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FACTORS THAT AFFECT CUSTOMERS' CONTINUANCE INTENTION TO USE ONLINE SHOPPING APPS DURING THE COVID-19 PANDEMIC

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COVID-19 Pandemisi Sırasında Müşterilerin Online Alışveriş Uygulamalarını Kullanmaya Devam Etme Niyetini Etkileyen Faktörler

Factors that Affect Customers' Continuance Intention to Use Online Shopping Apps During the COVID-19 Pandemic

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5. Online Alışveriş Uygulaması
6. COVID-19

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ABBREVIATIONS

CI: Continuance Intention

EE: Effort Expectancy

PE: Performance Expectancy

PS: Perceived Severity

PSB: Price-Saving Benefits

PV: Perceived Vulnerability

SI: Social Influence

TR: Trust

TSB: Time-Saving Benefits

TTF: Task-Technology Fit

UTAUT2: The Unified Theory of Acceptance and Use of Technology

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ABSTRACT

In 2019, the whole world was affected by an unknown disease that spread the world with undisclosed fears and unknown feelings. Not so long after the spread of the Nobel Corona Virus, COVID-19 created a new reality in every dimension of people's daily lives. Digital technologies like online shopping applications became one of the main strategies for coping with the fear generated by COVID-19 and a solution for consumers to resolve their daily needs. This research is trying to identify the factors that affect the continuance intention of online shopping application users under the circumstances of COVID-19 using the UTAUT2 and Task-Technology Fit models. Behavioral intentions of online shopping applications were analyzed using the responses from 304 respondents (303 valid responds) from the ages of 18 to 55. The quantitative results show that perceived severity in case of COVID-19, performance expectancy, trust, perceived task-technology fit, perceived benefits (price-saving and time-saving benefits), and satisfaction have significant effects on users' continuance intention, while social influence and effort expectancy's effect on continuance intention was not supported. Also, the effects of different variables on customer satisfaction, as one of the most important factors on continuance intention, has been measured and the results show that perceived task-technology fit, performance expectancy, effort expectancy, trust and social influence has significant positive effects on customer satisfaction.

Keywords: UTAUT2, Users' Continuance Intention, Perceived Task-Technology Fit, User Satisfaction, Online Shopping Applications, COVID-19

ÖZET

2019 yılında tüm dünya, açıklanmayan korkular ve bilinmeyen duygularla dünyaya yayılan bilinmeyen bir hastalıktan etkilendi. Nobel Corona Virüsünün yayılmasının üzerinden çok geçmeden COVID-19, insanların günlük hayatlarının her boyutunda yeni bir gerçeklik yarattı. Çevrimiçi alışveriş uygulamaları gibi dijital teknolojiler, COVID-19'un yarattığı korkuyla başa çıkmanın ana stratejilerinden biri ve tüketicilerin günlük ihtiyaçlarını çözmeleri için bir çözüm haline geldi. Bu araştırma, UTAUT2 ve Task-Technology Fit modellerini kullanarak online alışveriş uygulaması kullanıcılarının COVID-19 koşullarında devam etme niyetini etkileyen faktörleri belirlemeye çalışmaktadır. Çevrimiçi alışveriş uygulamalarının davranışsal niyetleri, yaşları 18 ile 55 arasında değişen 304 katılımcının (303 geçerli yanıt) yanıtları kullanılarak analiz edildi. Nicel sonuçlar, COVID-19 durumunda algılanan ciddiyet, performans beklentisi, güven, algılanan görev teknolojisi Uyum, algılanan faydalar (fiyat tasarrufu sağlayan ve zaman kazandıran faydalar) ve memnuniyet, kullanıcıların devam etme niyeti üzerinde anlamlı etkilere sahipken, sosyal etki ve çaba beklentisinin devam etme niyeti üzerindeki etkisi desteklenmemiştir. Ayrıca devam niyeti üzerindeki en önemli faktörlerden biri olan müşteri memnuniyeti üzerinde farklı değişkenlerin etkileri ölçülmüş ve sonuçlar algılanan görev-teknoloji uyumu, performans beklentisi, çaba beklentisi, güven ve sosyal etkinin anlamlı pozitif etkileri olduğunu göstermiştir. müşteri memnuniyeti üzerine.

Anahtar kelimeler: UTAUT2, Kullanıcıların Devam Niyeti, Algılanan Görev-Teknoloji Uyumu, Kullanıcı Memnuniyeti, Online Alışveriş Uygulamaları, COVID-19

INTRODUCTION

The e-commerce sector is growing at an unprecedented rate around the world. People are more open than ever before to incorporating new technologies into their daily lives, and as a result, technology has become more fully integrated into modern life than ever before. Mobile devices have had a profound impact on the daily lives of humans over the past two decades (Einav et al., 2014). People can shop from their mobile devices whenever and wherever they want. In contrast to previous purchasing methods, today's consumers frequently use their mobile devices to conduct product searches and make purchases (Siau et al., 2001; Zhou et al., 2007). In addition, mobile applications are a type of add-on software that can be downloaded and used on smartphones and other portable devices (Tarasewich et al., 2002). In the mobile app market, users have access to a wide variety of services provided by third-party developers. Installing these programs extends the capabilities of their smart phones, including online shopping applications. An increasing variety of consumer needs are being met by mobile apps, which can be attributed to the growth in the mobile app market (Einav et al., 2014; Siau et al., 2001).

In the year 2020, a global crisis occurred for which no one could have prepared. Life and work have been altered because of the contagious virus COVID-19 (Singh, & Singh, 2020). In December 2019, the virus was first discovered in Wuhan, China, and has since spread globally and is still spreading (Singh & Singh., 2020; Güner et al., 2020). The COVID-19 pandemic was a milestone in online shopping and drastically shifted customers’ shopping behavior through online and internet-based shopping tools. Challenges specific to each country included things like maintaining a functional healthcare system and allocating enough medical supplies to control the spread (Verma et al., 2020). In addition, countries had to shut down and enforce social separation in order to reduce the rate of contagion and the number of resulting fatalities.

During the first year of the pandemic, people were either prohibited or afraid to go out and break the social distancing rules. Moreover, shopping malls were closed, and people couldn’t go out to restaurants or eat out. People had no choice but to rely on online services for grocery shopping, ordering food, and even buying clothes or getting consultations. The COVID-19 pandemic posed new challenges for consumers worldwide (Singh & Singh, 2020). As a direct result of this disaster, users of digital technologies have been compelled to adopt and use specialized technological applications for online shopping (Güner et al., 2020; Verma et al., 2020). Lockdown restrictions imposed by governments have an obvious impact on both the ability of consumers to make online purchases and the ability of businesses to function (Güner et al., 2020). As a result of the response to the pandemic, people's daily routines, business operations, and online purchasing patterns have all undergone sudden, dramatic changes (Özmen et al., 2021).

The recent pandemic boosted digitalization providing researchers a unique opportunity to examine the adoption process and explore the determinants by which the consumers’ behavior shapes and leads to the decision-making process. Witnessing such a rise in digitalization and technology-dependent shopping opens new doors to investigate further the incentives and behavioral motivations behind the process (Koch et al., 2020). That is mostly due to the fact that there is a tendency for consumers to alter their preferences and behaviors. This entails utilizing alternative pickup and delivery options and transitioning to online shopping in general (Koch et al., 2020). Moreover, shopping malls were closed, and people could not go out to restaurants or eat out. People had no choice but to rely on online services for grocery shopping, ordering food, and even buying clothes or getting consultations (Özmen et al., 2021; Iivari et al., 2020).

On the other hand, the pandemic changed the game for digital marketers since new demographics have now turned to using e-commerce. People of different ages and tastes who preferred offline shopping over online space had no choice but to turn to online applications and websites and applications for their needs. This shift, in many cases, happened in a very short period. Customers had no choice but to adapt and use internet-based shopping technology to avoid health problems and obey the quarantine rules.

However, the effects of the pandemic and the technology adoption might be of temporary nature for some consumers to fulfill their needs, and in many cases, this adoption could leave a more permanent effect on consumers depending on how they received the service and how trustworthy and convenient their online shopping experience has been throughout the pandemic. There are various components and motives before and after the decision-making that make a customer keep their developed behavior of adopting the technology in their everyday life after the restrictions are lifted.

Digital marketing practices in such circumstances must consider the technology adoption components to successfully bridge the gap and examine customers' behavior. However, technology adoption in the recent pandemic has been different from normal circumstances and makes the studying of such situations different from those of normal circumstances. At the same time, the "unified theory of acceptance and use of technology" (UTAUT) theory combined with the task-technology fit model could be used to examine to what extent the determinants are true of pandemics and special circumstances. And at the same time, what variables lead to the continuance intention of those who have adopted the new technologies, in this case, online shopping applications, into their daily lives?

1.1. Research Purpose

The aim of this thesis is to determine the factors that influence the users' intention to continue using online shopping apps during the COVID-19 pandemic. Utilizing different factors from the UTAUT2 and the task-technology fit model, this study is aimed to examine the effectiveness of the factors that directly influence the customer satisfaction of using online shopping applications and users' continuance intention of using such apps. The model and data collection methods enable us to examine those variables from the perspective of the consumer.

1.2. Study Outline

The current study tries to analyze the factors that affect customers' continuance intention to use online shopping apps during the COVID-19 pandemic in six chapters. The first chapter introduces the research background and research purpose, while a brief outline of what you might be expecting is provided. Chapter two contains the literature review of the terms and concepts that are used in the research model. The second chapter also includes relevant topics and previous studies that used the same concepts in their research. Chapter three is dedicated to the proposed research model and introduces the hypotheses. The fourth chapter of the study includes the research design and the methodology, while scales and details related to them are included. In chapter five, you can find the results and the data analysis where the final research model is created. The final chapter of the study includes the conclusion and points out the limitations of the study while further study opportunities are mentioned.

2. THEORETICAL BACKGROUND

2.1. COVID-19 Crisis

The world has been repeatedly influenced by pandemics over the past several decades, as evidenced by historical records. Insights from the scientific study of various disciplines undertaken during these events are required to prepare for future pandemics and other global disasters (Platto et al., 2020). This study opportunity is presented by the novel SARS-CoV-2 virus, which began to spread globally at the beginning of 2020 (Güner et al., 2020).

In the year 2020, a global disaster occurred for which no one could have planned. The viral disease COVID-19 has impacted the way of life on a global scale. In December 2019, the virus was first detected in Wuhan, China, and has since expanded globally and continues to do so. The COVID-19 pandemic has triggered one of the most significant social and healthcare disasters in human history (Singh & Singh, 2020; Güner et al., 2020).

Within a few weeks, the situation surrounding this virus morphed into a pandemic, paralyzing global economies and financial markets and driving national health systems to the verge of collapse (Singh & Singh, 2020; Platto et al., 2020). In order to limit the rapid spread of the virus, the majority of nations imposed severe social restrictions. These restrictions included bans on large-scale gatherings, the temporary closure of schools and institutions, and a partial shutdown of the economy (Singh & Singh, 2020).

In countries that imposed a lockdown, most stores and services had to shut down. Concurrently, consumers faced increasing levels of economic insecurity because of rising unemployment and short-term employment. Due to the closing of brick-and-mortar retailers, internet shopping is now the sole option for consumers to fulfill their demands. In his study, Fernandes (2020) underlines the negative impact of COVID-19 on economic growth rates. In 2020, the majority of the world's leading economies anticipated an economic downturn. In 2020, countries like Spain, Portugal, and Mexico, whose economies rely heavily on tourism, suffered significant GDP declines (Fernandes et al., 2020).

During the COVID-19 epidemic, e-commerce has dominated, and retailers have devoted significant resources to constructing, enhancing, and promoting online storefronts (Bhatti et al., 2020). Some small shops that did not have online stores prior to the shutdown created interim methods to sell their products online, such as posting products on social media and providing product pick-up or delivery services. Others have provided discounts on their web platforms and launched social media marketing efforts. To ensure the success of these activities, it is crucial to examine customers' online shopping motivations during the epidemic (Bhatti et al., 2020; Miljenović & Beriša, 2022).

Prior research on the drivers of purchase intentions in the setting of e-commerce highlights the significance of both hedonic and utilitarian factors. While utilitarian incentives pertain to the usefulness of conduct, hedonic motives refer to the entertainment and pleasure derived from an action (Rajamma et al., 2007). However, the COVID-19 pandemic represents a unique circumstance, and factors beyond utilitarian and hedonistic considerations must be examined (Platto et al., 2020; Bhatti et al., 2020). During the crisis, there has been extensive media coverage of the epidemic, and consumers are exposed to a great deal of information about the present economic climate. The current crisis illustrates the necessity of accounting for the normative implications of these authoritative third parties. Increasing levels of economic uncertainty during the COVID-19 crisis present a unique opportunity to explore the ways in which pressures emanating from media coverage of the current economic situation and pressures stemming from close social networks influence customers' buying decisions (Bhatti et al., 2020).

2.2. Online or Offline Shopping

Customers choose their own shopping methods according to their preferences. A majority of people, prior to the pandemic, still preferred to make purchases at brick-and-mortar stores, as they felt that doing so provided a more genuine interaction with the products they were purchasing (Rajamma et al., 2007). Each buyer has their own reasons for favoring either online or traditional stores (Zhou et al., 2007; Cho et al., 2006). While some buyers place a premium on convenience and a wide selection of products, others would rather speak with a knowledgeable sales associate in person and examine the product up close. In addition, numerous reports have demonstrated that shoppers much rather make a final decision after personally examining the products of interest (Zhou et al., 2007).

Brick-and-mortar stores have more experience and wisdom than their virtual counterparts. A traditional "brick and mortar" store is a storefront where goods are displayed for sale. They then go to the store to look around, chat with staff, try things on, and buy goods and products. Customers who go with those items are less likely to shop around for a better price. In contrast, shoppers who prefer to do their purchasing online tend to be more price-conscious, always looking for the best possible deal by perusing a number of different online retailers (Rajamma et al., 2007). Consumers' preferences for in-store purchases over online ones are also influenced by the weather. Based on projections, sales could balloon or plummet dramatically (Cho et al., 2006).

Badorf et al. (2019) noted that the weather could account for a 25.9% swing in business. However, online stores can operate regardless of the weather. It is more difficult for traditional stores to compete with the aggressive sales tactics of online retailers due to the higher operating costs inherent in maintaining a physical location, which include things like water and electricity bills (Ganesha et al., 2020). However, brick-and-mortar stores will always have one major advantage over virtual ones: in-person assistance. Maintaining valuable, long-term client relationships is often difficult but can be greatly aided by a company's customer service department. Despite efforts by online stores to address this issue through the use of chatbots and instant customer support, neither of these methods is a suitable substitute for human sales associates who can investigate and attempt to resolve a customer's problem directly (Cho et al., 2006).

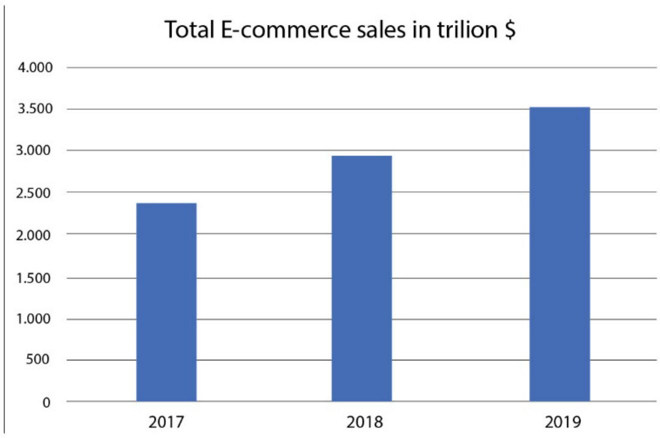

Figure 2.1 Global e-commerce sales 2017-2019 (Orero-Blat. et al., 2020)

From 2017 to 2019, the growth of e-commerce is depicted in Figure 2.1. e-commerce sales worldwide reached a staggering $2.382 trillion in 2017. In 2018, worldwide sales soared to an all-time high of $2.982 trillion, an increase of 25.19% from the previous year. As 2019 progressed, so did global e-commerce sales, which reached a staggering \$3.535.0 trillion. The 2019 increase over 2018 was respectively 20.71%. Online retail has tremendous future potential, as evidenced by the 48.4 % increase in e-commerce sales in just three years. Significant ongoing changes in the global retail industry are also reflected in the growing influence of e-commerce. In 2015, international online sales accounted for 7.4 % of the world's total. Online retail accounted for 14.1% of all retail sales in the world in 2019, up from just 1.6% in 2015. Global e-commerce as a percentage of total retail sales is projected to reach 22% by 2023 (Orero-Blat et al., 2020).

Though projections of 2023 sales were made before the global pandemic, the estimate has since been revised downward. The explosive growth of e-commerce has been greatly aided by the widespread availability of mobile devices. In 2019, it was found that roughly 52% of all internet users had made a purchase online in the previous month (Chiang et al., 2021). Even more impressive is the fact that 38% of Austrian consumers have made an online purchase in the last month alone. It was reported that there was a 34.8% increase in overall online traffic to supermarket websites between January 2020 and October 2020. Unfortunately, the opposite is true, as there has been a 43.7% drop in visits to travel-related websites (Miljenović & Beriša, 2020).

2.3. Online Shopping Applications

Transactions between businesses and consumers that are made possible using electronic commerce are known as e-commerce. Mobile e-commerce, an offshoot of electronic commerce, makes it possible to conduct business online using mobile devices rather than just computers (smartphones, tablets). Banking, booking trips, and making purchases are all examples of mobile commerce that can be started or finished with the help of a smartphone device and a connection to a computer-mediated network (Holzer et al., 2011; Hoehle & Venkatesh, 2015). In 2014, mobile access surpassed fixed internet access, and m-commerce expanded rapidly. It is becoming increasingly common for today's consumers to use their mobile devices to shop for, purchase, and receive merchandise (Hoehle & Venkatesh, 2015; Kang et al., 2014).

The term "m-shopping" refers to purchasing goods and services online from a mobile device using a wireless Internet connection. In addition, mobile users have two primary locations to access online content while doing m-shopping from websites and mobile applications. To perform specific functions for people who are using mobile devices, developers create mobile applications. Mobile applications are distinct from websites in that they must be downloaded from the mobile application store. This store serves as a database where users can browse, find, and download apps for their mobile devices (Al Dmour et al., 2014).

