Review

2.1 Theoretical Background

Venkatesh et al. [13] developed the UTAUT model to test technology acceptance and use a more unified approach. UTAUT asserts that behavioral intention is determined by effort expectancy, performance expectancy, and social influence and that these factors, together with facilitating conditions, impact how to utilize technology. It was discovered that UTAUT was the second most common theoretical lens for analyzing consumer acceptance of mobile payment, online shopping, and online education. TTF was first introduced in the mid-1990s by Goodhue and Thompson [14]. Individuals may accomplish specific activities or groups of tasks with the help of technology if task needs and technology features are aligned or fit, according to the model's presumption that technology's value/performance is generated by the alignment or fit. TTF has been extensively utilized to better understand how information systems are used and the outcomes of their usage in a variety of scenarios, including mobile browsers [15], online shopping [16], and social media use [17]. Although UTAUT is considered more efficient than previous models such as the Theory of Planned Behavior, Technology Acceptance Model, And Innovation Diffusion Theory, it still has limitations in explaining technology adoption behavior. For example, even if consumers find technology useful and simple to use, they will not utilize it in the present environment if it does not meet their wants or gadgets. As a result, the combination of TTF and UTAUT will well describe the technological adoption behavior. This combination has been emphasized through the studies related to the banking industry [18, 19], online learning [20], and health care [21].

Task specifies what must be done in response to stimuli, described as a stimulus complex. The instructions specify what subjects should do in response to stimuli and the overall objective. It is following Hackman's "task as behavior description" that information system researchers have usually relied on the viewpoint of "task as behavior requirement" that sees a task in terms of which response should be emitted by the subject [22]. In commerce activities, shopping is the main task of the buyer. The customer always wants to purchase the best product and get a fair price in transactions. In m-commerce activities, shopping in apps is expected to benefit customers who decided to use apps during the COVID-19 pandemic.

Furthermore, e-commerce has come a long way in the past decade and is sure to do so for the foreseeable future. Mobile devices have become the primary purchasing instruments as a result of the unique benefits offered by mobile internet technology, including ubiquity, convenience, localization, and customization; therefore, mobile devices have become the main facility to connect the buyer and seller in m-commerce. The perceived severity of COVID-19 is growing not just in the health business but also in the general public [7] but also in education [8] and economics [9]. Because of the perceived severity of COVID-19, most Chinese individuals engage in health-protective behaviors such as remaining at home, severely limiting their social life, i.e., Chinese citizens' social participation levels have decreased to less than 2 out of 5 [10]. While health-protective practices of individuals have successfully halted the spread of Coronavirus, they have also generated a dramatic surge in psychological strain, leading to various degrees of mental stress [11]. Anyone's guess is what happens when COVID-19 spreads widely across the community, particularly among people who believe they are vulnerable or see the hazards as serious [12]. Evidence supports the theory that social norms that conflict with the behaviour can prevent the implementation of preventative measures. As a result, there are strong arguments for merging TTF and UTAUT and adding m-commerce characteristics, mobile app characteristics, and COVID-19's perceived severity to study Gen X's buying behavior in the e-marketplace through applications in COVID-19. Figure 1 depicts the theoretical model used in this study.

