MESTRADO EM

GESTÃO DE SISTEMAS DE INFORMAÇÃO

TRABALHO FINAL DE MESTRADO

DISSERTAÇÃO

SOCIAL COMMERCE ADOPTION AND THE PANDEMIC IMPACT

ANA CLÁUDIA ROPIO RODRIGUES

NOVEMBRO – 2020

LISBON SCHOOL OF ECONOMICS & MANAGEMENT
UNIVERSIDADE DE LISBOA

MESTRADO EM
GESTÃO DE SISTEMAS DE INFORMAÇÃO

TRABALHO FINAL DE MESTRADO
DISSERTAÇÃO

SOCIAL COMMERCE ADOPTION AND THE PANDEMIC IMPACT

ANA CLÁUDIA ROPIO RODRIGUES

ORIENTAÇÃO:

PROFESSORA DOUTORA WINNIE PICOTO

NOVEMBRO - 2020

Acknowledgments

I would like to express my deep gratitude to my research supervisor. For all the guidance throughout this study, believing in me even when the goal seemed so difficult to achieve.

To my parents for all the support and encouragement.

To João, for all the love and for being the voice that always pushed me forward.

To my friends that were always there for me and made this task feasible. Bia, Sofia, and Catarina, this is also thanks to you.

List of acronyms

ACEPI: Association of the Digital Economy

AVE: Average Variance Extracted

EC: Electronic Commerce

GSMA: Global System for Mobile Communications

IS: Information Systems

OECD: Organization for Economic Cooperation and Development

PLS: Partial Least Squares

SC: Social Commerce

SCT: Social Cognitive Theory

SNSs: Social Networking Sites

SPSS: Statistical Package for the Social Sciences

TAM: Technology Acceptance Model

TBRC: The Business Research Company

TRA: Theory of Reasoned Action

TPB: Theory of Planned Behavior

UN: United Nations

UNCTAD: United Nations Conference on Trade and Development

UTAUT: Unified Theory of Acceptance and Use of Technology

UTAUT2: Unified Theory of Acceptance and Use of Technology 2

WHO: World Health Organization

VIF: Variance Inflation Factor

Abstract

The increased popularity of social networking sites and the establishment of Electronic Commerce has given rise to a new business model entitled Social Commerce (SC). SC involves using Web 2.0 social media technologies that support users' interactions, facilitating the online selling and acquisition of products and services. SC is increasingly attracting the attention of academic researchers within the Information Systems (IS) field, being implicit a need to understand SC users' behavior. Additionally, since the COVID-19 pandemic has impacted consumers online behavior, it becomes important to analyze its role in the intention and usage of a technology. To investigate this aspect, the second version of Unified Theory of Acceptance and Use of Technology (UTAUT2) was extended in order to determinate which factors impact Behavioral Intention and Use of Social Commerce. For that, additional determinants in Social Commerce acceptance and adoption were identified, taking in consideration the COVID-19 pandemic context. A quantitative approach was conducted, based on data collected from a sample of 209 respondents and the Statistical Package for the Social Sciences (SPSS) and Partial Least Squares (PLS) path modeling were used to assess the model. The study results showed that Habit, Hedonic Motivation, Performance Expectancy, Social Commerce Constructs are significant in the formation of Behavioral Intention and Use of SC. However, Effort Expectancy, Social Influence, Facilitating Conditions and Perceived Trust revealed not to have a statistically significant impact. This study findings also revealed that the pandemic had impacted the frequency of use of SC, being the Perceived Lack of Alternatives a determinant in the intention to use SC. On the other hand, the factors Perceived External Pressure and Perceived risk were not considered relevant.

Resumo

O aumento da popularidade das redes sociais e a utilização do Comércio Eletrónico deram origem a um novo modelo de negócios denominado Social Commerce (SC). SC envolve o uso de tecnologias Web 2.0 que possibilitam a interação dos utilizadores, facilitando a venda e compra online de produtos e serviços. A necessidade de entender o comportamento dos utilizadores do Social Commerce tem vindo a ser sugerida por autores académicos na área dos Sistemas de Informação (SI). Além disso, tendo em consideração que a pandemia COVID-19 afetou o comportamento online dos consumidores, torna-se importante analisar seu papel na intenção e uso efetivo de uma tecnologia. Para tal, a segunda versão da Teoria Unificada de Aceitação e Uso de Tecnologia (UTAUT2) foi adaptada a fim de determinar quais fatores impactam a intenção e uso do Social Commerce. Neste contexto, construtos adicionais foram identificados, tendo em consideração o contexto pandémico atual. Foi realizada uma análise quantitativa, a partir de dados recolhidos de uma amostra de 209 inquiridos. O software Statistical Package for the Social Sciences (SPSS) e a abordagem Partial Least Squares (PLS) foram utilizadas para avaliar o modelo conceptual. Os resultados deste estudo revelaram que os construtos Hábito, Motivação Hedónica, Expectativa de Desempenho e Construtos do Social Commerce são significativos na formação da intenção comportamental e uso do SC. Por outro lado, a Expectativa de Esforço, Influência Social, Condições Facilitadoras e Confiança Percebida revelaram não ter um impacto estatisticamente significativo. Também a pandemia revelou ter impacto na frequência de utilização do SC, sendo o construto Falta de Alternativas Percebida, um determinante na intenção de uso desta tecnologia. Os fatores Pressão Externa Percebida e Risco Percebido não foram considerados relevantes.