Apps for mobile devices are distinct from websites, and they excel in some respects where the latter fall short. For example, mobile applications can function locally without an internet connection, can display content natively on the user's smartphone, can send and receive push notifications, and can make use of all of the device's features (location, camera, phone, etc.) (Kim et al., 2017). Mobile applications can also load and perform better, be sold through a dedicated app store, and have a more streamlined buying and shipping process. There is a wide variety of apps for mobile devices, such as time-management and organization aids (like a calendar, notes, flashlight, and alarm clock), entertainment (like games and music), and online shopping (like Amazon) tools. As part of our research, we consider the environment in which people use shopping apps on their mobile devices (Al Dmour et al., 2014; Kim et al., 2017).

The term "online shopping applications" (online shopping apps) will be used throughout this study to refer to programs that can be installed on a user's mobile device and used to shop for and research products on the go. Additionally, m-shopping apps have features that can make shopping more convenient, including a map of nearby stores, alerts when prices drop or new deals become available, the ability to share products on social media, and trending news and videos (Kim et al., 2017; McLean et al., 2019).

2.4. Behavioral Intention and Continuance Intention

The term "behavioral intention" describes an individual's drive and eagerness to carry out a planned action. When someone is highly motivated, he is more likely to act in the way he should. The term "purchase intention" is commonly used to describe a consumer's predetermined intent to buy a good or service. Consumers' willingness to take part in an online transaction is another definition of purchase intent in the context of e-commerce (Warshaw et al., 1985; Gu et al., 2009).

The exchange process includes sharing private information and transaction history and starting a business relationship. According to another definition provided by Shah et al. (2012), purchase intention can be linked to consumers' motivation to buy a specific brand. According to Chang et al. (1994), the extent to which consumers value a product has a significant impact on whether they decide to buy it. Customers are more likely to make a purchase decision if they perceive a high quality in the advertised product.

Consumers are less likely to make a purchase if they perceive a lack of value. A shopper's propensity to engage in electronic transactions exemplifies their intention to make purchases online (Bagdoniene et al., 2009). These transactions involve a process in which information gets transferred in order to purchase a product online. Buyer intent is also heavily impacted by how a product is displayed. It has been established that online retailers who use photographs for advertising their products from a variety of perspectives, including in realistic use scenarios, increase consumers' propensity to make a purchase (Zhou et al., 2007; Bagdoniene et al., 2009).

Previous research into the topic of technology acceptance and users’ continuance intention has established that an individual's behavioral intention is defined as their propensity to make use of a given technology system. According to Venkatesh et al. (2003), the definition of behavioral intention in this study is the users' propensity to engage in a specific technological behavior; in this case, the users are those who engage in online shopping via mobile applications. Furthermore, researchers agree that a user's intent to use a given technological system is a robust predictor of that user's actual use. Thus, the technology acceptance models revolve around the concept of the behavioral intention to use technology. However, there is little agreement among researchers about what influences people to take a particular action, in this case, to use mobile shopping apps (Siau et al., 2007; Jih et al., 2007; Lin et al., 2005). In the context of technology, researchers have identified a wide range of factors that influence behavioral intention. This will be demonstrated in the following sections through an examination of several technology acceptance models and prior research.

The likelihood and enthusiasm with which a consumer continue using a product or service are heavily influenced by a wide range of external factors. Despite the fact that risk, loyalty, trust, and convenience are among the most common motivational drivers, even relatively minor factors can have a significant impact on an individual's intent (Mirabi et al., 2015). Customers' propensity to make a purchase is profoundly affected by the aesthetics of an app. Apps with a colorful and cheery design, for instance, are more likely to generate sales because they positively affect the user's state of mind, which in turn increases the likelihood that the user will make a purchase (Cho et al., 2006; Mirabi et al., 2015). During the pandemic, such factors could go beyond the aforementioned factors and related elements to health can come to the calculations.

2.5. Theories and Models of Technology Acceptance

Understanding what motivates people to accept technology and why users of technology tend to accept or reject a certain technology has been a difficult problem to solve. Research into user acceptance of cutting-edge technologies like the most recent sales technology and the mobile platform in relation to a specific class of goods and vendor-related factors is essential in light of the exponential growth of new technological systems in the modern world (Samaradiwakara et al., 2014). Technology acceptance theories and models share a common premise: that an intention to use technology will lead to the actual usage of the technology.

However, these theories and models disagree on which factors have the greatest impact on people's behavioral intentions with regard to using a particular technology (Zhou et al., 2007; Samaradiwakara et al., 2014).

Developed by Fishbein and Ajzen (1977), the Theory of Reasoned Action (TRA) is a behavioral intention model and theory that can be used to pinpoint the origins of an individual's free-willed actions. According to TRA, an individual's behavioral intention (their desire to act in a certain way) is the deciding factor in whether that behavior is enacted. In addition, the attitude toward the individual's behavior and subjective norm plays a role in determining the behavioral intention. This mindset refers to the conviction that the implementation of a given piece of technology will yield desirable results (Fishbein & Ajzen, 1977; Hagger et al., 2019).

As a response to the challenge of explaining behaviors over which an individual has only limited control of their own volition, the Theory of Planned Behavior (TPB) was developed (Cheng et al., 2019). Therefore, TPB incorporates one more factor, namely perceived behavioral control (PBC), which is a determinant of both intentions to use and actual usage behavior, in comparison to TRA. People's beliefs about their capability (PBC) are people's perception of the ease or difficulty of performing the behavior of interest, and they have a significant impact on people's actions. According to TPB, people are more likely to engage in risky behavior when they feel they have some degree of control over their actions. Having a higher level of intent to use predicts increased actual usage (Cheng et al., 2019; Troise et al., 2020).

Davis (1989) first proposed the Technology Acceptance Model (TAM), a theory in the field of information systems that attempts to predict how people will employ new technologies. Davis et al. revised the TPB and TRA in 1989 and found that perceived usefulness (PU) and perceived ease of use (PEU) were the most important factors in predicting future technology adoption (Davis et al., 1989).

The Unified Theory of Acceptance and Use of Technology (UTAUT), developed by Venkatesh, Thong, and Xu (2003), combines eight user acceptance models and theories. The UTAUT was designed to examine the acceptance of technology in an organizational setting. In addition, the UTAUT2 model has been empirically validated and is shown to outperform each of the eight individual models (Ahmad, M.I., 2015). This model makes it useful for researchers investigating the factors influencing the acceptance of technology (Williams et al., 2015).

UTAUT studies the users' acceptance of technology through the perception, acceptance, and willingness models that were established before. For this purpose, UTAUT includes four main determinants of performance expectancy, social influence, facilitating conditions, and effort expectancy (Venkatesh et al., 2003). The model consists of four predictors for the intention to use technology and the actual usage of technology (Williams et al., 2015). These consist of Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC). PE is the extent to which using technology provides benefits to individual users in performing certain activities. EE is the degree of ease associated with the individual users' use of technology. SI is the extent to which individual users of technology perceive that important others believe they should use the technology, and FC refers to individual users' perceptions of the resources and support available to perform a behavior (Ahmad, M.I., 2015). To be more specific, PE, EE, and SI affect behavioral intention to use technology, while facilitating conditions and behavioral intention to use technology are what ultimately determine technology adoption and usage. Moreover, these dimensions are influenced by the moderator variables, which include gender, age, experience, and voluntariness of use (Venkatesh et al., 2003). The UTAUT model is displayed in Figure 2.2.

There are many examples of using UTAUT2 to verify different variables like social influence, trust, and task-technology fit and how they positively affect consumers to adopt the new technology in their everyday life.

UTAUT2 application could be seen in many studies, including the work of Khalilzadeh et al. (2017) to verify that the trust variable, when associated with security and risk factors, affects the users' intention to adopt mobile payment technology. In another study by Zhou et al. (2010), UTAUT2 was integrated with other models like the Task-Technology fit model and found that PE, SI, TTF, and facilitating conditions have effects on the adoption of mobile banking in China.

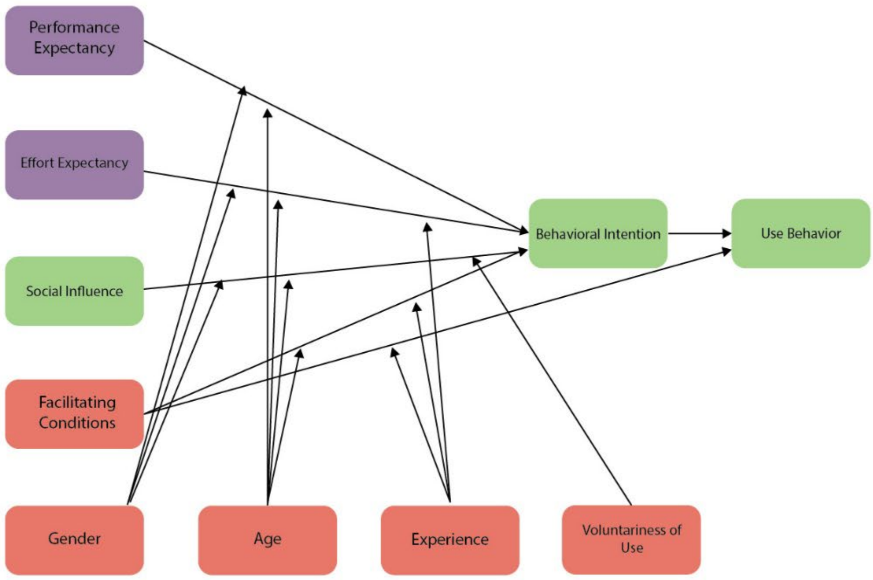

Figure 2.2 UTATU model (Venkatesh et al., 2003)

As a result, with the help of additional variables, UTAUT2 is used in this study to measure the factors that could affect users' intentions to continue using online shopping applications after the pandemic is over.

2.5.1. Performance Expectancy

In UTAUT2, Performance Expectancy (PE), as one of the core determinants, is a determinant that shows the degree to which a user could benefit from the technology they are adopting or how it can improve their performance in certain activities such as shopping or financial services (Venkatesh et al., 2003). As one of the main determinants of the UTAUT2, previous studies suggest (Yeo et al.,2017; Roh et al., 2019) that customers take PE as the most important determinant of adopting new technology. This is a determinant that measures the amount of confidence an individual has while using new technology to improve their performance

(Venkatesh et al., 2003). In other words, PE is a determinant that measures the evaluation of the costs and benefits of adopting new technology (Perea Y Monsuwé et al., 2004). On the other hand, Tarhini et al. (2019) suggest that PE, along with behavioral intention, are among the main factors in e-commerce adoption. In a recent study on food delivery applications in China (Zhao and Bacao, 2020), it has been proved that PE has a significant positive effect on users' continuance intention in using food delivery applications. Furthermore, users who perceive the utility of food delivery applications at a higher level are more intended to continue using the applications in the future (Roh et al., 2019; Yeo et al., 2017).

Previous studies that examined the effects of PE prove that older adults are more likely to adopt online applications when their performances satisfy them and they assume that technology benefits them in different aspects, such as with "health services" (Hoque & Sorwar, 2017) and "online shopping" (Lian and Yen, 2014). Furthermore, studies on the effect of PE in adopting new technologies, namely mobile internet (Zhou, T., 2011), Mobile Social Networking apps (Alvi, I., 2021), and mobile shopping applications (Chopdar & Sivakumar, 2019), have shown that PE has a significant positive effect on users to change their older habits and adopt new technologies. Also, those studies suggest that PE has a positive effect on the continuance intention of users. Keeping in mind the fact that most studies have been conducted in normal circumstances and in the pre-pandemic era, the effects of every determinant, including PE, could be stronger when the access to physical stores is limited and there is a concern for using financial services such as banks and doctors' offices (Rahi et al., 2019). Studies like the one by Chayomchai et al. (2020), which were conducted during the COVID-19 pandemic situation, state that the pandemic did not leave a strong effect on the role of PE in users' intention to use online technologies during the lockdown conditions. Therefore, online shopping applications being of the same nature as online technologies, we assumed the same effect of PE would apply to the continuance intention of using online shopping apps during the pandemic and "would positively affect customer satisfaction and users' continuance intention of online shopping applications".

PE is a variable that could eventually lead to users' satisfaction. In this case, the variable could also be used as a determinant that positively affects the users' continuance intention of using the technology they have adopted (Chen et al., 2020). This could be further proved by referring to the literature. As prior studies on e-learning suggest, PE has a positive impact on using intention of the user, as proved by Sangeeta and Tandon (2020). Furthermore, Gunden et al. (2020), in their study of online food delivery, prove that PE significantly affects customers' adoption intention of online food delivery systems, which is similar in nature to online shopping applications. In terms of UTAUT2, studies by Marinkovi´c et al. (2020) and Chong (2013) has conducted studies using UTAUT2 that verify the significant positive effect of PE on the continuance intention of users in terms of mobile commerce.

2.5.2. Effort Expectancy

Like PE, Effort Expectancy (EE) has a significant yet important effect on technology adoption and using online shopping applications is no exception. In the UTAUT2 model, EE is defined as the degree of ease with which customers can use new technology (Venkatesh et al., 2003).

Users mostly prefer to use user-friendly technology that can give them a higher efficiency with less hassle (Godoe & Johanse, 2012). Moreover, previous studies suggest that the adoption of new technology is more likely when it takes less effort for the customers to adopt that technology (Godoe & Johansen, 2012; Kang, 2014). Academicians also believe that e-learning platforms are more easily adopted by both students and teachers when they are hassle-free to use (Gunasinghe et al., 2019).

When users are in the adoption phase, EE could influence the purchase intention (Venkatesh et al., 2000). Moreover, a study on Food delivery apps proves the direct effect of EE on users' behavioral intention to adopt and use the new technology (Ghorai & Ray, 2019).

Using a new technology could be challenging for users, especially for users of a higher age demographic. That is the reason why more modern user interface designs for Online Shopping applications and other smartphone applications are investing more in improving the users' shopping experience (Chen et al., 2020). In this study, we used EE to measure the degree of user-friendliness of online shopping applications that would result in more satisfaction and consequently lead to continuance intention of the users who have adopted the new technology during the COVID-19 pandemic.

Although previous studies utilizing UTAUT2 show that EE could affect the continuance intention of users (Venkatesh et al., 2011), some studies suggest that this variable does not affect the continuance intention of users of mobile technologies (Yuan et al., 2016) and online shopping apps (Chopdar & Sivakumar, 2019). Such studies suggest that after the adoption, users get familiar with the online shopping app, and EE is no longer valid for determining the continuance intention. On the other hand, Marinkovic et al. (2020) facilitated UTAUT to validate the impact of EE on satisfaction and continuance intention of mobile commerce (Marinković & Kalinić, 2020).

Since the effect of EE on satisfaction and continuance intention has been controversial, to validate the effect of EE in online shopping applications, we had to refer to different previous studies. There are different studies that used EE with the UTAUT model to discuss the continuance intentions of users in the field of IT (Venkatesh et al., 2003). Previous studies in the field of health services suggest that EE affects older adults' continuance intention positively when there is no pandemic (Hoque & Sorwar, 2017). However, other examples, especially in online shopping, prove the other way (Lian et al., 2014). Such findings could lead to the hypothesis that EE could have a positive effect on the continuance intention of online shopping applications during the pandemic situations when people's health is at risk by visiting physical locations in the shops.

2.5.3. Social Influence

Based on UTAUT2, Social Influence (SI) is defined as the degree to which people gain the idea and willingness to use a certain technology through their friends and family or other acquaintances (Venkatesh et al., 2003). SI not only affects users' intention to adopt and use new technologies like in online-to-offline delivery services (Roh et al., 2019), but it could also directly affect the continuance intentions of users of mobile technologies (Lai et al., 2015) as a very important variable.

SI includes the three concepts of social factor, subjective norm, and image. The social environment has a great effect on people when it comes to their social behavior. On the other hand, subjective norm suggests that every individual's behavior is influenced by those people around that person who are considered important (Ajzen, 199; Davis et al., 1989). The SI could count as a crucial determinant in adopting and continuing the use of online shopping applications (Chopdar & Sivakumar, 2019). Moreover, UTAUT2 has shown that the adoption of different technologies gets affected differently depending on the influence and the person who receives the influence (Escobar-Rodríguez et al., 2014). Considering the fact that UTAUT combines both subjective and normative as a unified component (Workman 2014), It is important to mention that Venkatesh et al. (2012) state that the SI variable of UTAUT2 mostly relies on the latter.

Previous studies suggest that SI could positively affect technology adoption and continuance intention. In a study about online shopping, Shim et al. (2001) suggests that the effect of subjective norms on online shopping is only marginally important. In contrast, Foucault et al. (2005) find a significant connection between online shopping adoption and the SI of friends and family when a person the subject is discussed in groups. In another study, George (2002) suggests that if online shopping is a desirable behavior, then it is more likely for an individual to adopt and use online shopping technology.

However, studies of pre-pandemic circumstances show that SI positively affects older adults to adopt and continue using online shopping apps (Erjavec & Manfreda, 2022; Zhang et al., 2017). There are not so many studies on the impact of SI after the COVID-19 pandemic. At the same time, UTAUT2, known as the revised model of UTAUT, states that SI could have an important impact on the continuance intention of using mobile or other new technologies. This study aims to take a deeper look into SI and its effects on the continuance intentions of users after the pandemic.

2.5.4. Trust

Online or offline, trust is the cornerstone of any successful business transaction. Because of this, mistrust can reduce productivity and cut sales. The concept of trust in an e-commerce context refers to the promises made by both the buyer and the seller that are expected to be fulfilled (e.g., the buyer makes the payment, and the seller provides the promised good or service) (Grabner-Kraeuter, S., 2002; Hsu, et al., 2014). According to research by Wang et al. (2009), there is a positive correlation between trust and buying goods and services online. Consumers are more likely to make a purchase when there is a high level of trust between the business and its potential customers. It has been found that consumers who have extensive knowledge about online retailers tend to have a higher degree of trust in those retailers. It is also widely believed that customer trust is crucial to the success of an online store (Wang et al., 2009).

Online shopping generates more uncertainty and greater risks than offline shopping. Consumers are concerned with more issues and challenges when deciding to use online shopping applications rather than shopping from brick-and-mortar shops (Madinga et al., 2022). This study tries to focus more on the continuance intention of users after the COVID-19 pandemic, and the trust variable has proven to be significantly effective in users' perception of online shopping apps being reliable. This could be translated to the fact that if users find themselves trusting an online shopping application, they tend to continue using it after their initial adoption.