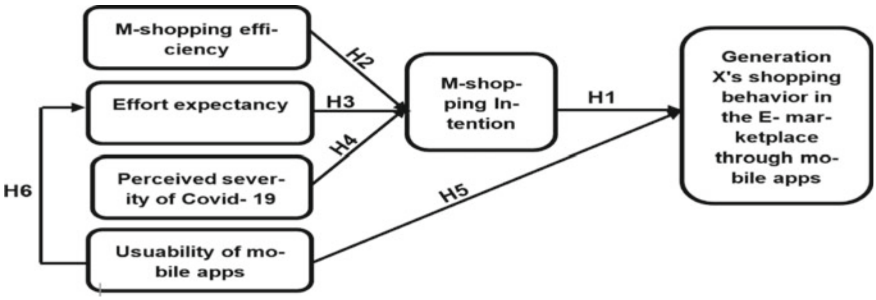

Fig. 1 Theoretical model

2.2 Hypotheses Development

According to previous research, attitudes regarding shopping malls may directly impact purchasing behavior at shopping malls; however, the link between these two constructs is weak. It is conceivable that an intention omits to blame. Several theorists believe that purpose, rather than attitude, is the most closely related cognitive precursor to actual behavioral execution [23, 24]. "The degree to which a person has created conscious intentions to conduct or not execute some specified future activity" is defined as "intention" [25]. A few meta-analyses of empirical research have shown that behavior may accurately predict intentions [25, 26]. Many different forms of behavior have provided evidence for a link between intentions and subsequent behaviors/actions [27]. Their buy intention for online shopping measures the willingness of a customer to purchase in apps. As indicated by theories like the Theory of Planned Behavior, this research aims to learn how Gen X customers use mobile apps to buy products from the e-marketplace. In numerous m-commerce research, intention, first introduced by Ajzen and Fishbein [23], has been employed to predict online purchase behavior or an outcome variable in place of actual buy behavior [28]. According to Taylor and Todd [29], for persons with prior experience and familiarity with technology, User behavior is well predicted by behavioral intention. Hence, this study proposed the H1:

H1: Shopping Intention has a positive impact on Generation X's shopping behavior in the E-marketplace through mobile apps

Shoppers may use their mobile devices to access the wireless internet through mobile shopping (m-shopping), a new sales channel that makes responsive websites available on mobile devices (e.g., location-based technology). M-shopping refers to customers making purchases while connected to the wireless internet on their mobile devices [30]. With their unique characteristics in shopping environments, mobile devices give customers more convenience than conventional online shopping done with desktop or laptop computers, despite privacy and security concerns. Modern customers are increasingly using their mobile devices to pay for things, according to recent research on the topic of "m-shopping" [31]. M-shopping has distinct benefits over traditional e-commerce, such as better convenience, localization, and immediacy, only possible with mobile internet technology [32]. In m-shopping, customers must choose, order, and pay for things on their mobile devices; these activities can be challenging for Generation X; however, Gen X customers ought to use apps to make transactions in COVID-19. M-shopping activities are expected to finish the shopping in the COVID-19 pandemic. Hypothesis H2 was proposed:

H2: M-shopping efficiency has a positive impact on Generation X's shopping intention in the E-marketplace through mobile apps

A user's desire to do a task on a portable device is strongly influenced by perceptions of utility, security, and fun. The perceived ease of use for information system adoption in a workplace and an e-commerce setting has been studied before [33, 34]. The user design in mobile apps is improved day by day, especially for the elders

[35]; consequently, it is easy for Gen X customers to interact with shopping activities. UTAUT pointed out that effort expectancy and performance expectancy will positively impact user intention [13]. Hence, hypothesis H3 was formed as:

H3: Effort expectancy has a positive impact on Generation X's shopping intention in the E-marketplace through mobile apps

Customers' attitudes, interests, and opinions are shaped by their perceptions of things, behaviors, and events. Decisions are influenced by how people perceive risk and safety [36]. The desire to direct activities as travel decreases as the severity of a disease or the associated health risks become more apparent [37]. The COVID-19 pandemic is dangerous to older customers; hence, Gen Z customers intend to shop through mobile apps to ensure their safety. The apparent severity of the COVID-19 epidemic predates internet purchase through an electronic marketplace or mobile applications [9]; hence, the hypothesis H4 was proposed:

H4: Perceived severity of the COVID-19 pandemic has a positive impact on Generation X's shopping intention in the E-marketplace through mobile apps