Table of Contents

Table of Contents - Tables

Table of Figures

1. Introduction

The world is turning digital. The UN (2020) states that in 2019 nearly 87% of people in developed countries used internet and GSMA (2020) estimates there are close to 5.2 billion mobile phones used in 2019, worldwide. Evolving in such environment, new digital trends keep developing with the average user spending increasingly more time connected.

This digital takeover affects retail that is currently being reshaped, with the branch of Electronic Commerce (EC) growing sharply. According to Turban et al., (2018), EC is a business model that allows electronic transactions through the Internet, allowing electronical innovations, communication, and collaboration between people, impacting consumer behavior and affecting businesses. According to Business Wire (2020), EC has an expected growth of 70% until 2023, when comparing to 2019.

At the same time, the COVID-19 pandemic that grew exponentially throughout 2020, heavily transformed the day-to-day life of millions throughout the world, reshaping not only the way of living, but also the buying behavior. Restrictions imposed by governments, such as quarantining, and the climate of uncertainty associated to the pandemic, made consumers find alternative ways from the more traditional physical shopping. This was a key factor in the consolidation of EC that due to its intrinsic characteristics of being virtual, became a helpful source to comply with the precaution measures advised by the World Health Organization (WHO) and local government policies. It seems that this is a trend that will stand, McKinsey (2020) stated that even after the pandemic people are willing to continue buying through EC platforms.

Additionally, social media had risen exponentially in usage within the last years, being social networking one of the most popular digital activities worldwide (Statista, 2020a). Social Networking Sites (SNSs) can be defined as virtual communities where users can have individual public profiles and interact with other people based on shared interests (Kuss and Griffiths, 2011). In 2004, Facebook, was launched as an online community for students and has since become the world’s most popular SNS (Kuss and Griffiths, 2017). According to Statista (2020b), there were 2.7 billion active users in this platform as of the second quarter of 2020, meaning approximately 34% of the world population. This suggests that SNSs have become an important leisure activity, allowing individuals to connect with each other. Hollenbeck and Kaikati (2012), reinforce that SNSs are the area of largest growth on the Internet and argue that they have changed the way consumers and businesses interact. According to Turban et al., (2018) SNSs represent an important development in the EC field. Hence, the increased acceptance of SNSs has given rise to new concept: Social Commerce (SC). Social Commerce can be defined as an Internet-based commercial application that leverages social media and Web 2.0 technologies to support social interaction and user generated content in order to facilitate the online purchasing process (Huang and Benyoucef, 2013). Consumers' interactions in SNSs can create a social environment favorable to online purchases (Huang and Benyoucef, 2013). Therefore, companies see this as an opportunity to enhance their performance and increase their business revenue (Wang and Zhang, 2012).

Given the limited research in this area in Portugal, and considering that the actual pandemic phenomenon is recent (few studies are published), it becomes important to study the end use behavior concerning the acceptance and adoption of SC. Taking this in consideration, the following research questions are formulated: "What factors determine users' acceptance and adoption of Social Commerce?" and "What is the impact of the COVID-19 pandemic on Social Commerce usage?".

Since EC is an Information Systems (IS) phenomenon (Turban et al., 2018) and SC can be characterized as a subset of EC (Liang and Turban, 2011; Kim and Park, 2013), technology acceptance models are suitable to understand the user behavior (Sarker et al., 2019). Thus, the present investigation aims to adapt the second version of the Unified Theory of Acceptance and Use of Technology (UTAUT2) to the SC context, identifying additional determinants that could affect Behavioral Intention and Use Behavior as well as understanding the impact that COVID-19 pandemic may have had. Therefore, the research is structured in seven different sections: Section II, presents the literature review where it is analyzed SC and User Acceptance Models; section III, describes the research model and hypotheses development; section IV, refers to methodological approach; Section V, analyzes the results and finally sections VI and VII discuss the most important findings, study limitations and potential trails for future research. This study intends to improve the empirical understanding of behavioral intention and usage of SC under the influence of the COVID-19 pandemic, attempting to contribute with valuable knowledge for to the companies that operate in this area.

2. Review of Literature

2.1 Electronic Commerce

Electronic Commerce (EC) includes any form of economic activity conducted via electronic connections (Wigand, 1997). It is a business model where transactions take place over electronic networks, mostly the Internet. Even though the term is frequently referred the sales of physical products online, EC includes buying and selling goods, services, and information (Turban et al., 2018). The widespread use of EC platforms has been contributed to a substantial growth in online retail. Furthermore, the increasing adoption of social media platforms play an important role in EC. The development of Web 2.0 and growth of Social Network Sites (e.g., Facebook), provides a huge potential to transform EC from a product-oriented environment to a social and customer-centered one (Wigand et al., 2008; Turban et al., 2018) and hence help businesses expand their reach and engage customers, consequently increasing sales.