Since this research uses UTAUT2 as a model, trust has been validated as an additional variable for UTAUT2 as it can significantly affect the users' behavioral intentions of adopting and continuing to use an online shopping application (Chen et al., 2020). Moreover, building trust is one of the significant components of every online business, and users tend to buy from those online shipping applications they trust more, sometimes regardless of the price factor (Grabner-Kraeuter et al., 2002) and this variable could positively affect continuance intentions of customers.

Online businesses that cannot establish reliable customer relationships are doomed to fail because customers will be wary of making purchases out of fear of being victims of cybercrime (Setiawan et al., 2018; Ali et al., 2016). False product advertisements and failed deliveries are two forms of cyber fraud. In addition, shoppers worry that online stores will sell their personal information to third parties without their knowledge or consent. By implementing elements like service quality, security features, warranties, and reasonable privacy policies, online merchants can help consumers feel more at ease with their purchases (Yeoh et al., 2011).

In a study on online grocery services, which have a likely nature to online shopping applications, Asti et al. (2021) found that if a potential customer trusts an online shopping service, they are more likely to make a purchase and continue using the application in the future. Also, previous research argues that trust has a positive influence on a user's intention to shop online (Kim and Ko, 2010). In another study, McCloskey (2006) suggests that older adults in the US tend to continue using an e-commerce website more when they can trust the service, and this variable affects their behavior positively. Ryu et al. (2009), in a study using TAM with trust variable that studies the willingness of older individuals' willingness to use "video user-created content", found that trust has a positive effect on users' technology adoption and continuance intention.

Furthermore, trust is one of the most significant predictors of users' continuance intentions toward online shopping apps and mobile technologies in general (Hoffman et al., 1999; Merhi et al., 2019). Trust also could affect users' satisfaction with mobile technologies use and adoption like websites (Nguyen et al., 2019), mobile banking (Merhi et al., 2019; Lafraxo et al., 2018), and mobile shopping apps (Marriott et al., 2018; Phong et al., 2018).

2.6. Perceived Task-Technology Fit

Perceived task-technology fit (TTF) is a crucial factor extracted from the original Task-Technology Fit model, which affects users' adoption of technology.

Even though users perceive or consider a new technology as an advanced and modern tech that could change their lives, they might not tend to adopt that technology if it does not fit their tasks and think it is incapable of improving their performance (Lee et al., 2007). Goodhue and Thompson (1995) were the first ones to propose the Task-Technology Fit model in "Task-Technology Fit and individual performance". In that research, the aspects of technology adoption, characteristics of technology, and functions of that technology that condition the performance of individual tasks and meet their needs are measured by the Task-Technology Fit. This study is trying to analyze the users' continuance intentions of online shopping apps during the pandemic caused by COVID-19 and its features. Hence, it is important that the expectations of the users are met by the applications they have used for online shopping during the lockdown.

Using the TTF model combined with UTAUT2 could study different aspects of the adoption and continuance intention of the users since task technology fit will also affect PE (Dishaw et al., 1999) as one of the UTAUT2 variables. Previous studies used TTF to analyze customers' behavioral intentions of adopting new technology in different fields of online commerce. Lee et al. (2007) utilized the Task-Technology Fit model to analyze users' technology adoption in mobile commerce and in the insurance section. Furthermore, TTF has been used in research by Junglas et al. (2008) to study the mobile information systems adoption for mobile locatable information systems. In further research, the Task-Technology Fit model has been used combined with UTAUT2 to study the adoption of mobile banking technology (Zhou et al., 2010). Another example of using TTF in mobile banking adoption is the research by Tam et al. (2016) that used the Task-Technology Fit model with the "Delone & McLean" model.

Such studies make the use of the Task-Technology Fit model valid for measuring the users' continuance intention of using online shopping applications during the pandemic. In line with the purposes of this research, Yuan et al. (2016) utilized the TTF model combined with TAM to measure and analyze the factors that positively affect users' continuance intention of mobile banking applications.

Considering the COVID-19 pandemic, TTF represents the advantages of online shopping applications that users can conveniently search and buy clothing, accessories, or any other goods that they find in brick-and-mortar stores, whenever they feel the need and at any place they are located. Meeting such requirements, online shopping applications could be continuously used by the users who have adopted them during the pandemic. Therefore, the task-technology fit could affect the continuance intention of the users positively.

2.7. Customer Satisfaction

The original UTAUT has been criticized for not paying enough attention to customer satisfaction and instead focusing more on behavioral intentions and variables (Orlikowski W J et al., 2001). Min et al. (2008) proposed to extend the UTAUT model by combining it with the satisfaction theory to make it applicable to m-commerce. Moreover, Hung et al. (2012) suggest that satisfaction combined with trust can significantly affect users' continuance intentions. In another study Chong (2013) finds that satisfaction with other variables like trust play a significant role in the continuance intention of users of m-commerce in China.

When users are satisfied with a service or application, they tend to use that application or service in the future. As a part of the extended UTAUT, satisfaction could play a significant role in customers' continuance intention. The importance of satisfaction is related to how it can be affected by other determinants, such as PE or EE. For example, satisfaction is significantly affected by PE when it comes to the continuance intention of mobile technology adoption (Tam et al., 2018).

In this study, we have used satisfaction as a determinant that is affected by various UTAUT2 determinants and could positively affect users' continuance intention.

2.8. Perceived Severity and Vulnerability (PS and PV)

When we are in a pandemic situation, a community is going through severe levels of increased fear and anxiety (Asai et al., 2021). In this case, the perception of risk shifts through the fear of getting infected with the Nobel Corona Virus when they come in contact with other individuals and break social distancing rules in physical stores and retailers. Zanetta et al. (2021), in a study about food delivery application adoption, state that although there's a relationship between risk perception and practices of adopting new technology, this relationship could get confusing in some cases. Observations show that risk perception can lead to some practices, but somehow the relationship could be the contrary.

Since the start of the COVID-19 Pandemic, governments all around the world have tried to prevent the spread of the virus through person-to-person transmission by mandating practices like work from work or curfews (Sibley et al., 2020). The lockdowns not only changed people's lifestyles but also had a psychological effect on individuals (Laato et al., 2020). Furthermore, the situation changed consumers buying behavior drastically when individuals showed unusual behaviors like panic buying after COVID-19 spread. Therefore, the COVID-19 pandemic could lead to the adoption of new technologies when customers' buying behaviors are changing.

Studying the effects of the COVID-19 pandemic on users' continuance intention of online shopping apps requires analyzing how the risks of the disease might affect consumers' decision-making and technology adoption. Everyone has a perception of the severity of the disease, and their vulnerability to the disease affects their final decision (Ali et al., 2019). Perceived vulnerability (PV) and perceived severity (PS) are amongst the most widely used measurements to determine individuals' perception of disease (Hochbaum, 1958). Cahyanto et al. (2016) defines perceived severity as a personal concern about the seriousness of the situation and perceived vulnerability as a personal belief about getting ill with a disease. At the same time, Health Belief Model explains that when a health-threatening situation happens, those with higher PS and PV are more likely to change their behavior to reduce the risks of getting exposed (Carpenter, 2010).

There is previous research that has studied the effects of PV and PS on customer behavior and adoption, especially in the hospitality sector. Ali et al. (2019), in a study on "Consumers' Return Intention" at the time of foodborne disease, found that both perceived vulnerability and perceived severity significantly affect the customers' intentions to return to restaurants when a foodborne disease is happening. Similarly, in the event of COVID-19, people with higher PS and PV might prefer to stop going out shopping and choose online shopping apps that expose them to fewer risks of getting infected with the virus. Therefore, perceived risk and perceived vulnerability can significantly affect the users' technology adoption and continuance intention during the COVID-19 pandemic.

2.9 Perceived Benefits

Online shopping applications offer numerous different benefits to their users. Two of the most important benefits every e-commerce service could offer to its consumers are time-saving and price-saving benefits.

2.9.1. Time-Saving Benefits

Due to increased professional responsibilities that tend to consume more time, consumers typically have less time available for purchasing goods and services. Therefore, consumers are required to seek out new time-saving alternatives. Online shopping provides numerous opportunities to save time, such as the availability of numerous online stores (Mirabi et al., 2015).

Time-saving benefits are those benefits when a user chooses to substitute online shopping apps with brick-and-mortar stores; they save time from traveling to and from those retail stores they used to do before (Morganosky et al., 2000). This is an important advantage for a time-sensitive and modern society that could have a significant effect on the adoption of new technologies and continue using them.

Changes in online shopping applications show that they are investing efforts in saving more time for their customers. Online shopping apps store customers' financial data like credit card number and their favorite payment method to make the checkout time quicker and enable their customers to save time (Satista, 2020). In a study on “Why People Use Food Delivery Apps”, Ray et al. (2019) suggest that time-saving benefits do not have a significant effect on the usage intention of such applications. On the other hand, studies like Zhou et al. (2019) found that time-saving benefits positively affect the customers’ intention to adopt the technology. Another study by Yeo et al. (2017) finds a powerful link between time-saving benefits and users’ continuance intentions.

Due to the lack of large crowds and lengthy lines, online retailers appear to be more convenient. In addition, Online search convenience refers to the easiness of accessing product information online and is regarded as one of the most influential factors when deciding whether to shop online or offline. Online channels are favored by consumers due to the high level of convenience they provide Change (Chang et al., 2021). Without significant physical exertion, online channels provide valuable information about recent offers, price discounts, and personalized recommendations. In addition, consumers can shop for countless items across multiple platforms without being restricted by time or location. In addition to the convenience of having countless products available online 24 hours a day, seven days a week, the consumer also avoids large crowds, making online shopping even more convenient and secure (Zhou et al., 2007).

Online retailers, to enhance the shopping experience, have implemented several new features. New presentation features, such as simple product descriptions and review systems, assist consumers in locating their ideal product. Short product descriptions and a reviews section can facilitate a quicker search for information and a more convenient shopping experience. Moreover, online retailers maximize customer convenience by implementing simple and well-known payment methods. If the provided payment methods are too complicated, the online store reduces the convenience of shopping and increases the likelihood that consumers will abandon their shopping carts (Yeoh et al., 2011).

Time-saving benefits play an important role in technology adoption and continuance intention of users when they find that they can save time by using online shopping applications.

2.9.2. Price-Saving Benefits

Price is defined as the financial cost that a user pays to use a product (Xu et al., 2015). On the other hand, value, as an abstract concept, could carry different meanings based on the context of the price paid (Chiu et al., 2005). When it comes to online shopping applications, they are offered to users free of charge. Therefore, users do not have to pay the price to obtain them. In such a case, the cost of using the application is indirect (Venkatesh et al., 2012). Statistics show that the most popular food delivery application in Brazil, Charges the merchants 12% to 23% (iFood, 2020) while this fee is usually passed on to the customers. It means both customers and sellers are paying an indirect cost to adopt and use such services.

There are many online services that charge their customers additional fees like extra delivery fees (Lichtenstein, 2020). While others are trying to attract more users with special offers that could save money for the customers and make use of online shopping applications and other e-commerce-related services cost friendlier. Such offers include free delivery or other sales promotions that could cover those delivery fees. For example, Grubhub offers their new customers a $10 promotion coupon and provides student discounts (Groupon, 2021).

In a study on food delivery applications, Karu et al. (2021) found that price-saving benefits could significantly affect the use of such applications by users. Furthermore, Ray and Bala (2021) suggest that free delivery or lowering the delivery fees could positively affect users to adopt such applications. The aforementioned studies prove price-saving benefits as an important variable for the adoption of new technology and especially online shopping applications. Price-saving benefits could translate to money-saving advantages for customers of online shopping applications, as price-saving benefits are the main marketing strategies in online shopping applications (Karu et al., 2021). In this study, we assume that such benefits positively affect users' adoption and continuance intention of using online shopping applications.

On the other hand, many sellers offer competitive prices on online shopping applications. That is mostly due to lower costs like taxes, inventory or rent that merchants of online shopping applications are paying when selling on online shopping applications. Therefore, as Tandon et al. (2021) suggest, when customers find out the price-saving benefits of online shopping apps, it can positively affect their continuance intention of using such applications.

3. HYPOTHESES

In this study, UTAUT2 combined with the Task-Technology Fit model is used to quantify the factors that might influence users' continuance intention of online shopping apps during the pandemic that could extend to the post-pandemic situation. Upon completion of the literature review, the researcher proposed the following hypotheses.

3.1. Performance Expectancy, Customer Satisfaction and Users' Continuance Intention

PE is a determinant that justifies the degree of benefit a user takes from a technology (Venkatesh et al., 2003). If a user receives the expected performance from an online shopping application, they are more satisfied with the technology they have adopted and consequently, they tend to continue using that application. PE plays an important role in users' satisfaction when it comes to online shopping and e-commerce services (Tarhini et al., 2019). Studies suggest that when an online shopping application's performance satisfies the user, they are more likely to continue using the application for their needs in the future (Yeo et al., 2017).

The following hypotheses are suggested:

H1a: PE has a positive effect on satisfaction.

H1b: PE has a positive effect on continuance intention.

3.2. Effort Expectancy, Customer Satisfaction, and Users' Continuance Intention

Today, online shopping is not limited to the process of buying and selling products. Providing satisfactory and unique services to enable customers to get the most out of an application with less hassle is an important aspect of an online shopping application. Such a feature could persuade customers to continue using the online shopping application they have adopted. When a new technology is more user-friendly and customers can perform tasks easier using them, they tend to continue using them (Godoe & Johanse, 2012).

Every new technology should be easy to use for users so that the users are willing to adopt and use that technology (Koksal, 2016) and online shopping applications are no exception in this matter. Speaking of ease of use, it is important that a user would be able to easily navigate through different parts of the application with less effort to be willing to continue using the service (Farah et al., 2018).

On the other hand, when a user finds the features and options of an online shopping application to their standards, they are most satisfied with the performance of the application and, therefore, will continue using that application in the future.

Since EE could also affect PE (Elhajjar & Ouaida, 2020; Malaquias & Silva, 2020), the following hypotheses are proposed:

H2a: EE has a positive effect on customer satisfaction.

H2b: EE has a positive effect on users' continuance intention.

H3: EE has a positive effect on PE.

3.3. Social Influence, Customer Satisfaction and Users' Continuance Intention

UTAUT2 considers SI one of the important variables in adopting a new technology (Venkatesh et al., 2003) and the continuance intention of such technologies. Considering the rapid growth and development of information technology, its applications, and services such as e-commerce, e-banking, and electronic city, it can be hoped that the use of these services, especially online shopping applications, will increase day by day with the emergence and expansion of access to the global internet network. Some studies suggest that SI only has a marginal effect on the continuance intention of customers of online shopping applications (Shim et al., 2001). On the other hand, there are studies that prove SI in older adults plays a positive role in the continuance intention of using online shopping apps (Zhang et al., 2017). Thus, we hypothesized that:

H4a: Social influence has a positive effect on customer satisfaction.

H4b: Social influence has a positive effect on continuance intention.

3.4. Trust, Customer Satisfaction and Users' Continuance Intention

Trust is a significant variable in both adoption and continuing using an online shopping application (Chen et al., 2020). As important as it is in any field of business, if an online shopping application fails to build a trusted relationship with customers, cannot satisfy one of the most important psychological and behavioral needs, and as a result, cannot persuade them to continue using the online shopping platform (Setiawan et al., 2018). In the case of online shopping apps, trust could have various concepts, like the risk of exposing customers' personal information or financial information, especially when a business is trying to affect the continuance intentions of older adults (Ryu et al., 2009). The following hypotheses are tested:

H5a: Trust has a positive effect on customer satisfaction.

H5b: Trust has a positive effect on users' continuance intention.

3.5. Perceived Task-technology Fit, Customer Satisfaction and Users' Continuance Intention

task-technology fit (TTF) could affect users' continuance intention by directly affecting users' satisfaction. It means that if a user perceives an online shopping application as capable of doing their demanded tasks, they are more willing to continue using such applications (Lee et al., 2007). There are many studies that used perceived task-technology fit to understand the effects of different factors on users' continuance intention. For example, Yuan et al. (2016) used the model with other models to find out the users' continuance intention in mobile banking.

Perceived task-technology fit is a factor that could directly impact users' continuance intention because when the fitness between a technology and user expectation from that technology is high, users are more intended to use that technology in the future (Thompson, 1995). Online shopping applications are no exception in this matter.

Based on previous literature and elements of the Task-Technology Fit Model, we hypothesize that:

H6a: TTF has a positive effect on customer satisfaction.

H6b: TTF has a positive effect on users' continuance intention.

3.6. Customer Satisfaction and Users' Continuance Intention

The satisfaction of users of online shopping applications is the main factor in the long-term success of many organizations and affects behavioral and attitudinal loyalty. There is a clear relationship between customer satisfaction and intention to continue using the application, and this relation is pointed out in different literature (DeLone & McLean 2003). Research shows that if a user is satisfied with a service, the resulting satisfaction from experience affects their intention of using the same service in the future (Raman et al., 2021). A study on m-banking by Sharma and

Sharma (2019) shows that customers who are satisfied with their experience are more motivated to possibly continue using the service.

Thus we hypothesize that:

H7: Customer satisfaction has a positive effect on users' continuance intention.

3.7. Perceived Severity, Perceived Vulnerability and Continuance Intention

COVID-19, however, has led to a rise in the worry that customers have about making purchases in physical stores. Due to the ongoing spread of the infectious disease, consumers are more likely to shop online to limit their exposure to COVID-19. Corona Virus appears to pose a greater threat to consumers than other threats, encouraging consumers to shop online (Jensen et al., 2021). In this study, we are focusing on two risk factors that could arise from a pandemic and analyze their effect on users' technology adoption and their continuance intention.

Especially during a pandemic situation, customers go through a phase of fear, and unknown characteristics of an illness might affect their shopping behaviors. Therefore, customers' perceived severity of a situation could affect their technology adoption and, in this case, their continuance intention of using online shopping applications. In fact, no matter how much the severity of an illness would be, the perceived vulnerability and perceived severity of that illness play an important role in the decision of users (Ali et al., 2019)

PS and PV have been used widely in previous literature to measure people's perceptions of disease (Hochbaum, 1958). For example, Cayhano et al. (2016) found that people with higher PS and PV are less likely to continue traveling after the outbreak of Ebola compared to those with less PV and PS.