Mobile apps are often the mobile counterparts of internet sites. Businesses often create and launch applications closely related to their online sites when they extend their operations to the mobile platform [38]. Despite this, cellphones and personal computers continue to have significant disparities. Information search habits on mobile phones vary from desktop computers [39] because mobile material is shown on smaller displays; people only read it when they have time. Ghose et al. [40] came to a similar conclusion because the lower display size of mobile devices raises search costs, making the first search result more attractive than the second on mobile devices than on desktops in the long term. Mobile phone users who value ubiquitous availability choose their phones over desktops [41]. These results highlight the differences between internet and mobile platforms. Inferring mobile behavior from online behavior research, on the other hand, may provide erroneous findings. Consequently, mobile apps characteristics were predicted to decrease Gen X's shopping behaviour and effort expectancy in m-commerce as they purchase from e-marketplace apps. So, the hypotheses H5 and H6 were proposed:

H5: Usability of mobile apps has a negative impact on Generation X's shopping behavior in the E-marketplace through mobile apps

H6: Usability of mobile apps has a negative impact on Generation X's effort expectancy as shopping in the E-marketplace through mobile apps

3 Research Method

The speculative model was examined using a cross-sectional design in this research. To build our sample, we used a non-probabilistic sampling strategy (purposive sampling). The data was acquired in Vietnam for five months, from February to June 2021, for a mobile shopping app of Tiki, Lazada, Sendo, and Shopee, the four leading e-marketplaces in Vietnam. From a total of 500 replies, 467 legitimate and full consumer responses were obtained, and each one was given instructions on how

Table 1 The respondent information

Characteristics		n	%
Gender	Male	258	55.2
	Female	209	44.8
Age group	41–50	201	43.0
	51–56	266	57.0
Times of using m-shopping apps (in months)	1–2	114	24.4
	3–6	111	23.8
	6–12	134	28.7
	>12	108	23.1
Screen size of the mobile device (inches)	≤5	248	53.1
	>5	219	46.9
Occupation	Lecturer	146	31.3
	Office worker	163	34.9
	Housewife	158	33.8

to use the equipment before being asked to complete a brief questionnaire. Table 1 summarizes the participants' sociodemographic characteristics. Participants were asked to complete a questionnaire that contained assessments of the variables under research after being instructed on the goal of the study.

This research used a survey questionnaire that examined 20 different items for six research constructs. The research carefully selected and verified all metrics using data from previous studies to meet the study's objectives. All questions were scored from 1 ("strongly disagree") to 5 ("strongly agree") on a five-pointed Likert scale. Some of the items were slightly reworded to better meet our research's objectives. In addition, the survey asked respondents a series of demographic and app use questions. The detailed scale items and their corresponding sources include m-shopping efficiency (3 items, ME, [32]), Effort expectancy (4 items, EE, [13]), perceived severity of COVID-19 (3 items, PS, [42]), the usability of mobile apps (3 items, US, [43]), shopping intention (4 items, SI, [42]), Generation X's shopping behavior (3 items, SB, [13]).

The results were investigated using Anderson and Gerbing's two-step structural equation modeling technique [44]. At first, the validity and reliability criteria were verified, and then the structural model was evaluated. The data in the study was analyzed using SPSS 21.0 and SmartPLS. The data was processed in two phases. In the first stage, the measurement model's validity and reliability were evaluated. Second, the weight and size of the connections between variables were assessed by evaluating the structural model.

4 Data Analysis

4.1 Measurement Scale Assessment

To begin, this research evaluates construct reliability using Cronbach's Alpha (CA) and the composite reliability measure (CR), both of which had values more than 0.7. The average variance collected was used to test for convergent validity (AVE). According to the findings, all of these components' loads were significant and larger than 0.7, with an average extracted variance (AVE) value greater than 0.5. Furthermore, the outer loading (OL) of all products was greater than 0.708. In view of this conclusion, Fornell and Larcker [45] measurement models show adequate convergent validity. The results in Table 2 allow us to establish the convergent validity and reliability of the scales used to measure the different components in the research model.