Preventing theft and disclosure of information is only one aspect of security. In addition, access to information at the required time and the non-change of information in the way of sending are also considered other aspects of security. In the case of this research, perceived vulnerability is used as a variable of the extent to which people consider themselves vulnerable to the noble coronavirus. Since individuals have different perceived vulnerabilities to diseases, their perceptions could cause different levels of psychological distress. PV could lead to users' adoption of new technology, online shopping applications, and intention to continue using such applications during the pandemic. Therefore, the following hypotheses are suggested:

H8: Perceived severity has a positive effect on continuance intention
H9: Perceived vulnerability has a positive effect on continuance intention

3.8. Perceived Benefits

3.8.1. Time-Saving Benefits

The rapid growth of electronic information exchange and the development of communication networks in recent years have opened new horizons in the business sector. This has facilitated trade and increased the competitiveness of the commercial sector. Saving time is one of the most important factors for different users to adopt online shopping applications instead of using rick-and-mortar stores and could affect the continuance intention (Morganosky et al., 2000) if they perceive online shopping applications benefit them by saving time (Correa et al., 2018).

The following hypothesis are tested in this study:

H10: Time-saving benefits have a positive effect on continuance intention

3.8.2. Price-Saving Benefits

Benefits may vary from offering better prices than physical stores since pricing and pricing strategies are one of the main marketing aspects of online shopping applications (Karu et al., 2021). Such benefits can directly affect users' continuance intentions. Factors such as free or lower delivery prices can affect users' intentions to continue using a particular online shopping app in the future (Ray et al., 2021).

H11: Price-saving benefits have a positive effect on continuance intention

The purpose of this study is to investigate the factors that determine and influence users' continuance intentions to use online shopping apps during the covid-19 pandemic. This research model is based on the UTAUT2 model developed by Venkatesh et al. (2003). In addition, previous studies of technology acceptance have emphasized the importance of various factors in the context of online shopping (Venkatesh et al., 2003; Dwivedi et al., 2020). To make the model more applicable to our topic, this study added more external factors that are directly related to the behavioral intention to use online shopping apps. Figure 3.1 depicts the proposed research model.

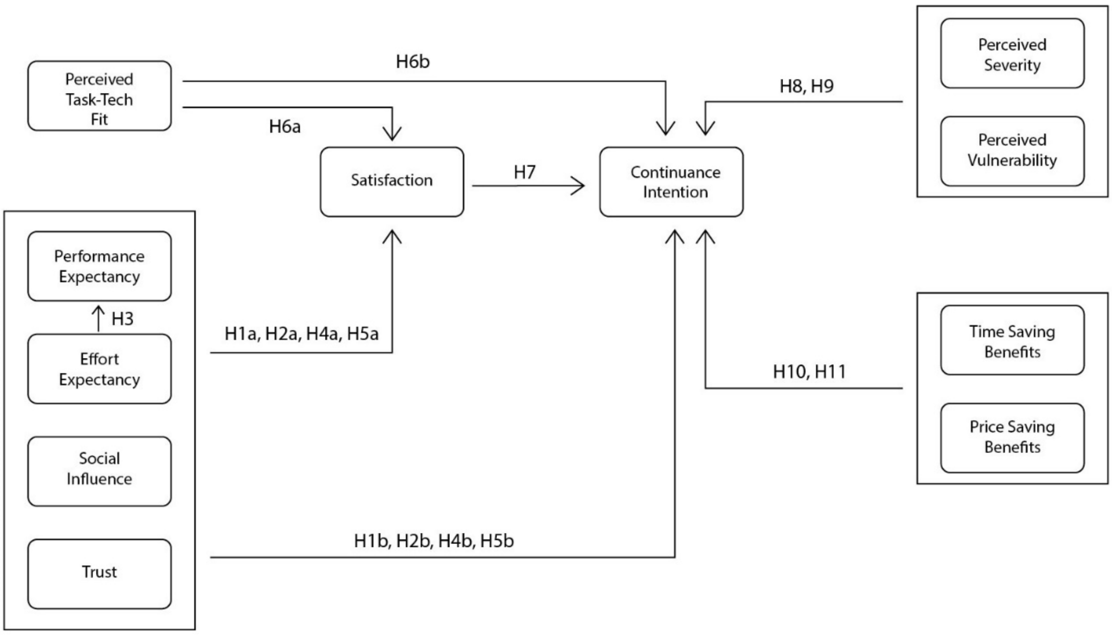

Figure 3.1 Proposed Research Model

4. RESEARCH DESIGN AND METHODOLOGY

The main purpose of this research is to examine the effects of various factors of PE, EE, SI, trust, perceived benefits, and perceived vulnerability and severity on customer satisfaction, and consequently, on users' continuance intentions of using such applications during a pandemic. Some aspects of an online shopping application might lead to satisfaction during special situations like an infectious disease pandemic, and that satisfaction will lead to users' continuance intention of those applications, while some variables could directly lead to the continuance intention of users during the COVID-19 pandemic.

4.1. Data Collection and Scales

To collect primary data, the population of this study consists of all individuals of various demographics, mostly in Turkey, Iran, Germany, and the Netherlands, who have used online shopping apps during the COVID-19 pandemic. This population was chosen because the UTAUT2 model was designed to be tested on users. For instance, the model includes factors such as perceived task-technology fit, which can only be tested on survey respondents who have used the technology (Venkatesh et al., 2003; Phillips et al., 2000). In addition, non-users of online shopping apps have no experience or knowledge of these applications. It is difficult to obtain very meaningful information from non-users because they can barely form any expectations regarding these apps. Users have been the focus of primary research in previous studies of technology acceptance because of their firsthand knowledge of the technology under study (Venkatesh et al., 2003). Therefore, a question was designed to understand if users have used online shopping applications during the pandemic.

The primary data is gathered via an online questionnaire made using Google Forms. The data collection method selected is nonprobability sampling. Non-probability sampling is a group of sampling techniques that allows researchers to select units from a population they are interested in studying. These techniques are beneficial for quantitative, qualitative, and mixed research designs. Regarding non-probability samples, the probability of each respondent's selection from the entire population is unknown (Saunders et al., 2007).

The questionnaire is designed in three main parts; the first part gives the users some examples of online shopping applications and asks if they have used such applications during the pandemic to understand if they are eligible for the sampling. The second part of the questionnaire is dedicated to questions designed to measure the scales of PE, EE, Trust, SI, TTF, TSB, PSB, PV, PS, satisfaction, and users' continuance intention on a 5-Point Likert scale (1= Strongly disagree, 2= Disagree, 3= Neither disagree nor agree, 4= Agree, and 5= Strongly agree). The results of this part were then used in the analyses.

This study aims to provide a general picture of the factors that affect customer satisfaction and continuance intention of using online shopping applications during the COVID-19 pandemic; however, it does not focus on investigating the effect of individual difference variables such as age, gender, and experience that moderate the effect. Although convenience sampling has its drawbacks, without it, the authors would not have been capable of collecting primary data.

4.1.1. Measuring Users' Continuance Intention to Use Online Shopping Applications

In the current research, the variable UTAUT2 combined with the task-technology fit and perceived benefits are used as variables for factors affecting users' continuance intention for online shopping applications.

4.1.2. Measuring Performance Expectancy

They involve customers in the development of their products. Being customer-oriented usually means paying attention to the needs of a certain type of customer in the market - the average customer. But for one-to-one and relational marketing, the company must continuously interact with each and every customer. For this, customers expect good performance from online shopping applications. In this research, four questions taken from Erjavec and Manfreda (2022) were used to measure performance expectations.

4.1.3. Measuring Effort Expectancy

Today, online shopping is not limited to the process of buying and selling products but providing services to customers is one of the major activities in this field, and due to the importance of customer relationship management, the software is used under the name of customer relationship management. Therefore, customers expect efforts to improve the defects of online shopping applications. In this research, this variable is measured by four questions from Erjavec and Manfreda (2022) research.

4.1.4. Measuring Social Influence

Considering the rapid growth and development of information technology, its applications, and services such as e-commerce, e-banking, and electronic city, it can be hoped that the use of these services, especially online shopping applications, will increase day by day with the emergence and expansion of access to the global internet network. The day is expanding. Electronic commerce has brought about a huge transformation in the way of customer and seller communication and, in general, in commerce and the economy. Due to the fact that the origin and development of this technology are in the western developed countries, therefore there are always many cultural and social obstacles in front of its expansion and development in other developing countries. In this research, four questions were adopted from Erjavec and Manfreda (2022) to measure this variable.

4.1.5. Measuring Trust

Recent studies have empirically tested some of these sources of trust and dimensions of trust, but in all this research, the focus has always been on one dimension or on a pair of sources. The uniqueness of this study is that it uses empirical tests and combines all dimensions of trust and sources of trust in the path model of different countries with different levels of online shopping in order to track and influence behavioral trends online. The result of this research shows an evaluation framework for measuring the dimensions of consumer trust in online shopping applications. Consequently, by specifying this guiding framework, this research can be used to formulate measures to ensure consumer trust in online shopping applications. In this research, six questions have been used to measure the variable of trust. The questions were taken from Hong et al. (2021).

4.1.6. Measuring Perceived Task-Technology Fit

In this research, four questions were adopted from Zhao et al. (2020) article to investigate the effects of perceived task-technology fit. Considering that online shopping apps and their adoption mean the adoption of new technology in the direction of re-engineering all business processes, therefore, in line with the methodology of a factor in the adoption of technology in which one of the basic and effective factors of the nature of technology is considered is taken, technical requirements are used as representative of the nature of the technology.

4.1.7. Measuring Customer Satisfaction

The satisfaction of users of online shopping applications is the main factor in the long-term success of many organizations and affects behavioral and attitudinal loyalty. For this reason, numerous research has pointed out the relationship between customer satisfaction and word-of-mouth advertising, repeat purchases, and increasing the profitability of organizations. In this research, four questions taken from Zhao et al. (2020) were used to measure satisfaction.

4.1.8. Measuring Time-Saving Benefits

The rapid growth of electronic information exchange and the development of communication networks in recent years have opened new horizons in the business sector. New methods of information production, processing, and transmission have increased efficiency, productivity, accuracy, speed of communication and cost reduction in companies and commercial organizations. This has facilitated trade and increased the competitiveness of the commercial sector. Saving time is the most important factor for different users to adopt online shopping applications instead of using rick-and-mortar stores and could affect the continuance intention if they perceive this benefit useful. In this research, three questions adopted from Hong et al. (2021) are used to measure this variable.

4.1.9. Measuring Price-Saving Benefits

Online shopping applications give users the advantage of comparing pieces from different vendors and stores, while the nature of online shopping saves time and costs of traveling to and from physical stores. Price-saving benefits could be one of the most important factors for users to adopt and continue using online shopping applications. Three questions have been used to investigate this issue in the current research. The questions related to this variable were also adopted from Hong et al. (2021).

4.1.10. Measuring Perceived Severity

In this research, five questions from Hong et al. (2021) were used to measure this factor. Especially during a pandemic situation, customers go through a phase of fear, and unknown characteristics of an illness might affect their shopping behaviors. Therefore, customers' perceived severity of a situation could affect their technology adoption and, in this case, their continuance intention of using online shopping applications.

4.1.11. Measuring Perceived Vulnerability

Preventing theft and disclosure of information is only one aspect of security. In addition, access to information at the required time and the non-change of information in the way of sending are also considered other aspects of security. In the case of this research, perceived vulnerability is used as a variable of the extent to which people consider themselves vulnerable to the noble coronavirus. Since individuals have different perceived vulnerabilities to diseases, their perceptions could cause different levels of psychological distress. PV could lead to users' adoption of new technology, online shopping applications, and intention to continue using such applications during the pandemic. In this study, four questions adopted from Hong et al. (2021) were used to measure this variable and its effect on users' continuance intention.

4.2. Questionnaire

An online questionnaire was generated utilizing Google Forms and distributed through the use of social media platforms, email, and messenger applications among those who used online shopping applications during the pandemic. The link to the survey was posted on various Telegram and WhatsApp groups, which facilitated the collection of responses from various geographical locations. The questionnaire was distributed face-to-face, mostly through tablets, and mobile phones, to increase response rates.

Table 4.1 Questionnaire Items

Factor	Item
Performance Expectancy (Erjavec & Manfreda, 2022)	1. I feel that online shopping apps are useful for shopping during the pandemic. 2. I feel that online shopping apps are convenient to search and choose the products I needed during the pandemic. 3. Using online shopping apps improved the process of ordering and receiving delivery of products during the pandemic. 4. Using online shopping apps improved the efficiency of ordering and receiving delivery of products during the pndemic.
Effort Expectancy (Erjavec & Manfreda, 2022)	5. Learning how to use an Online shopping app is easy. 6. It is easy to follow steps and finalize shopping in online shopping apps. 7. When I interact with online shopping websites, they are always clear and easy to understand. 8. It is easy to interact with different sections of online shopping apps.
Social Influence (Erjavec & Manfreda, 2022	9. I started using Online shopping apps based on friends and family recommendations during the pandemic. 10. My friends and family think online shopping apps are beneficial during the pandemic.

	11. My friends and family think it is a good idea to use online shopping apps during the pandemic. 12. My friends and family supported me in using online shopping apps during the pandemic.
Trust (Hong et al., 2021)	13. I believe Online shopping apps are trustworthy. 14. I believe online shopping apps keep customer's interests in mind. 15. I felt secure while using online shopping apps and receiving my delivery. 16. I can rely on the information provided by online shopping apps. 17. I feel safe sharing my personal information with online shopping apps. 18. I am not concerned about the violation of my privacy on online shopping apps.
Perceived Task-Technology Fit (Zhao et al., 2020)	19. The features of online shopping apps are enough to search, order, and receive the products I needed. 20. The features of online shopping apps are convenient to help manage the searching, ordering, and receiving the products during the pandemic. 21. The features of online shopping apps meet my requirements for searching, ordering, and receiving the products I needed during the pandemic. 22. The features of online shopping apps met my safety concerns regarding social distancing during the pandemic.
Customer Satisfaction (Zhao et al., 2020)	23. I am very satisfied that online shopping apps meet my requirements during the COVID-19 pandemic. 24. I am satisfied with online shopping apps' efficiency during the COVID-19 pandemic.

	25. My experience with online shopping apps is very satisfactory. 26. I think using online shopping apps during the pandemic was a good choice.
Continuance Intention (Erjavec & Manfreda, 2022)	27. I will use online shopping apps if another pandemic occurs. 28. If I get to choose, I continue shopping using online shopping apps. 29. I still prefer online shopping apps over my past shopping behavior. 30. I will continue using online shopping apps in the future.
Time-Saving Benefits (Hong et al., 2021)	31. Using online shopping applications is time-saving. 32. Using online shopping applications helps me do shopping quicker. 33. It is important to me that I can search, purchase, and receive my items fast on online shopping applications.
Price-Saving Benefits (Hong et al., 2021)	34. Using online shopping applications saves money. 35. I can get cheaper deals on online shopping applications. 36. I get better value for my money using online shopping applications. 37. Online shopping apps provided me with lower prices.
Perceived Severity (Hong et al., 2021)	38. I could get sick with the new coronavirus for a long time. 39. Getting COVID-19 could have a severe, negative effect on my life quality. 40. I am afraid that I might die if I get COVID-19. 41. Those who get sick by the new coronavirus go through more severe times than those who are infected with other illnesses. 42. Recovering from COVID-19 infection is very hard.
Perceived Vulnerability (Hong et al., 2021)	43. The fact that someone else got COVID-19 does not mean I would also get infected.

	44. In my opinion, the COVID-19 outbreak as shown by the media is a contained thread and it is not a threat to me. 45. I consider myself healthy and I do not count myself susceptible to COVID-19.

4.3. Data analysis

Quantitative data collected through surveys can be analyzed in two main ways, including descriptively and inferentially (Saunders et al., 2015; Saunders, M., P. Lewis, 2007). Descriptive statistics summarize the collected data and enable researchers to provide additional context, a more concise overview, or a more accurate representation of the phenomenon of interest. In order to gain a deeper understanding of the behavioral intention of the users of online shopping apps during the COVID-19 pandemic and to visualize the data, a sample descriptive analysis will be performed on the demographic information gathered from the questionnaire. Inferential statistics will be used to test hypotheses and draw conclusions based on the data. All the analyses in this study will be conducted using the statistical analysis software SPSS.

In order to prove the connection between an independent and dependent variable, regression analysis can be used as a statistical tool. Multiple linear regression analysis is a technique that allows additional variables to be analyzed independently so that the effect of each independent variable can be estimated.

In addition, multicollinearity in the data must be eliminated before conducting multiple regression analysis (Pallant, 2020). There is a multicollinearity problem when the independent factors are overly correlated with one another, which makes it difficult to determine which independent factors influence the dependent factor (Hew et al., 2015). In order to check for multicollinearity, this study will use a Pearson correlation analysis.

Since stepwise linear regression can be used to examine the impact of multiple independent variables on a dependent one, this type of regression analysis will be utilized to investigate the components of the proposed research model in SPSS. The impact of these variables on the analyzed dependent variable, the tendency to continue using online shopping apps during the COVID-19 pandemic, will be examined in greater depth.

4.4. Reliability

To assess the reliability of this questionnaire, the internal correlation method, Cronbach's alpha, was used by SPSS. Cronbach's alpha method for measuring the reliability of the questionnaire is a statistical test that results in a coefficient called Cronbach's alpha. Cronbach's alpha method is used to test the reliability of a questionnaire that is designed as a Likert scale (Connelly, 2011). The value of the alpha coefficient is between zero and one, and values greater than 0.7 are acceptable for the reliability of the questionnaire.

4.5 Data Analysis Method

After the survey responses were collected, the raw data was analyzed using SPSS Version 26. By analyzing the data with SPSS, the validity and reliability of dimensions were measured through factor analysis and reliability tests. Analysis of the data was carried out by Pearson Correlation Analysis and Regression Analysis.

5. DATA ANALYSIS AND RESULTS

5.1. Demographic Profile

In this part of the statistical analysis, the distribution of the statistical samples in terms of demographic variables such as gender, age, income, geographical location, nationality, and education has been investigated.

Table 5.1 Demographic Profile of the Survey Respondents

GENDER	FREQUENCY	SAMPLE
Male	125	41%
Female	179	59%

LEVEL OF EDUCATION		
Highschool	1	.32%
Bachelor's Degree	149	49%
Master's Degree	125	41%
PhD	29	9.5%
AGE		
18-24	38	12%
25-34	163	53%
35-44	85	27%
45-54	11	3.6%
55 and older	7	2.3%
MONTHLY PERSONAL INCOME		
Less than $200	43	14%
$200-$349	53	17%
$350-$499	40	13%
$500-$649	32	10%
$650-$799	11	3.6%
$800-$949	16	5.2%
$950 AND MORE	109	3.5%
NATIONALITY		
Iranian	104	34%
Turkish	72	23%
German	56	18%
American	49	16%
Nigerian	3	1%
Dutch	20	6%

In the statistical sample studied in the current research, out of 304 respondents, about 41% were men, and nearly 59% were women.

Statistical analysis of the sample in terms of education level showed that less than 1% of the respondents had high school, 49% of them had a bachelor's degree, 41% of the respondents had a master's degree, and 9% had a Ph.D.

The statistical analysis of the sample in terms of age showed that 12% of them are between the ages of 18-24 years and 53% of the respondents are between the ages of 25-34 years, and 27% of the respondents are between the ages of 35-44 and 3% of the respondents are between the ages 45-54 and 2% of respondents were 55 and older.

Statistical analysis of the sample in terms of monthly personal income showed that 14% of the respondents have an income of less than \$200, 17% of the people with an income between \$200-\$349, 13% of the people with an income between \$350-\$499 and 10% of the respondents between \$500 -\$649 and 3% of respondents have an income between \$650-\$799, 5% have \$800-\$949, and 35% of respondents have an income of \$950 and more.

5.2. Factor Analysis and Reliability

To check the construct validity and reliability of the scales, exploratory factor analysis and reliability analysis were applied (Kim et al., 1978; Bolarinwa, 2015).

5.2.1. Reliability Analysis for Performance Expectancy

Kaiser-Meyer-Olkin test of sampling adequacy for the PE shows to be .788, which is higher than the .5 minimum score suggested. Therefore, the results are adequate. Moreover, the anti-image analysis shows a score of .5 and above for all other items in the factor.

Doing the reliability analysis shows that Cronbach's alpha of the factor is .843, which is above .7 and makes the factor reliable. Furthermore, no items yield the Cronbach's alpha score higher than the total Cronbach if they are deleted; hence all items in the scale are acceptable, and none of them were removed.

Following the analysis, the total variance explained is 68.39%, and the inter-item correlation between the items is high. The reliability analysis makes the factor reliable for testing the hypothesis.

Table 5.2 Reliability test for Performance Expectancy

Factor Name	Items	Item's Cronbach	Cronbach Alpha	Variance Explained
Performance Expectancy	PE1	.804	.843	
	PE2	.784		
	PE3	.80		
	PE4	.819		
Total				68.39%
Kaiser Mayer Olkin Measure of Sampling				.788
Bartlett's Test of Sphericity			Approx. Chi-Square	503.282
			df.	6
			Sig.	.000

5.2.2. Reliability Analysis for Effort Expectancy

Kaiser-Meyer-Olkin test of sampling adequacy for the EE scale shows to be .698, which is higher than the .5 minimum score suggested. Therefore, the results are adequate. Moreover, the anti-image analysis shows a score of .5 and above for all other items in the factor.

Doing the reliability analysis shows that Cronbach's alpha of the factor is .810, which is above .7 and makes the factor reliable. Furthermore, no items yield the Cronbach's alpha score higher than the total Cronbach if they are deleted; hence all items in the scale are acceptable, and none of them were removed.

Following the analysis, the total variance explained is 63.919%, and the inter-item correlation between the items is high. The reliability analysis makes the factor reliable for testing the hypothesis.

Table 5.3 shows the reliable items of the EE scale used in this study.

Table 5.3 Reliability test for Effort Expectancy

Factor Name	Items	Item's Cronbach	Cronbach Alpha	Variance Explained
Effort Expectancy	EE1	.778	.810	
	EE2	.739		
	EE3	.770		
	EE4	.761		
Total				63.919%
Kaiser Mayer Olkin Measure of Sampling				.698
Bartlett's Test of Sphericity			Approx. Chi-Square	436.486
			df.	6
			Sig.	.000

5.2.3 Reliability Analysis for Social Influence

For the reliability of the SI scale, four items were in the analysis. It turned out that if the item SI1 is included in the analysis, Cronbach's alpha score is .692, which will be below .7 and will affect the credibility of the factor. Removing one item, SI1, the new Cronbach's alpha will be .810, which is an acceptable score.

Moreover, the Kaiser-Meyer-Olkin test of sampling adequacy for the EE scale is .672, which is higher than the .5 minimum score suggested. Therefore, the results are adequate. Moreover, the anti-image analysis shows a score of .4 and above for all other items in the factor.

Following the analysis, the total variance explained is 63.919%, and the inter-item correlation between the items is at a sufficient score. The reliability analysis makes the factor reliable for testing the hypotheses.

Table 5.4 shows the reliable items of the SI scale used in this study.

Table 5.4 Reliability test for Social Influence

Factor Name	**Items**	**Item's Cronbach**	**Cronbach Alpha**	**Total Variance Explained**
Social Influence	SI2	.732	.810	
	SI3	.653		
	SI4	.809		
Total				63.919%
Kaiser Mayer Olkin Measure of Sampling				.672
Bartlett's Test of Sphericity			Approx. Chi-Square	348.951
			df.	3
			Sig.	.000

5.2.4. Reliability Analysis for Trust

Kaiser-Meyer-Olkin test of sampling adequacy for the trust scale shows to be .782 and is higher than the .5 minimum score suggested. Therefore, the results are adequate. Moreover, the anti-image analysis shows a score of .5 and above for all other items in the factor.

Doing the reliability analysis shows that Cronbach's alpha of the factor is .743, which is above .7 and makes the factor reliable. Furthermore, no items yield the Cronbach's alpha score higher than the total Cronbach if they are deleted; hence all items in the scale are acceptable, and none of them were removed.

Following the analysis, the total variance explained is 45.416%, and the inter-item correlation between the items is high. The reliability analysis makes the factor reliable for testing the hypothesis.

Table 5.5 shows the reliable items of the trust scale used in this study.

Table 5.5 Reliability test for Trust

Factor Name	Items	Item's Cronbach	Cronbach Alpha	Variance Explained
Trust	TR1	.708	.743	
	TR2	.731		
	TR3	.672		
	TR4	.707		
	TR5	.682		
	TR6	.737		
Total				45.416%
Kaiser Mayer Olkin Measure of Sampling				.782
Bartlett's Test of Sphericity			Approx. Chi-Square	475.066
			df.	15
			Sig.	.000

5.2.5. Reliability Analysis for Task-Technology Fit

For the reliability of the TTF scale, four items were in the analysis. When TTF4 was removed from the analysis, there was some increase in the reliability and Cronbach's alpha is .823, which is acceptable.

Moreover, the Kaiser-Meyer-Olkin test of sampling adequacy for the EE scale is .714, which is higher than the .5 minimum score suggested. Therefore, the results are adequate. Moreover, the anti-image analysis shows a score of 0.4 and above for all other items in the factor.

Following the analysis, the total variance explained is 74.497%, and the inter-item correlation between the items is at a sufficient score. The reliability analysis makes the factor reliable for testing the hypotheses.

Table 5.6 Reliability test for Task-Technology Fit

Factor Name	Items	Item's Cronbach	Cronbach Alpha	Total Variance Explained
Task-Tech Fit	TTF1	.778	.823	
	TTF2	.718		
	TTF3	.777		
Total				74.497%
Kaiser Mayer Olkin Measure of Sampling				.714
Bartlett's Test of Sphericity			Approx. Chi-Square	341.369
			df.	3
			Sig.	.000

5.2.6 Reliability Analysis for Satisfaction

Kaiser-Meyer-Olkin test of sampling adequacy for the satisfaction scale shows to be .799 and is higher than the .5 minimum score suggested. Therefore, the results are adequate. Moreover, the anti-image analysis shows a score of .5 and above for all other items in the factor.

Doing the reliability analysis shows that Cronbach's alpha of the factor is .835, which makes our satisfaction factor reliable. Furthermore, no items yield a Cronbach's alpha score higher than .835, the total Cronbach, if they are deleted, hence all items in the scale are acceptable, and none of them were removed.

Following the analysis, the total variance explained is 66.986%, and the inter-item correlation between the items is high. The reliability analysis makes the factor reliable for testing the hypothesis.

Table 5.7 Reliability test for Satisfaction

Factor Name	Items	Item's Cronbach	Cronbach Alpha	Variance Explained
Satisfaction	SAT1	.782	.835	
	SAT2	.754		
	SAT3	.801		
	SAT4	.822		
Total				66.986%
Kaiser Mayer Olkin Measure of Sampling				.799
Bartlett's Test of Sphericity			Approx. Chi-Square 465.184	
			df. 6	
			Sig. .000	

5.2.7 Reliability Analysis for Continuance Intention

While conducting the reliability test for the continuance intention scale, three of the four items were used in the analysis and one item (CI1) was removed. The Cronbach's alpha for these three items is .850, which is an acceptable score. The reliability score was reached by removing the CI1 item, which resulted in some increases in the total Cronbach's alpha score.

Considering the three items of CI2, CI3, and CI4, the Kaiser-Meyer-Olkin test of sampling adequacy for the EE scale, is .715 and is higher than the .5 minimum score suggested. Therefore, the results are adequate. Moreover, the anti-image analysis shows a score of .4 and above for all other items in the factor.

Following the analysis, the total variance explained is 77.565%, and the inter-item correlation between the items is at a sufficient score. The reliability analysis makes the factor reliable for testing the hypotheses.

Table 5.8 Reliability test for Continuance Intention

Factor Name	Items	Item's Cronbach	Cronbach Alpha	Total Variance Explained
Continuance Intention	CI2	.764	.850	
	CI3	.740		
	CI4	.848		
Total				77.565%
Kaiser Mayer Olkin Measure of Sampling				.715
Bartlett's Test of Sphericity			Approx. Chi-Square 418.115	
			df.	3
			Sig.	.000

5.2.8. Reliability Analysis for Time-Saving Benefits

Kaiser-Meyer-Olkin test of sampling adequacy for the time-saving benefits scale shows to be .679 and is higher than the .5 minimum score suggested. Therefore, the results are adequate. Moreover, the anti-image analysis shows a score of .3 and above for all other items in the factor.

Doing the reliability analysis shows that Cronbach's alpha of the factor is .841, which makes our time-saving benefit factor reliable. Furthermore, no items yield a Cronbach's alpha score higher than .841, the total Cronbach, if they are deleted, hence all items in the scale are acceptable, and none of them were removed.

Following the analysis, the total variance explained is 76.042%, and the inter-item correlation between the items is high. The reliability analysis makes the factor reliable for testing the hypothesis.

Table 5.9 Reliability test for Time-Saving Benefits

Factor Name	Items	Item's Cronbach	Cronbach Alpha	Total Variance Explained
Time-Saving Benefits	TSB1	.727	.841	
	TSB2	.705		
	TSB3	.838		
Total				76.042%
Kaiser Mayer Olkin Measure of Sampling				.679
Bartlett's Test of Sphericity			Approx. Chi-Square	423.664
			df.	3
			Sig.	.000

5.2.9. Reliability Analysis for Price-Saving Benefits

Kaiser-Meyer-Olkin test of sampling adequacy for the price-saving benefits scale shows to be .885 and is higher than the .5 minimum score suggested. Therefore, the results are adequate. Moreover, the anti-image analysis shows a score of .3 and above for all other items in the factor.

Doing the reliability analysis shows that Cronbach's alpha of the factor is .906, which makes our price-saving benefit factor reliable. By removing one of the items, Cronbach's alpha of the factor yields .917, but as the reliability is at a very high level, the item was not removed. Therefore, all six items for the factor are in the analysis.

Following the analysis, the total variance explained is 68.837%, and the inter-item correlation between the items is high. The reliability analysis makes the factor reliable for testing the hypothesis.

Table 5.10 Reliability test for Price-Saving Benefits

Factor Name	Items	Item's Cronbach	Cronbach Alpha	Variance Explained
Price-Saving Benefits	PSB1	.886	.906	
	PSB 2	.885		
	PSB 3	.917		
	PSB 4	.883		
	PSB 5	.875		
	PSB 6	.604		
Total				68.837%
Kaiser Mayer Olkin Measure of Sampling				.885
Bartlett's Test of Sphericity			Approx. Chi-Square	1231.921
			df.	15
			Sig.	.000

5.2.10. Reliability Analysis for Perceived Severity

Kaiser-Meyer-Olkin test of sampling adequacy for the PS scale shows to be .773 and is higher than the .5 minimum score suggested (Hair et al., 2010). Therefore, the results are adequate. Moreover, the anti-image analysis shows a score of 0.5 and above for all other items in the factor.

Doing the reliability analysis shows that Cronbach's alpha of the factor is 0.773, which makes our PS measure reliable. Furthermore, no items yield Cronbach's alpha score higher than 0.773 and hence all items in the scale are acceptable, and none of them were removed.

Following the analysis, the total variance explained is 52.748%, and the inter-item correlation between the items is high. The reliability analysis makes the factor reliable for testing the hypothesis.

Table 5.11 Reliability test for Perceived Severity

Factor Name	Items	Item's Cronbach	Cronbach's Alpha	Variance Explained
Perceived Severity	PS1	.766	.773	
	PS2	.738		
	PS3	.723		
	PS4	.718		
	PS5	.708		
Total				52.748%
Kaiser Mayer Olkin Measure of Sampling				.773
Bartlett's Test of Sphericity			Approx. Chi-Square 382.844	
			df.	10
			Sig. .000	

5.2.11. Reliability Analysis for Perceived Vulnerability

The perceived vulnerability (PV) scale consisted of reverse code questions in the questionnaire. Therefore, before analyzing the data, reverse coding was performed. After the reliability test of three items, Cronbach's alpha turned out to be .581, which shows a low consistency between the items. As a result, item one was removed, yielding Cronbach's alpha score of .640. Considering the fact that there are only two items in the analysis, this score is accepted since it shows a score of above .6 after removing one item (Durmuş, 2013).

The Kaiser-Meyer-Olkin test of sampling adequacy for the PV scale shows to be .500 and meets the minimum score of .5 suggested. Therefore, the results are adequate. Moreover, the anti-image analysis shows a score of 0.5 and above for all other items in the factor.

Following the analysis, the total variance explained is 73.545%, and the inter-item correlation between the items is high. The reliability analysis makes the factor reliable for testing the hypothesis.

Table 5.12 Reliability test for Perceived Vulnerability

Factor Name	Items	Item's Cronbach	Cronbach's Alpha	Variance Explained
Perceived Vulnerability	PV2R	-	.640	73.545%
	PV3R	-		
Total				
Kaiser Mayer Olkin Measure of Sampling				
Bartlett's Test of Sphericity			Approx. Chi-Square	75.587
			df.	1
			Sig.	.000

5.3. Correlation Analysis

To understand the relationship between the variable, correlation analysis is performed. Literature suggests that for the discriminant validity between the constructs, the correlation should not exceed .85 (Kline, 2005). On the other hand, Hair et al. (2010) suggests that values greater than .85 are also acceptable if they are supported by other analyses.

You can see the Pearson Correlation results of the constructs in Table 5.13.

Table 5.13 Correlation Analysis

Correlations

		PE	EE	SI	Trust	TTF	SAT	CI	PSB	TSB	PS	PVRM
PE	Pearson Correlation	1	.425**	.442**	.292**	.369**	.643**	.619**	.386**	.549**	.063	.218**
	Sig. (2-tailed)		.000	.000	.000	.000	.000	.000	.000	.000	.274	.000
	N	303	303	303	303	303	303	303	303	303	303	303

EE	Pearson Correlation	.425**	1	.248**	.392**	.413**	.445**	.352**	.320**	.422**	.052	.058
	Sig. (2-tailed)	.000		.000	.000	.000	.000	.000	.000	.000	.365	.317
	N	303	303	303	303	303	303	303	303	303	303	303
SI	Pearson Correlation	.442**	.248**	1	.328**	.419**	.438**	.377**	.335**	.320**	.179**	-.240**
	Sig. (2-tailed)	.000	.000		.000	.000	.000	.000	.000	.000	.002	.000
	N	303	303	303	303	303	303	303	303	303	303	303
Trust	Pearson Correlation	.292**	.392**	.328**	1	.551**	.490**	.425**	.489**	.437**	.169**	-.100
	Sig. (2-tailed)	.000	.000	.000		.000	.000	.000	.000	.000	.003	.083
	N	303	303	303	303	303	303	303	303	303	303	303
TTF	Pearson Correlation	.369**	.413**	.419**	.551**	1	.609**	.447**	.459**	.380**	.284**	-.053
	Sig. (2-tailed)	.000	.000	.000	.000		.000	.000	.000	.000	.000	.357
	N	303	303	303	303	303	303	303	303	303	303	303
SAT	Pearson Correlation	.643**	.445**	.438**	.490**	.609**	1	.685**	.574**	.598**	.213**	.053
	Sig. (2-tailed)	.000	.000	.000	.000	.000		.000	.000	.000	.000	.355
	N	303	303	303	303	303	303	303	303	303	303	303
CI	Pearson Correlation	.619**	.352**	.377**	.425**	.447**	.685**	1	.527**	.588**	.206**	.034
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000		.000	.000	.000	.556
	N	303	303	303	303	303	303	303	303	303	303	303
PSB	Pearson Correlation	.386**	.320**	.335**	.489**	.459**	.574**	.527**	1	.425**	.110	-.069
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	.000		.000	.055	.232
	N	303	303	303	303	303	303	303	303	303	303	303
TSB	Pearson Correlation	.549**	.422**	.320**	.437**	.380**	.598**	.588**	.425**	1	.036	.022
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	.000	.000		.529	.699
	N	303	303	303	303	303	303	303	303	303	303	303
PS	Pearson Correlation	.063	.052	.179**	.169**	.284**	.213**	.206**	.110	.036	1	-.026
	Sig. (2-tailed)	.274	.365	.002	.003	.000	.000	.000	.055	.529		.648
	N	303	303	303	303	303	303	303	303	303	303	303

PVRM	Pearson Correlation	.218**	.058	-.240**	-.100	-.053	.053	.034	-.069	.022	-.026	1
	Sig. (2-tailed)	.000	.317	.000	.083	.357	.355	.556	.232	.699	.648	
	N	303	303	303	303	303	303	303	303	303	303	304

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

5.4. Regression Analysis

The regression analysis was done to find the effects of independent variables on a dependent variable. As a necessary step to find the relationship between the constructs of the model and for testing the hypotheses, stepwise and simple linear regression analyses were performed using SPSS version 26.