The discriminant validity has to be checked using the Fornell and Larcker criteria, which stipulates that the square root of the AVE of each variable must be greater than the correlations between that variable and the other variables in the model. As shown in Table 3, the square root AVE of each construct is greater than its correlation with any other construct; hence, there is discriminant validity between all constructs in the study model.

Table 2 Convergent validity and reliability

	CA	CR	AVE	OL
EE	0.877	0.915	0.73	[0.850–0.862]
ME	0.883	0.928	0.811	[0.863–0.937]
PS	0.917	0.948	0.858	[0.918–0.939]
SB	0.81	0.888	0.727	[0.746–0.925]
SI	0.912	0.938	0.791	[0.868–0.931]
US	0.808	0.887	0.724	[0.805–0.885]

Table 3 Fornell and Larcker criterion

	EE	ME	PS	SB	SI	US
EE	0.855					
ME	0.368	0.901				
PS	0.486	0.419	0.926			
SB	0.607	0.529	0.575	0.852		
SI	0.423	0.404	0.439	0.736	0.889	
US	−0.452	−0.54	−0.556	−0.672	−0.544	0.851

4.2 Structural Model Assessment

The structural model evaluation procedure was followed in this work, which included collinearity assessment, structural model path coefficients, coefficient of determination (R^2 value), effect size (f^2 value), blindfolding, and predictive relevance (Q^2 value) [46].

A standard tool for assessing the degree of collinearity among formative indicators is the variance inflation factor (VIF). If the VIF score is more than 5, there are severe difficulties with indicator collinearity among the assessed components. Even with VIF levels as low as 3, collinearity problems might emerge. The VIF values should ideally be less than or equal to 3. In Table 3, all maximum VIF is 1.434, which is less than 3; hence, there is no collinearity issue in this research.

Next, this study assesses the endogenous construct's R^2 value if collinearity is not a concern. A model's explanatory power may be measured by looking at the R^2, which calculates the variance explained by each endogenous component. Acceptable R^2 levels depend on context, and an R^2 value of 0.20 is regarded as satisfactory in certain areas as a stock return or behavior [47]. Usability of mobile apps explained 20.4% of the change of effort expectancy ($R^2_{EE} = 0.204$); m-shopping efficiency, effort expectancy, and perceived severity of COVID-19 impact 28.9% of the change of m-shopping intention ($R^2_{SI} = 0.289$); finally, the usability of mobile apps and m-shopping intention create 64.6% change in Generation X's shopping behavior in the E-marketplace through mobile apps ($R^2_{SB} = 0.646$).

The Q^2 value may be used to evaluate the predicting accuracy of the partial least squares path model. The Q^2 score for an endogenous construct is more significant than zero; it indicates that the structural model for that construct is accurate ($Q^2_{EE} = 0.144$; $Q^2_{SB} = 0.46$; $Q^2_{SI} = 0.222$).

When a predictive construct is removed, researchers may see how the R^2 value of the endogenous construct changes. This measure is redundant with the f^2 effect size in route coefficients. The relevance of the predictor construct in explaining the dependent construct in a structural model is often equivalent in rank order to comparing path coefficients and effect sizes in f^2 models, which are more precise measurements of effect size. Values larger than 0.02, 0.15, and 0.35, respectively, imply minor, medium, and large f^2 effect sizes. Based on Table 4, m-shopping efficiency, effort expectancy, and perceived severity of COVID-19 pandemic has a negligible effect on m-shopping intention ($f^2_{EE\to SI} = 0.053$; $f^2_{ME\to SI} = f^2_{EE\to SI} = 0.054$); usability of mobile apps has a medium effect on the effort expectancy and shopping behavior ($f^2_{US\to EE} = 0.256$; $f^2_{US\to SB} = 0.296$); m-shopping intention has a significant effect size on Generation X's shopping behavior in the E-marketplace ($f^2_{SI\to SB} = 0.551$).