5.4.1 Regression Analysis for Performance Expectancy, Effort Expectancy, Social Influence, Trust, and Satisfaction

PE, EE, SI, and trust are independent variables in this regression, while satisfaction performs as the dependent variable. The following regression analyses are aimed at testing hypotheses H1a, H2a, H4a, and H5a.

Analyzing the linear regression results, standardized beta coefficients scores show that all four constructs of PE (β= .464, p= .000), EE (β= .112, p= .016), SI (β= .116, p= .011), and trust (β= .273, p= .000) have significant positive effects on satisfaction, as none were excluded in the model summary. Thus, all four hypotheses are supported.

Based on Table 5.14, a cumulative 53% of changes in satisfaction are explained by these four constructs. At the same time, PE has the most significant effect on users' satisfaction, being accountable for more than 41% of changes in satisfaction.

Table 5.14 Multiple Linear Regression Analysis for PE, EE, SI, TR and SAT

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.643[a]	.413	.411	.47365
2	.716[b]	.513	.510	.43204
3	.724[c]	.523	.519	.42815
4	.730[d]	.533	.526	.42470

a. Predictors: (Constant), PE

b. Predictors: (Constant), PE, Trust

c. Predictors: (Constant), PE, Trust, SI

d. Predictors: (Constant), PE, Trust, SI, EE

Table 5.15Regression Analysis - Coefficients of PE, EE, SI, TR and SAT

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients			Correlations		
		B	Std. Error	Beta	t	Sig.	Zero-order	Partial	Part
1	(Constant)	1.530	.173		8.832	.000			
	PE	.588	.040	.643	14.551	.000	.643	.643	.643
2	(Constant)	.775	.185		4.193	.000			
	PE	.499	.039	.546	12.968	.000	.643	.599	.522
	Trust	.340	.043	.331	7.859	.000	.490	.413	.317
3	(Constant)	.663	.188		3.520	.000			
	PE	.459	.041	.502	11.114	.000	.643	.541	.444
	Trust	.314	.044	.306	7.123	.000	.490	.381	.284
	SI	.105	.041	.116	2.546	.011	.438	.146	.102
4	(Constant)	.493	.200		2.473	.014			
	PE	.425	.043	.464	9.787	.000	.643	.493	.388
	Trust	.281	.046	.273	6.115	.000	.490	.334	.242
	SI	.105	.041	.116	2.560	.011	.438	.147	.101
	EE	.108	.044	.112	2.425	.016	.445	.139	.096

a. Dependent Variable: SAT

Looking at table 5.15, the coefficient results also prove that all four constructs have a significant positive effect on satisfaction (Sig. < .05).

Table 5.16 Regression Analysis - ANOVA Results of PE, EE, SI, TR and SAT

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	47.498	1	47.498	211.722	.000[b]
	Residual	67.527	301	.224		
	Total	115.025	302			
2	Regression	59.027	2	29.513	158.112	.000[c]
	Residual	55.998	300	.187		
	Total	115.025	302			
3	Regression	60.215	3	20.072	109.494	.000[d]
	Residual	54.810	299	.183		
	Total	115.025	302			
4	Regression	61.276	4	15.319	84.932	.000[e]
	Residual	53.749	298	.180		
	Total	115.025	302			

a. Dependent Variable: SAT

b. Predictors: (Constant), PE

c. Predictors: (Constant), PE, Trust

d. Predictors: (Constant), PE, Trust, SI

e. Predictors: (Constant), PE, Trust, SI, EE

5.4.2 Regression Analysis for Effort Expectancy and Performance Expectancy

As one of the most important constructs of the model that is hypothesized to have a significant effect on satisfaction and continuance intention, we have also analyzed the relationship between EE and PE to better understand how EE can affect PE.

The regression analysis has EE as the independent variable and PE as the dependent variable and shows a significant correlation between the two constructs. With the R square score of 0.181, EE is responsible for 18% of changes in PE. Table 5.17

shows the model summary of the relationship between EE and PE and how EE affects PE.

Table 5.17 Multiple Regression Analysis for EE and PE

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.425[a]	.181	.178	.61194

a. Predictors: (Constant), EE

Table 5.18 Regression Analysis - Coefficients of EE & PE

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients			Correlations		
		B	Std. Error	Beta	t	Sig.	Zero-order	Partial	Part
1	(Constant)	2.452	.222		11.058	.000			
	EE	.448	.055	.425	8.145	.000	.425	.425	.425

a. Dependent Variable: PE

Table 5.19 Regression Analysis - ANOVA Results of EE and PE

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	24.842	1	24.842	66.338	.000[b]
	Residual	112.716	301	.374		
	Total	137.558	302			

a. Dependent Variable: PE

b. Predictors: (Constant), EE

Table 5.18 shows that EE (β= .425, p= .000) has a significant positive effect on PE. Therefore, the results of the regression analysis approve the H3 hypothesis of our proposed model.

5.4.3 Regression Analysis for Perceived Task-Technology Fit and Satisfaction

To analyze the relationship between the two constructs of TTF and customer satisfaction, the model has TTF as the independent and the latter as the dependent variable. The R square shows that TTF is responsible for 37% of changes in customer satisfaction. Table 5.20 shows the details of the model summary.

Table 5.20 Multiple Regression Analysis for TTF and SAT

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.609[a]	.371	.369	.49014

a. Predictors: (Constant), TTF

Table 5.21 Regression Analysis - Coefficients of TTF and SAT

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients			Correlations		
		B	Std. Error	Beta	t	Sig.	Zero-order	Partial	Part
1	(Constant)	1.826	.167		10.943	.000			
	TTF	.578	.043	.609	13.334	.000	.609	.609	.609

a. Dependent Variable: SAT

Considering the results of Table 5.21, we can say that H6a is supported and TTF (β= .609, p= .000) has a significant positive effect on satisfaction.

Table 5.22 Regression Analysis - ANOVA Results of TTF and SAT

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	42.714	1	42.714	177.800	.000[b]
	Residual	72.311	301	.240		
	Total	115.025	302			

a. Dependent Variable: SAT

b. Predictors: (Constant), TTF

5.4.4 Regression Analysis for PP, EE, SI, and Trust and Continuance Intention

PE, EE, SI, and trust are independent variables in this regression, while satisfaction performs as the dependent variable. The following regression analysis is aimed at testing the H1b, H2b, H4b, and H5b hypotheses.

Analyzing the stepwise regression results, correlation scores show only two constructs of PE (β= .541, p= .000) and Trust (β= .267, p= .000) have a significant positive effect on continuance intention (CI). While the relationship between the other two constructs, EE and SI, and CI were not so significant. Therefore, they were excluded from the model summary.

By considering two constructs of PE and trust, the overall power of the model is around 45%, while PE is responsible for 38% of changes in the Continuance Intention. Table 5.23 explains the model summary and the results.

Table 5.23 Multiple Regression Analysis for PE, EE, SI, Trust and CI

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.619[a]	.383	.381	.59014
2	.670[b]	.449	.445	.55886

a. Predictors: (Constant), PE

b. Predictors: (Constant), PE, Trust

Table 5.24 Regression Analysis - Coefficients of PE, EE, SI, Trust and CI

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Correlations Zero-order	Correlations Partial	Correlations Part
1	(Constant)	1.072	.216		4.969	.000			
	PE	.688	.050	.619	13.681	.000	.619	.619	.619
2	(Constant)	.331	.239		1.384	.167			
	PE	.602	.050	.541	12.079	.000	.619	.572	.518
	Trust	.334	.056	.267	5.970	.000	.425	.326	.256

a. Dependent Variable: CI

Table 5.25 Regression Analysis - ANOVA Results of PE, EE, SI, Trust and CI

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	65.187	1	65.187	187.174	.000[b]
	Residual	104.829	301	.348		
	Total	170.016	302			
2	Regression	76.317	2	38.159	122.174	.000[c]
	Residual	93.699	300	.312		
	Total	170.016	302			

a. Dependent Variable: CI

b. Predictors: (Constant), PE

c. Predictors: (Constant), PE, Trust

Table 5.24, the standardized coefficients scores, support two out of four hypotheses developed based on the model, H1b and H5b, while hypotheses H2b and H4b are not supported.

5.4.5. Regression Analysis for Perceived Task-Technology Fit and Continuance Intention

The regression analysis has two constructs of Task-Technology Fit (TTF) as the independent variable and Continuance Intention (CI) as the dependent variable. The results show a significant correlation between the two constructs of the model. At the same time, TTF is responsible for about 20% of changes in users' continuance intention. Table 5.26 shows the details of the model.

Table 5.26 Multiple Regression Analysis for TTF and CI

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.447[a]	.200	.197	.67225

a. Predictors: (Constant), TTF

Table 5.27 Regression Analysis - Coefficients of TTF and CI

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients			Correlations		
		B	Std. Error	Beta	t	Sig.	Zero-order	Partial	Part
1	(Constant)	2.032	.229		8.879	.000			
	TTF	.516	.059	.447	8.672	.000	.447	.447	.447

a. Dependent Variable: CI

Table 5.27 explains that TTF (β= .447, p= .000) has a significant positive effect on continuance intention, where the significance is less than .05.

Table 5.28 Regression Analysis - ANOVA Results of TTF and CI

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	33.988	1	33.988	75.208	.000[b]
	Residual	136.028	301	.452		
	Total	170.016	302			

a. Dependent Variable: CI

b. Predictors: (Constant), TTF

Therefore, our hypothesis H6b is supported, and task-technology fit has a positive effect on users' continuance intention.

5.4.6. Regression Analysis for Satisfaction and Continuance Intention

Satisfaction as the independent and continuance intention as the dependent variable are the two constructs tested in this regression to test our hypothesis H7.

The results of the linear regression analysis show that there is a significant relationship between the two constructs. And Table 5.29 explains that about 47% of continuance intention is because users are satisfied with the online shopping application they are using.

Table 5.29 Multiple Regression Analysis for SAT and CI

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.685[a]	.469	.468	.54741

a. Predictors: (Constant), SAT

Table 5.30 Regression Analysis - Coefficients of SAT and CI

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Correlations Zero-order	Correlations Partial	Correlations Part
1	(Constant)	.640	.207		3.087	.002			
	SAT	.833	.051	.685	16.321	.000	.685	.685	.685

a. Dependent Variable: CI

Table 5.31 Regression Analysis - ANOVA Results of SAT and CI

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	79.818	1	79.818	266.362	.000[b]
	Residual	90.198	301	.300		
	Total	170.016	302			

a. Dependent Variable: CI

b. Predictors: (Constant), SAT

While table 5.30 shows that customer satisfaction (β= .685, p= .000) statistically affects continuance intention significantly positively. Therefore, the tested hypothesis (H7) is approved.

5.4.7. Regression Analysis for Perceived Severity, Perceived Vulnerability, and Continuance Intention

In the stepwise linear regression analysis, two constructs of Perceived Severity (PS) and Perceived Vulnerability (PV) were chosen as independent variables, while Continuance Intention was chosen to be the dependent variable. The results did not show any significant relation between PV and continuance intention. Therefore, the construct was excluded from the model. On the other hand, the model summary, explained in table 5.32, shows only 4.3% of continuance intention is affected by the perceived severity.

Table 5.32 Multiple Linear Regression Analysis for Ps, PV and CI

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.206[a]	.043	.039	.73541

a. Predictors: (Constant), PS

Table 5.33 Regression Analysis - Coefficients of PS, PV and CI

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Correlations		
		B	Std. Error	Beta			Zero-order	Partial	Part
1	(Constant)	3.299	.193		17.100	.000			
	PS	.214	.058	.206	3.656	.000	.206	.206	.206

a. Dependent Variable: CI

Table 5.34 Regression Analysis - ANOVA Results of PS, PV and CI

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	7.227	1	7.227	13.363	.000[b]
	Residual	162.789	301	.541		
	Total	170.016	302			

a. Dependent Variable: CI

b. Predictors: (Constant), PS

Table 5.33, however, shows that there is a positive relationship between PS (β= .206, p= .000) and CI. Therefore, only one of the two hypotheses tested, H8, here is approved, and H9 is not supported by the results.

5.4.8. Regression Analysis for Time-Saving Benefits, Price-Saving Benefits and Continuance Intention

In order to test the two hypotheses of H10 and H11, the stepwise linear regression was done where time-saving benefits (TSB) and price-saving benefits (PSB) are the independent variables, and continuance intention is the dependent variable.

The analysis shows that the relationship between the two constructs of TSB and PSB with continuance intention is significant. Therefore, none of the constructs were removed from the model summary. The model summary shows that continuance intention is 34.5% affected by time-saving benefits, while a total of 44% of it is affected by TSB and PSB together. The details of the model summary are shown in Table 5.35 below:

Table 5.35 Multiple Linear Regression Analysis for TSB, PSB and CI

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.588[a]	.345	.343	.60806
2	.663[b]	.439	.435	.56384

a. Predictors: (Constant), TSB

b. Predictors: (Constant), TSB, PSB

Table 5.36 Regression Analysis - Coefficients of PSB, TSB and CI

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Correlations Zero-order	Correlations Partial	Correlations Part
1	(Constant)	1.381	.210		6.582	.000			
	TSB	.624	.049	.588	12.603	.000	.588	.588	.588
2	(Constant)	.985	.202		4.864	.000			
	TSB	.471	.051	.444	9.297	.000	.588	.473	.402
	PSB	.303	.043	.338	7.076	.000	.527	.378	.306

a. Dependent Variable: CI

Table 5.36 shows that PSB (β= .338, p= .000) and TSB (β= .444, p= .000) have positive effects on CI. Thus, both hypotheses H10 and H11 are supported.

Table 5.37 Regression Analysis - ANOVA Results of TSB, PSB and CI

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	58.726	1	58.726	158.835	.000[b]
	Residual	111.290	301	.370		
	Total	170.016	302			
2	Regression	74.643	2	37.322	117.396	.000[c]
	Residual	95.373	300	.318		
	Total	170.016	302			

a. Dependent Variable: CI

b. Predictors: (Constant), TSB

c. Predictors: (Constant), TSB, PSB

5.5. Hypotheses Results and Final Model

Table 5.38 Results of Hypotheses

Hypothesis	Result
H1a: Performance expectancy has a positive effect on customer satisfaction.	Supported
H1b: Performance expectancy has a positive effect on users' continuance intention.	Supported
H2a: Effort expectancy has a positive effect on customer satisfaction.	Supported
H2b: Effort expectancy has a positive effect on users' continuance Intention.	Not Supported
H3: Effort expectancy has a positive effect on performance expectancy.	Supported
H4a: Social influence has a positive effect on customer satisfaction.	Supported
H4b: Social influence has a positive effect on users' continuance intention.	Not Supported
H5a: Trust has a positive effect on customer satisfaction.	Supported
H5b: Trust has a positive effect on users' continuance intention.	Supported
H6a: Task-Technology Fit has a positive effect on satisfaction.	Supported
H6b: Task-Technology Fit has a positive effect on users' continuance intention.	Supported
H7: Satisfaction has a positive effect on users' continuance intention.	Supported
H8: perceived severity has a positive effect on users' continuance intention.	Supported
H9: Perceived vulnerability has a positive impact on users' continuance intention.	Not Supported

H10: Time-saving benefits has a positive effect on users' continuance intention.	Supported
H11: Price-saving benefits has a positive effect on users' continuance intention.	Supported

The reliability analyses show that all variables are reliable to be used in testing the hypotheses, while some of the questions were removed to increase the reliability of the constructs of the model.

The regression analyses support 13 hypotheses out of 16 proposed hypotheses. H2b and H4b were removed from the proposed model as the analysis shows that EE and SI have no significant relationship with Continuance Intention. Also, H9 was excluded from the final model since the regression analysis shows that there is no significant relationship between Perceived Vulnerability and Continuance Intention.

You can find the final research model in Figure 5.1, which is drawn in accordance with the analysis results.

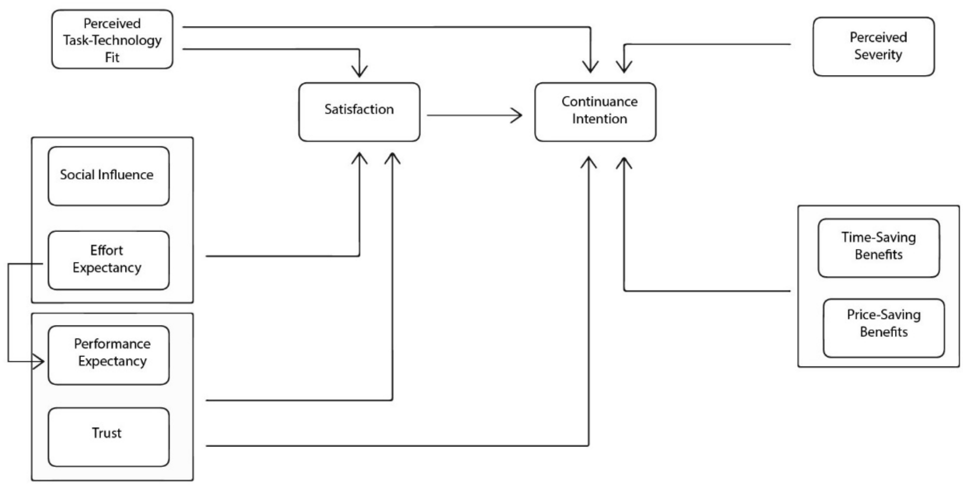

Figure 5.1 Final Research Model

DISCUSSION AND CONCLUSION

By removing the time and place limitations, online shopping applications take away the communication barriers between customers and businesses. As a result, e-commerce greatly impacts the costs of marketing for businesses by removing many limitations that exist in traditional commerce. Online shopping applications have removed time and location restrictions, and customers can access everything at the cost of unlocking their smartphones and opening their desired applications. With the growth of the internet and, consequently, technologies arising from the internet, online shopping applications become more epidemic every day. In such a saturated market, it is important to know how to acquire and, more importantly, maintain customers. As a result, marketers should focus on customer loyalty programs and develop strategies on how to develop strategies to increase loyalty. Studying factors that affect customers' continuance intention is one of the most important struggles in how to encourage customers to continue using an online shopping application after they have adopted the technology.

This study primarily aimed to identify the effects of different factors on users' continuance intention of using online shopping applications during the COVID-19 pandemic. According to the literature, there are different factors that could affect the continuance intention of online shopping applications and new technologies in general while normal conditions are accountable. Considering the fact that this research's goal is to study the effect of factors in a pandemic situation, some other pandemic-related factors were added to the hypothesized effective factors. Since the continuance intention of technologies was previously studied using the UTAUT2 model, four constructs of the model were selected to test their effects on continuance intention. Therefore, PE, EE, trust, and SI were chosen as constructs of extended UTAUT2 (Venkatesh et al., 2003) to function along with other factors in the study's hypothesized model. Results of this study show that out of the four mentioned constructs, only two constructs of PE and trust influence users' continuance intention. Even though previous studies found a positive relationship between continuance intention, SI and EE (Shim et al., 2001; Yuan et al., 2016), the results of this study suggest that SI and EE do not directly affect continuance intention.

Previous studies that used UTAUT2 also tested the effects of Satisfaction on continuance intention (Alaa Mamooni, 2020). Therefore, this study also tested the effects of users' satisfaction on customers' intention to continue using the online shopping application they have adopted. As proved in former studies, the results of this research also show that satisfaction has a significant positive effect on customers' continuance intention.

Furthermore, the effect of four constructs of UTAUT2 that was used in the study was also tested on satisfaction to better understand the factors affecting users' continuance intention. The analysis results show that all four factors of PE, EE, trust, and SI positively affect users' satisfaction. Prior literature (e.g., Yuan et al., 2016; Venkatesh et al., 2011) also approves the relationship between EE and continuance intention and SI and continuance intention. But, in this study, we couldn't find any significant direct relationship between them. This might be partly due to the effects of the COVID-19 pandemic.

If people are to use an application, they should understand that the technology is going to improve their performance (Lee et al., 2007). The Task-Technology Fit model is a model that could measure this perception in users' minds. In this research, the perceived task-technology fit was measured in the survey to study its effect on continuance intention. On the other hand, the effect of TTF on satisfaction was measured. The results show that task-technology fit has positive effects on both users' satisfaction and users' continuance intention. As a result, we can claim that if a customer is gaining what they are expecting from an online shopping application, they are more likely to continue using that application for their future transactions.

Considering all the factors mentioned so far, marketers should keep in mind that if their online shopping application meets users' expectations and can take care of their desired tasks flawlessly and with less hassle, customers are more likely to continue using their application.

Customers are usually chosen to continue using those applications that provide them with some benefits. In the case of online shopping applications, time-saving benefits and price-saving benefits could be two of the most important encouraging factors for users to adopt and continue using such technologies. Given the notion of the COVID-19 pandemic and people's struggles to avoid crowds and physical contact, time-saving benefits like not waiting in lines or traveling back and forth to brick-and-mortar stores could save both time and trouble for users and be an incentive to continue using such applications (Zhou et al., 2007). As found in previous studies, the results of this study also prove that time-saving benefits have positive effects on users' continuance intention.

Different studies, like that by Ray et al. (2021), have studied the effects of time-saving benefits on technology adoption and users' continuance intentions. During the pandemic, which was followed by a financial crisis, online shopping direct and indirect price-saving benefits could save some hassles for consumers. In this study, the results suggest that there's a significant positive relationship between price-saving benefits and users' continuance intention for using online shopping applications.

Noting the results from this study, online shopping applications and those who are marketing them should pay closer attention to the benefits they are providing to their customers so that they can affect their continuance intention positively and increase loyalty among their users.

Fear of getting infected with the coronavirus and the unknown effects of COVID-19 forced both people and governments to follow different preventive measures. The unknown and, in some cases, negative perceptions of getting sick with the coronavirus led to some people preferring not to leave their homes for shopping or other activities. Since this research is studying the factors that affect users' continuance intention of online shopping applications during the COVID-19 pandemic, two factors, perceived vulnerability and perceived severity and their effects on users' continuance intention of online shopping applications were measured. Perceived vulnerability defines as the perception of users about how much they are vulnerable to an illness, in this case, COVID-19. While Perceived Severity defines how much they think the illness is severe and could threaten their health. Surprisingly, the results show that perceived vulnerability does not have a significant effect on continuance intention, while perceived severity affects users' continuance intentions significantly positively.

6.1. Managerial Implications

The world of shopping is an intertwined world where consumers are not only in contact with brands and sellers but get influenced by the world around them. Mastering the knowledge of consumers' behavior has always been important. In special conditions and situations such as the COVID-19 pandemic or other pandemics, consumers show different sides of their behavior that could lead the way for marketers and businesses in their future acquisition strategies.

Online shopping applications and, in general, e-commerce have become a new way of life. People spend lots of time checking prices, researching goods and services, and comparing prices on different online shopping applications. This provides marketers with a distinguished opportunity to acquire customers and increase loyalty among their customers by studying different aspects of consumers' behaviors and their attitudes toward online shopping. Studying users' continuance intention in such situations could provide marketers with knowledge on how to increase customers' lifetime value.

One of the most important factors that could help marketers find solutions to become loyal customers and continue using their online shopping applications is to study what factors affect users' continuance intention. There are many studies that analyzed the effective factors on continuance intention, and marketers already use the findings to attract and nurture customers with different campaigns, offers, and sales based on the findings of such studies.

The COVID-19 pandemic introduced a new opportunity for both businesses and scholars to study consumers' behavior more effectively towards online shopping applications and, in general, mobile-based technologies. The world has experienced different pandemics before, but the COVID-19 pandemic happened in the era of the e-commerce boom, and the dimensions of the pandemic were like no other pandemic that happened in recent decades. Therefore, the pandemic and the existence of viral online shopping applications led to a drastic change in consumers' behavior toward shopping and performing their daily routines. This study was designed during the COVID-19 pandemic to find what factors affect users to continue using an online shopping application during the pandemic, but the findings could extend to general situations while the research studies the behavioral intentions of consumers.

Factors like price-saving benefits and time-saving benefits proved to have a significant effect on users' continuance intention. While marketers always focus on pricing and promotions related to pricing and discounts, there is still much room to grow online shopping applications in case of time-saving benefits such as faster deliveries, faster shopping processes, and faster transactions. Such factors could also generate more tendency to continue using an online shopping application, especially during a pandemic or any other unordinary situation.

Trust is another important factor in acquiring and keeping customers of online shopping applications. During a pandemic, customers, either due to personal reasons or governmental laws, are bound to use online shopping applications to meet their shopping needs. With the transformation of Online shopping from just company websites to marketplaces like Amazon and AliExpress, where every seller could have a store dedicated to selling their own products, building and maintaining trust has become more challenging. Losing a customer's trust could start with a simple inconvenience of a merchant of the marketplace and lead to an unpleasant experience for the customer and consequently increasing the churn rate of the whole company. Such cases negatively affect customers' continuance intention, and it's the sale and marketing team who is responsible for nurturing unsatisfied customers and gaining back their trust. Therefore, marketers are obliged to develop strategies to maintain the trust of the acquired customers and foresee the scenarios where a merchant or an unpleasant experience leads to customer dissatisfaction.

Furthermore, it is important to generate valid user stories and refine them to find what customers need and what they expect from the online shopping application that encourages them to continue using such applications. Factors such as PE, EE, and perceived task-technology fit are the factors that were studied in this research and proved to have significant effects on either users' satisfaction or continuance intention. It is the task of the marketing specialists to assist other departments in equipping online shopping applications with different tools and options that encourages the customers to return to the same application for their next purchase. Such goals could be achieved by analyzing customers' steps and journeys through finalizing the purchase and studying the needs that are derived from special situations such as the COVID-19 pandemic. Since when the situations are out of the ordinary, the shopping behavior of the customers might change, or a new demographic of consumers that were not the target audience of their business might come into the calculations.

Finally, the COVID-19 pandemic taught marketers to expect drastic changes in every aspect of businesses. Those who are ready to comfort their audience with exact analyses of their needs and learn how to satisfy them will be able to encourage them to adopt and continue using their online shopping applications during such periods.

6.2. Limitations and Further Study

The study was done to measure the effective factor on users' continuance intention of online shopping applications during the COVID-19 pandemic. The questionnaire was sent through a link on different messenger applications and distributed on different social media. As a result, the respondents of the questionnaire are from different geographical locations, and different governmental preventive actions related to COVID-19 could have different effects on the respondents' replies to questions from factors such as PV and PS. Furthermore, the personal experience of the respondents could be affected by their degree of illness if they got infected with COVID-19.

The study was conducted while COVID-19 was still a threat, and it was not possible to access several demographic groups because the coronavirus was a greater risk to them. Factors like perceived vulnerability and perceived severity could be measured more precisely by having access to that demographic group.

Since the study could also measure the long-lasting effects of the variables that were analyzed in the research, measuring other variables such as age, gender, experience, and facilitating conditions can help to understand the behavioral changes of the customers better and more effectively. Also, by investing more time, we can analyze the demographic factor of this study with more detail and find the relations between those factors and how they can affect satisfaction and continuance intention.

REFERENCES

- Ahmad, M. I. (2015). Unified theory of acceptance and use of technology (UTAUT). LinkedIn Pulse, 179-211.
- Ahmad, S., Bhatti, S. H., & Hwang, Y. (2020). E-service quality and actual use of e-banking: Explanation through the Technology Acceptance Model. Information Development, 36(4), 503-519.
- Ajzen, I. (1991). The theory of planned behavior. Organizational behavior and human decision processes, 50(2), 179-211.
- Al Dmour, H., Alshurideh, M., & Shishan, F. (2014). The influence of mobile application quality and attributes on the continuance intention of mobile shopping. Life Science Journal, 11(10), 172-181.
- Ali, B. J. (2020). Impact of COVID-19 on consumer buying behavior toward online shopping in Iraq. Ali, BJ (2020). Impact of COVID-19 on consumer buying behavior toward online shopping in Iraq. Economic Studies Journal, 18(42), 267-280.
- Ali, F., Harris, K. J., & Ryu, K. (2019). Consumers' return intentions towards a restaurant with foodborne illness outbreaks: Differences across restaurant type and consumers' dining frequency. Food control, 98, 424-430.
- Ali, N. I., Samsuri, S., Sadry, M., Brohi, I. A., & Shah, A. (2016, November). Online shopping satisfaction in Malaysia: A framework for security, trust and cybercrime. In 2016 6th International Conference on Information and Communication Technology for The Muslim World (ICT4M) (pp. 194-198). IEEE.
- Alvi, I. (2021). College students’ reception of social networking tools for learning in India: an extended UTAUT model. Smart Learning Environments, 8(1), 1-18.
- Ariffin, S.K., T. Mohan, and Y.-N. Goh (2018). Influence of consumers’ perceived risk on consumers’ online purchase intention. Journal of Research in Interactive Marketing.

- Asai, Y., Nguyen, P. and Hanna, T.P. (2021). Impact of the COVID-19 pandemic on skin cancer diagnosis: a population-based study. PloS one, 16(3), 248-292.
- Badorf, F. and K. Hoberg (2020). The impact of daily weather on retail sales: An empirical study in brick-and-mortar stores. Journal of Retailing and Consumer Services, 52, 1-21.
- Bagdoniene, L. and J. Zemblyte (2009). Online shopping motivation factors and their effect on Lithuanian consumers. Economics and Management, (14): 367-374.
- Bhatti, A., Akram, H., Basit, H. M., Khan, A. U., Raza, S. M., & Naqvi, M. B. (2020). E-commerce trends during COVID-19 Pandemic. International Journal of Future Generation Communication and Networking, 13(2), 1449-1452.
- Bosnjak, M., I. Ajzen, and P. Schmidt (2020). The theory of planned behavior: selected recent advances and applications. Europe's Journal of Psychology, 16(3): 352.
- Bouaghi, E. The E-commerce business in time of Covid-19: Positive impact.
- Cahyanto, I., Wiblishauser, M., Pennington-Gray, L., & Schroeder, A. (2016). The dynamics of travel avoidance: The case of Ebola in the US. Tourism Management Perspectives, 20, 195–203.
- Carpenter, C.J. (2010). A meta-analysis of the effectiveness of health belief model variables in predicting behavior. Health communication, 25(8), 661-669.
- Chang, C.-T., X.-Y.M. Chu, and I.-T. Tsai (2021). How cause marketing campaign factors affect attitudes and purchase intention: Choosing the right mix of product and cause types with time duration. Journal of Advertising Research, 61(1): 58-77.
- Chang, T.-Z. and A.R. Wildt, Price (1994). product information, and purchase intention: An empirical study. Journal of the Academy of Marketing science, 22(1): 16-27.

- Chen, J., Li, R., Gan, M., Fu, Z., & Yuan, F. (2020). Public acceptance of driverless buses in China: an empirical analysis based on an extended UTAUT model. Discrete Dynamics in Nature and Society, 2020.
- Cheng, E.W. (2019). Choosing between the theory of planned behavior (TPB) and the technology acceptance model (TAM). Educational Technology Research and Development, 67(1): 21-37.
- Chiang, C.T., (2020). Developing an eMarketing model for tourism and hospitality: a keyword analysis. International Journal of Contemporary Hospitality Management.
- Cho, C.-H., J. Kang, and H.J. Cheon (2006). Online shopping hesitation. CyberPsychology & Behavior, 9(3): 261-274.
- Chong, A.Y.L., (2013). Predicting m-commerce adoption determinants: A neural network approach. Expert systems with applications, 40(2), 523-530.
- Chopdar, P.K. and V. Sivakumar (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): 29-56.
- Chopdar, P.K. and V. Sivakumar (2019). Understanding continuance usage of mobile shopping applications in India: the role of espoused cultural values and perceived risk. Behaviour & Information Technology, 38(1): 42-64.
- Connelly, L.M. (2011). Cronbach's alpha. Medsurg nursing, 20(1): 45-47.
- Correa, J. C., Garz´on, W., Brooker, P., Sakarkar, G., Carranza, S. A., Yunado, L., & Rinc´on, A. (2019). Evaluation of collaborative consumption of food delivery services through web mining techniques. Journal of Retailing and Consumer Services, 46, 45–50.
- Davis, F.D., R.P. Bagozzi, and P.R. Warshaw (1989). User acceptance of computer technology: A comparison of two theoretical models. Management Science, 35(8): 982-1003.

- Dennis, C., Morgan, A., Wright, L. T., & Jayawardhena, C. (2010). The influences of social e-shopping in enhancing young women's online shopping behaviour. Journal of customer behaviour, 9(2), 151-174.
- Durmuş, B. (2013). Sosyal bilimlerde SPSS'le veri analizi. Beta Basım Yayım.
- Dwivedi, Y.K., et al. (2020). A meta-analysis based modified unified theory of acceptance and use of technology (meta-UTAUT): a review of emerging literature. Current opinion in psychology, 36: 13-18.
- Einav, L., Levin, J., Popov, I., & Sundaresan, N. (2014). Growth, adoption, and use of mobile E-commerce. American Economic Review, 104(5), 489-94.
- Elhajjar, S., & Ouaida, F. (2019). An analysis of factors affecting mobile banking adoption. International Journal of Bank Marketing, 38(2), 352-367.
- Erjavec, J. and A. Manfreda, (2022). Online shopping adoption during COVID-19 and social isolation: Extending the UTAUT model with herd behavior. Journal of Retailing and Consumer Services, 65: 102-167.
- Escobar-Rodríguez, T. and E. Carvajal-Trujillo (2014). Online purchasing tickets for low-cost carriers: An application of the unified theory of acceptance and use of technology (UTAUT) model. Tourism Management, 43: 70-88.
- Farah, M.F., Hasni, M.J.S. and Abbas, A.K. (2018). Mobile-banking adoption: empirical evidence from the banking sector in Pakistan. International Journal of Bank Marketing.
- Fernandes, N. (2020). Economic effects of coronavirus outbreak (COVID-19) on the world economy.
- Fishbein, M. and I. Ajzen (1977). Belief, attitude, intention, and behavior: An introduction to theory and research. Philosophy and Rhetoric, 10(2).
- Forsythe, S., et al. (2006). Development of a scale to measure the perceived benefits and risks of online shopping. Journal of interactive marketing, 20(2): 55-75.

- Ganesha, H., P. Aithal, and P. Kirubadevi (2020). Changes in Consumer Perspective towards Discount at Brick-and-Mortar Stores owing to Emergence of Online Store Format in India. International Journal of Management, Technology, and Social Sciences (IJMTS), 5(1): 43-83.
- George, J.F. (2002). "Influences on the intent to make Internet purchases", Internet Research, Vol. 12 No. 2, pp. 165-180. https://doi.org/10.1108/10662240210422521
- Ghorai, K. and P. Ray (2019). Factors Affecting the Acceptance of Mobile Based Multi-Feature Service for Smoking Cessation Using UTAUT. European Journal of Biomedical Informatics.
- Godoe, P. and Johansen, T.S. (2012). Understanding adoption of new technologies: Technology readiness and technology acceptance as an integrated concept. Journal of European Psychology Students, 3(1), 38–52. DOI: http://doi.org/10.5334/jeps.aq.
- Goodhue, L.D., Thompson, L.R., 1995. 'Task-technology fit and individual performance.'. Mis Q. 19 (213-), 236.
- Grabner-Kraeuter, S. (2002). The role of consumers' trust in online-shopping. Journal of business ethics, 39(1): 43-50.
- Gu, J.-C., S.-C. Lee, and Y.-H. Suh (2009). Determinants of behavioral intention to mobile banking. Expert Systems with Applications, 36(9): 11605-11616.
- Gunasinghe, A., Hamid, J.A., Khatibi, A. and Azam, S.M.F. (2020). "The adequacy of UTAUT-3 in interpreting academician's adoption to e-Learning in higher education environments", Interactive Technology and Smart Education, Vol. 17 No. 1, 86-106. https://doi.org/10.1108/ITSE-05-2019-0020.
- Güner, H.R., İ. Hasanoğlu, and F. Aktaş (2020). COVID-19: Prevention and control measures in community. Turkish Journal of medical sciences, 50(9): 571-577.
- Hagger, M.S. (2019). The reasoned action approach and the theories of reasoned action and planned behavior.