The Smart PLS 3.2.7 software was used with 5000 subsamples of the original sample size for a Bootstrapping study using partial least squares structural equation modeling to verify the assumptions (PLS-SEM). Table 5 showed that all hypotheses had a 99% confidence level (t-value >2.58).

Table 4 VIF, R^2, f^2, Q^2

	VIF			R^2	f^2			Q^2
	EE	SB	SI		EE	SB	SI	
EE			1.368	0.204			0.053	0.144
ME			1.268				0.054	
PS			1.434				0.054	
SB				0.646				0.46
SI		1.42		0.289		0.551		0.222
US	1.000	1.42			0.256	0.296		

Table 5 PLS-SEM result

Relationship	Beta	Standard deviation	t-value	Hypothesis	Result
SI → SB	0.526	0.046	11.367	H1	Supported
ME → SI	0.222	0.053	4.203	H2	Supported
EE → SI	0.227	0.062	3.642	H3	Supported
PS → SI	0.236	0.059	4.015	H4	Supported
US → SB	−0.386	0.053	7.282	H5	Supported
US → EE	−0.452	0.069	6.533	H6	Supported

5 Discussion

Based on the UTAUT, this research result reaffirmed the relationship between effort expectancy, m-shopping intention, and shopping behavior [13]. To begin, effort anticipation has a favorable influence on Gen X consumers' m-shopping intention (Beta = 0.227, t-value = 3.642, p-value = 0.000); hence, hypothesis H3 was accepted with 99% confidence. Furthermore, m-shopping intention influenced Generation X's purchasing behavior in the E-marketplace through mobile applications (Beta = 0.526, t-value = 11.367, p-value = 0.000); as a result, hypothesis H1 was validated in 99% of cases. In the COVID-19 pandemic, Gen X consumers' choices for using a portable device are inextricably tied to their perceptions of its utility, security, and even entertainment aspects; hence, perceived ease of use for the office and online shopping is critical [33, 34]. The less they effort to learn or use the shopping apps, the more customers want to use them for their shopping activities on mobile. Mobile app user interfaces and functions are becoming better, particularly for the elderly in Gen X, who has a simple time interacting with the online retail environment [35]. A relationship between intentions and subsequent behaviors has been found in a wide range of behaviour [25, 48]. Gen X customers' desire to make purchases via mobile applications is gauged by their buy intention when shopping online, particularly in the COVID-19 pandemic. Gen X shoppers are using mobile applications to acquire things from the e-marketplace, as well as intention was used as a predictor of online purchase behavior or as an outcome variable instead of actual purchase behavior in various m-commerce studies [28, 49].

The result pointed out similarities and differences under the integration of TTF in UTAUT. Firstly, M-shopping efficiency influences m-shopping intention positively (Beta = 0.222, t-value = 4.203, p-value = 0.000); therefore, hypothesis H2 was supported with the 99% of confidence level. M-shopping efficiency can be the performance expectancy in UTAUT [13], which positively impacts the technology adoption intention. In the COVID-19 pandemic, m-shopping helps Gen X customers shop easily and make them safer at home. These benefits have a large impact on the shopping intention of Gen X [50]. For Gen X customers, the mobile apps bring difficulties in usability, which are mentioned as four aspects: navigation, communication, visual recognition, or screen reading. The mobile apps screen is small for Gen X customers to read the product information or touch to shop the product; furthermore, some Gen X users are not familiar with the navigation in the smartphone. Hence, the mobile apps in the e-marketplace do not receive high agreement about usability, which negatively impacts Generation X's shopping behavior in the E-marketplace through mobile apps (Beta = −0.386, t-value = 7.282, p-value = 0.000). Moreover, the negative usability can create many disadvantages for Gen X customers, so the customers in this generation must invest more effort to learn or use the apps. The empirical result in this study supported the H6 as the usability of mobile apps negatively impacts Generation X's effort expectancy as shopping in the E-marketplace through mobile apps (Beta = −0.452, t-value = 6.533, p-value = 0.000).