- Hair, J.F., Ortinau, D.J. and Harrison, D.E. (2010). Essentials of marketing research (Vol. 2). New York, NY: McGraw-Hill/Irwin.
- Hanjaya, M., K. Kenny, and F. Gunawan (2019). Understanding factors influencing consumers online purchase intention via mobile app: perceived ease of use, perceived usefulness, system quality, information quality, and service quality. Marketing Instytucji Naukowych i Badawczych, 2(32): 175-206.
- Hew, J. J., Lee, V. H., Ooi, K. B., & Wei, J. (2015). What catalyses mobile apps usage intention: an empirical analysis. Industrial Management & Data Systems.
- Ho, C.-F. and W.-H. Wu. (1999). Antecedents of customer satisfaction on the Internet: an empirical study of online shopping. in Proceedings of the 32nd Annual Hawaii International Conference on Systems Sciences.
- Hochbaum, G., Rosenstock, I., & Kegels, S. (1952). Health belief model. United states public health service. 1.
- Hoehle, H. and V. Venkatesh (2015). Mobile application usability. MIS quarterly, 39(2): 435-472.
- Hoffman, D.L., T.P. Novak, and M. Peralta (1999). Building consumer trust online. Communications of the ACM, 42(4): 80-85.
- Holzer, A. and J. Ondrus (2011). Mobile application market: A developer's perspective. Telematics and informatics, 28(1): 22-31.
- Hoque, A., Shikha, F.A., Hasanat, M.W., Arif, I. and Hamid, A.B.A. (2020). The effect of Coronavirus (COVID-19) in the tourism industry in China. Asian Journal of Multidisciplinary Studies, 3(1), 52-58.
- 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.
- Hsu, M.-H., L.-W. Chuang, and C.-S. Hsu (2014). Understanding online shopping intention: the roles of four types of trust and their antecedents. Internet research.

- Iivari, N., S. Sharma, and L. Ventä-Olkkonen (2020). Digital transformation of everyday life–How COVID-19 pandemic transformed the basic education of the young generation and why information management research should care? International Journal of Information Management, 55: 102183.
- Islam, R., R. Islam, and T. Mazumder (2010). Mobile application and its global impact. International Journal of Engineering & Technology, 10(6): 72-78.
- Jensen, K. L., Yenerall, J., Chen, X., & Yu, T. E. (2021). US consumers' online shopping behaviors and intentions during and after the COVID-19 pandemic. Journal of Agricultural and Applied Economics, 53(3), 416-434.
- Jih, W.-J. (2007). Effects of consumer-perceived convenience on shopping intention in mobile commerce: an empirical study. International Journal of E-Business Research (IJEBR), 3(4): 33-48.
- Lian, J. W., Yen, D. C., & Wang, Y. T. (2014). An exploratory study to understand the critical factors affecting the decision to adopt cloud computing in Taiwan hospital. International Journal of Information Management, 34(1), 28-36.
- Junglas, I., Johnson, N. & Spitzmüller (2008). C. Personality traits and concern for privacy: an empirical study in the context of location-based services. Eur J Inf Syst 17, 387–402. https://doi.org/10.1057/ejis.2008.29.
- Kang, S. (2014). Factors influencing intention of mobile application use. International Journal of Mobile Communications, 12(4): 360-379.
- Kim, H. W., Xu, Y., & Gupta, S. (2012). Which is more important in Internet shopping, perceived price or trust? Electronic Commerce Research and Applications, 11(3), 241-252.
- Kim, M., et al. (2017). Mobile shopping through applications: Understanding application possession and mobile purchase. Journal of Interactive Marketing, 39: 55-68.
- Kim, R.Y. (2020). The impact of COVID-19 on consumers: Preparing for digital sales. IEEE Engineering Management Review, 48(3): 212-218.

- Koch, J., B. Frommeyer, and G. Schewe (2020). Online shopping motives during the COVID-19 pandemic—lessons from the crisis. Sustainability, 12(24): 10247.
- Koksal, M.H. (2016). The intentions of Lebanese consumers to adopt mobile banking. International Journal of bank marketing.
- Kwak, S.G. and J.H. Kim (2017). Central limit theorem: the cornerstone of modern statistics. Korean journal of anesthesiology, 70(2): 144-156.
- Laato, S., Islam, A.N., Farooq, A. and Dhir, A. (2020). Unusual purchasing behavior during the early stages of the COVID-19 pandemic: The stimulus-organism-response approach. Journal of Retailing and Consumer Services, 57, 102224.
- Lafraxo, Y., Hadri, F., Amhal, H., & Rossafi, A. (2018). The Effect of Trust, Perceived Risk and Security on the Adoption of Mobile Banking in Morocco. In ICEIS (2) (pp. 497-502).
- Lai, I.K.W. and G. Shi (2015). The impact of privacy concerns on the intention for continued use of an integrated mobile instant messaging and social network platform. International Journal of Mobile Communications, 13(6): 641-669.
- Laudon, K.C. and C.G. Traver (2013). E-commerce, Pearson Boston, MA.
- Lawshe, C.H., 1975. A quantitative approach to content validity. Personnel psychology, 28(4): 563-575.
- Lee, C.C., Cheng, H.K., Cheng, H.H. (2007). 'An empirical study of mobile commerce in insurance industry: task – technology fit and individual differences.'. Decis. Support Syst. 43, 95–110.
- Lian, J.W., Yen, D.C. (2014). Online shopping drivers and barriers for older adults: age and gender differences. Comput. Hum. Behav. 37, 133–143.
- Lin, H.-H. and Y.-S. Wang (2005). Predicting consumer intention to use mobile commerce in Taiwan. in International Conference on Mobile Business (ICMB'05).

- Luarn, P. and H.-H. Lin (2005). Toward an understanding of the behavioral intention to use mobile banking. Computers in human behavior, 21(6): 873-891.
- Madinga, N.W. and J. Lappeman (2022). Social Media Sentiment Analysis: Online versus ‘Brick and Mortar’Retailers in South Africa. Journal of African Business, 1-18.
- Malaquias, R. F., & Silva, A. F. (2020). Understanding the use of mobile banking in rural areas of Brazil. Technology in Society, 62, 101260.
- Marinković, V. and Z. Kalinić (2020). Understanding consumers' continuance intention and word of mouth in mobile commerce based on extended UTAUT model, in Impact of Mobile Services on Business Development and E-Commerce. IGI Global. 108-125.
- Mark T Dishaw, Diane M Strong (1999). Extending the technology acceptance model with task–technology fit constructs, Information & Management, Volume 36, Issue 1, pp. 9-21.
- Marriott, H.R. and M.D. Williams (2018). Exploring consumers perceived risk and trust for mobile shopping: A theoretical framework and empirical study. Journal of retailing and consumer services, 42: 133-146.
- Martin, S.S., C. Camarero, and R.S. José (2011). Does involvement matter in online shopping satisfaction and trust? Psychology & Marketing, 28(2): 145-167.
- McLean, G. and A. Wilson (2019). Shopping in the digital world: Examining customer engagement through augmented reality mobile applications. Computers in Human Behavior, 101: 210-224.
- Medina, M. and I. Portilla (2015). Media market research on immigrant audiences: lessons learned from a critical analysis of the Spanish media survey. International Journal of Communication, 9: 22.
- Merhi, M., K. Hone, and A. Tarhini (2019). A cross-cultural study of the intention to use mobile banking between Lebanese and British consumers: Extending UTAUT2 with security, privacy and trust. Technology in Society, 59: 101151.

- Miljenović, D. and B. Beriša (2022). Pandemics trends in E-commerce: drop shipping entrepreneurship during COVID-19 pandemic. Pomorstvo, 36(1): 31-43.
- Min, Q., Ji, S. and Qu, G. (2008). Mobile commerce user acceptance study in China: a revised UTAUT model. Tsinghua Science and Technology, 13(3), 257-264.
- Mirabi, V., H. Akbariyeh, and H. Tahmasebifard (2015). A study of factors affecting on customers purchase intention. Journal of Multidisciplinary Engineering Science and Technology (JMEST), 2(1).
- Morens, D.M., G.K. Folkers, and A.S. Fauci (2009). What is a pandemic? The Journal of infectious diseases, 200(7): 1018-1021.
- Morganosky, M. A., & Cude, B. J. (2000). Consumer response to online grocery shopping. International Journal of Retail & Distribution Management, 28(1), 17–26.
- NGUYEN, H.M. and B.T. KHOA (2019). The relationship between the perceived mental benefits, online trust, and personal information disclosure in online shopping. The Journal of Asian Finance, Economics and Business, 6(4): 261-270.
- Obaid, T. (2021). Predicting Mobile Banking Adoption: An Integration of TAM and TPB with Trust and Perceived Risk. Available at SSRN 3761669.
- Orero-Blat, M., Simón-Moya, V., Guerrero, H. M., Carrubi, D. B., & Sendra, J. (2020, June). Client orientation in fashion e-commerce: a comparative study. In 2020 15th Iberian Conference on Information Systems and Technologies (CISTI) (pp. 1-6). IEEE.
- Orlikowski, W.J. and Barley, S.R. (2001). Technology and institutions: What can research on information technology and research on organizations learn from each other? MIS quarterly, 145-165.
- Özmen, S., Özkan, O., Özer, Ö., & Yanardağ, M. Z. (2021). Investigation of COVID-19 fear, well-being and life satisfaction in Turkish society. Social work in public health, 36(2), 164-177.

- Pallant, J., 2020. SPSS survival manual: A step by step guide to data analysis using IBM SPSS: Routledge.
- Park, H.S. (2000). Relationships among attitudes and subjective norms: Testing the theory of reasoned action across cultures. Communication Studies, 51(2): 162-175.
- Perea y Monsuwé, T., Dellaert, B.G.C. and de Ruyter, K. (2004), "What drives consumers to shop online? A literature review", International Journal of Service Industry Management, Vol. 15 No. 1, 102-121.
- Phillips, D.C. and N.C. Burbules (2000). Postpositivism and educational research. Rowman & Littlefield.
- Phong, N.D., N.H. Khoi, and A.N.-H. Le (2018). Factors affecting mobile shopping: a Vietnamese perspective. Journal of Asian Business and Economic Studies.
- Platto, S., T. Xue, and E. Carafoli (2020). COVID-19: an announced pandemic. Cell Death & Disease, 11(9): 1-13.
- Rahi, S., et al. (2019). Integration of UTAUT model in internet banking adoption context: The mediating role of performance expectancy and effort expectancy. Journal of Research in Interactive Marketing.
- Rajamma, R.K., A.K. Paswan, and G. Ganesh (2007). Services purchased at brick and mortar versus online stores, and shopping motivation. Journal of Services Marketing.
- Raman, B., Cassar, M.P., Tunnicliffe, E.M., Filippini, N., Griffanti, L., Alfaro-Almagro, F., Okell, T., Sheerin, F., Xie, C., Mahmod, M. and Mózes, F.E. (2021). Medium-term effects of SARS-CoV-2 infection on multiple vital organs, exercise capacity, cognition, quality of life and mental health, post-hospital discharge. EClinicalMedicine, 31, 100683.
- Ray, A., & Bala, P. K. (2021). User generated content for exploring factors affecting intention to use travel and food delivery services. International Journal of Hospitality Management, 92, 102730.

* Ray, A., Dhir, A., Bala, P. K., & Kaur, P. (2019). Why do people use food delivery apps (FDA)? A uses and gratification theory perspective. Journal of Retailing and Consumer Services, 51, 221–230.
* Roh, M. and K. Park (2019). Adoption of O2O food delivery services in South Korea: The moderating role of moral obligation in meal preparation. International Journal of Information Management, 47: 262-273.
* Roh, M., Park, K. (2019). 'Adoption of O2O food delivery services in South Korea: the moderating role of moral obligation in meal preparation'. Int. J. Inf. Manag. Elsevier 47, 262–273 (September 2018).
* Samadi, M. and A. Yaghoob-Nejadi (2009). A survey of the effect of consumers' perceived risk on purchase intention in e-shopping. Business Intelligence Journal, 2(2): 261-275.
* Samaradiwakara, G. and C. Gunawardena (2014). Comparison of existing technology acceptance theories and models to suggest a well improved theory/model. International technical sciences journal, 1(1): 21-36.
* Saunders, M., P. Lewis, and A. Thornhill (2003). Research methods for business students. Essex: Prentice Hall: Financial Times.
* Saunders, M., P. Lewis, and A. Thornhill (2007). Research methods. Business Students 4th edition Pearson Education Limited, England.
* Saunders, M.N., et al. (2015). Understanding research philosophy and approaches to theory development.
* Setiawan, B., Trisdyani, N.L.P., Adnyana, P.P., Adnyana, I.N., Wiweka, K. and Wulandani, H.R., 2018. The profile and behaviour of 'digital tourists' when making decisions concerning travelling case study: Generation Z in South Jakarta. Advances in research, 17(2), 1-13.
* Setiawan, N., Tarigan, V. C. E., Sari, P. B., Rossanty, Y., Nasution, M. D. T. P., & Siregar, I. (2018). Impact Of Cybercrime In E-Business and Trust. Int. J. Civ. Eng. Technol, 9(7), 652-656.

- Shah, S. S. H., Aziz, J., Jaffari, A. R., Waris, S., Ejaz, W., Fatima, M., & Sherazi, S. K. (2012). The impact of brands on consumer purchase intentions. Asian Journal of Business Management, 4(2), 105-110.
- Shim, S., Eastlick, M.A., Lotz, S.L. and Warrington, P. (2001). An online prepurchase intentions model: the role of intention to search: best overall paper award—The Sixth Triennial AMS/ACRA Retailing Conference, 2000☆. Journal of retailing, 77(3), 397-416.
- Siau, K., E.-P. Lim, and Z. Shen (2014). Mobile commerce: Promises, challenges and research agenda. Journal of Database Management (JDM), 2001. 12(3): 4-13.
- Sibley, C.G., Greaves, L.M., Satherley, N., Wilson, M.S., Overall, N.C., Lee, C.H., Milojev, P., Bulbulia, J., Osborne, D., Milfont, T.L. and Houkamau, C.A., 2020. Effects of the COVID-19 pandemic and nationwide lockdown on trust, attitudes toward government, and well-being. American Psychologist, 75(5), p.618.
- Singh, J. and J. Singh (2020). COVID-19 and its impact on society. Electronic Research Journal of Social Sciences and Humanities.
- Tam, C., Santos, D., Oliveira, T. (2020). 'Exploring the influential factors of continuance intention to use mobile Apps: extending the expectation confirmation model.'. Inf. Syst. Front. 22 (1), 243–257.
- Tarasewich, P., R.C. Nickerson, and M. Warkentin (2002). Issues in mobile e-commerce. Communications of the association for information systems, 8(1): 3.
- Troise, C., O'Driscoll, A., Tani, M., & Prisco, A. (2020). Online food delivery services and behavioural intention–a test of an integrated TAM and TPB framework. British Food Journal.
- Ueltschy, L.C., R.F. Krampf, and P. Yannopoulos (2004). A cross-national study of perceived consumer risk towards online (internet) purchasing. Multinational Business Review, 12(2): 59-82.

- 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.
- Venkatesh, V., Thong, J. Y., Chan, F. K., Hu, P. J. H., & Brown, S. A. (2011). Extending the two-stage information systems continuance model: Incorporating UTAUT predictors and the role of context. Information systems journal, 21(6), 527-555.
- Venkatesh, V., J.Y. Thong, and X. Xu (2012). Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology. MIS quarterly, 157-178.
- Verma, A.K. and S. Prakash (2020). Impact of covid-19 on environment and society. Journal of Global Biosciences, 9(5): 7352-7363.
- Verma, J. and P. Verma, Springer. Understanding concepts in estimating sample size in survey studies, in Determining Sample Size and Power in Research Studies. 2020, 29-40.
- Wang, C.-C., C.-A. Chen, and J.-C. Jiang (2009). The Impact of Knowledge, and Trust on E-Consumers' Online Shopping Activities: An Empirical Study. J. Comput., 4(1): 11-18.
- Warshaw, P.R. and F.D. Davis (1985). Disentangling behavioral intention and behavioral expectation. Journal of experimental social psychology, 21(3): 213-228.
- Williams, M.D., N.P. Rana, and Y.K. Dwivedi (2015). The unified theory of acceptance and use of technology (UTAUT): a literature review. Journal of enterprise information management.
- Zhao, Y., & Bacao, F. (2020). What factors determining customer continuingly using food delivery apps during 2019 novel coronavirus pandemic period?. International journal of hospitality management, 91, 102683.
- Yang, K., & Kim, H. Y. (2012). Mobile shopping motivation: an application of multiple discriminant analysis. International Journal of Retail & Distribution Management.

- Yeo, V.C.S., Goh, S.K., Rezaei, S. (2017). Consumer experiences, attitude, and behavioral intention toward online food delivery (OFD) services. J. Retailing Consumer Services. Elsevier 35, 150–162 (December 2016).
- Yeoh, E. and J.K.L. Chan (2011). Malaysian low cost airlines: Key influencing factors on customers' repeat purchase intention. World Applied Sciences Journal, 12(35): 35-43.
- Yuan, S., et al. (2016). An investigation of users' continuance intention towards mobile banking in China. Information Development, 32(1): 20-34.
- Yuan, S., Liu, Y., Yao, R., Liu, J. (2016). An investigation of users' continuance intention towards mobile banking in China. Inf. Dev. 32 (1), 20–34.
- 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. and 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, 110671.
- Zhang, T., Tao, D., Qu, X., Zhang, X., Zeng, J., Zhu, H. and Zhu, H. (2020). Automated vehicle acceptance in China: Social influence and initial trust are key determinants. Transportation research part C: emerging technologies, 112, 220-233.
- Zhang, Y., et al. (2017). Online shopping and social media: friends or foes? Journal of Marketing, 81(6): 24-41.
- Zhou, L., L. Dai, and D. Zhang (2007). Online shopping acceptance model-A critical survey of consumer factors in online shopping. Journal of Electronic Commerce Research.
- Zhou, T. (2011). Understanding mobile Internet continuance usage from the perspectives of UTAUT and flow. Information Development, 27(3): 207-218.
- Zhu, D.H., Lan, L.Y., Chang, Y.P. (2017). Understanding the intention to continue use of a mobile payment provider: an examination of Alipay Wallet in China. Int. J. Bus. Inf. 12 (4), 369–390.