Lastly, the perceived severity of COVID-19 has a positive factor in improving the m-commerce intention (Beta = 0.236, t-value = 4.015, p-value = 0.000); hence hypothesis H4 was supported by the empirical result. The perceived severity of COVID-19 is the part of threat appraisal, which is popular with Gen X customers. Consumers were more likely to take the copying activity to escape the dangerous scenario when it was severe. Therefore, the perceived severity of COVID-19 strengthened the capacity to regulate one's actions [9]. Consumers' conviction in their ability to manage their conduct grew due to the threat motive to avoid COVID-19 [51]. Because of this, Gen X customers would believe they have more influence over their buying behavior if they experience high risks from COVID-19, such as shopping in the e-marketplace the mobile apps [10].

6 Conclusion

Smartphones, which are becoming more common, provide a third option for shopping and the traditional offline and internet options. A conceptual model was established that considers both the advantages and disadvantages of mobile shopping [52]. Mobile shopping's perceived value rises due to their model's time-related advantages in efficiency, leading to increased buy intent. Gen X's behavioral intention to utilize mobile applications was influenced by the four indicators studied in this research. Research results pointed out that the shopping intention of Gen X customers in mobile commerce is positively affected by shopping efficiency, effort expectancy, and perceived severity of COVID-19.

Moreover, the customer's m-shopping behavior on e-marketplace through m-apps was influenced by the usability of mobile apps and the intention to shop online. In addition, the usability of mobile apps was negative antecedence of the Gen X consumers' effort expectancy. The study's results have theoretical and practical implications for the acceptability and development of mobile applications for individuals with vision impairments.

In theoretical contribution, this study combined the UTAUT and TTF model in generation X's shopping behavior in the E-marketplace through mobile apps. The root of the theoretical model is UTAUT; however, some constructs related to mobile apps, m-shopping, and the COVID-19 pandemic were added to achieve the research objective. M-shopping efficiency and usability of mobile apps as task characteristics and technical characteristics in TTF; and as performance expectancy and facilitating conditions in UTAUT. Moreover, this result discovered the negative relationship between the usability of mobile apps and (1) effort expectancy and (2) shopping behavior in the E-marketplace through mobile apps.

Some managerial implications were proposed for managers who manage the e-marketplace. Regarding effort expectancy and usability of mobile apps, businesses might enhance mobile technology's usability and, in particular, its learnability. Animated training is helpful for Gen X customers who are unfamiliar with touchscreens—because of this, completing the recommended activities will take longer if users are not provided with training sessions on how to utilize the apps. The apps should provide less information on a screen and be easier for new users. Simplified apps do not rely on scrolling or swiping for navigational purposes. Many publications advocate improving usability by making texts more intelligible and increasing font sizes for Gen X customers. In both cases, the text of the apps is a common thread. Applications should utilize terminology that matches that of intended Gen X consumers. E-marketplace businesses should update the information on news, benefits of m-shopping, or coordinate with other businesses to generate promotion campaigns, emphasizing the role and benefit of m-shopping.

Our interpretation was hampered by the study's limitations, which sparked new ideas for future research. Firstly, the findings may not be generalizable to other situations where the circumstances of mobile app users are different because of the online survey and non-probability sample. To find out whether the links between the UTAUT model's variables are constant across various user groups with diverse cultural traits, it would be beneficial to compare them in the same context. Another area that requires investigation is why mobile app performance expectancy is essential. The other three predictors (m-shopping efficiency, effort expectancy, perceived severity of COVID-19) are not as effective at predicting behavioral intention to adopt and use mobile apps in Gen X customers. Further study is needed to determine why some modifiers (such as gender or years of experience) do not affect the link between predictors and behavioral intention.

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