2.2 Social Commerce

Social Commerce (SC) is frequently referred as an innovation or a subset of Electronic Commerce (Kim and Park, 2013; Liang and Turban, 2011; Huang and Benyoucef, 2013). The growth of social media and networks, as well as Web 2.0 tools, resulted in new ways of conducting EC by making it social (Turban et al., 2018). According to Huang and Benyoucef (2013), SC can be defined as an Internet-based commercial application, leveraging social media and Web 2.0 technologies that supports social interaction and user generated content in order to assist consumers in the online purchasing process. The differences between EC and SC are highlighted in terms of business goals, customer connection and system interaction (Huang and Benyoucef, 2013). Regarding business goals, maximizing efficiency of transactions is the focus of EC, while SC is more oriented toward social goals, such as networking and information sharing (Wang and Zhang, 2012). Moreover, in EC customers usually interact with e-commerce platforms individually, while in SC people are encouraged to interact with each other in online communities (Kim and Srivastava, 2007). Also, the system interaction in EC usually provides a one-way browsing, while SC develops more social and interactive approaches that let customers interact with each other (Huang and Benyoucef, 2013).

Due to the popularity of social media, social networking sites (SNSs) have become the station of SC (Hajli, 2014; Liang and Turban, 2011; Maia et al., (2018). SNSs are Internet-based applications built on Web 2.0 that allow communication, collaboration and conveyance between interconnected networks of people and organizations (Boyd and Ellison, 2007). According to Kuss and Griffiths (2011), refer to SNSs as virtual communities where users can build an individual online profile and interact with others. Facebook, YouTube, WhatsApp and Instagram are some the most used SNSs in 2020, globally (Statista, 2020c). As mentioned by Shin (2010), these platforms enable consumers to be active content creators on the Internet, connect and interact with other people as well as seek common interests, experiences and information. The SNSs usage have been growing exponentially by the years. According to Satista (2020a), in 2020, over 3.6 billion people were using SNSs, a number projected to increase to almost 4.4 billion in 2025. Within this environment, customers have access to information to better support them and in making accurate purchase decisions (Liang and Turban, 2011). The potential that these interactions bring, make companies join popular SNSs in order to sell products and services and create a more closed relationship with consumers (Wang and Zhang, 2012). That said, Maia et al., (2018) mention that SC can be characterized in two main forms: the first type is related to traditional EC websites (e.g. eBay) that incorporate social networking capabilities in facilitate customers' content generation; the second type refers to SNSs that integrate e-commerce features. Mechanisms for users to buy directly from the Apps are constantly being improved by SNSs. Facebook for instance has been expanding the access to social commerce features. The SNS launched the Facebook Shop in May 2020, that enables businesses to sell products directly on the platform (Facebook, 2020a). Similarly, Instagram is currently testing and implementing new features in order to raise the awareness of direct shopping through the App (Instagram, 2020). The research context of this study limits to the second type of Social Commerce mentioned above. It is assumed that the social interactions between customers on SNSs have influence in the online purchasing decisions, whether the purchase is made directly on a Social Networking Site or through an external website. Hence, this research considers Social Commerce as any interaction within SNSs that lead to an online purchase.

2.3 COVID-19 pandemic and its impact on online behavior

COVID-19 is an infectious disease caused by the recently discovered coronavirus. Due to the rapid spread of cases globally, it was characterized as a pandemic (WHO, 2019). COVID-19 outbreak is having a huge impact in the way people live. Preventive measures avoid the spread of the virus such as quarantining, closure of commercial establishments and restricted movement of people have affected consumer behavior and motivated people to spend more time online. The uncertain environment created with the virus, potentiality increases online shopping attractiveness due to the possibility of avoiding stores that are usually crowded places. According to OECD (2020), in Europe April 2020, sales via Internet increased 30% compared to same period in the previous year. In Portugal, a study developed by ACEPI and IDC (2020) revealed that the percentage of users with access to online platforms have been increasing along the years. Considering the effect of the pandemic, it is expected 81% of population have access to internet by the end of 2020. Also, more than half of the Internet users made online purchases in 2019 (51%) with an expected growth in 2020 to 57% due to the pandemic. It's undoubted that COVID-19 had a major impact in the acceleration of EC. According to a report made by TBRC (2020), there is already the expectation of a 33% increase from 2019 and this growth will stand through 2023 where a stabilization is expected reaching an increase of nearly 70%, from the 2019 figures. Mckinsey (2020) divulged that more people expect to continue to purchase online after the COVID-19 pandemic is over. Facebook itself stated that in the countries that were most affected by the virus, messaging was up by more than 50% whereas Messenger and Whatsapp presented the same increases in voice and video calling. Using Italy as an example, there was a 70% increase in time spent across the apps with over 50% increases in Facebook and Instagram live views (Facebook, 2020b). These factors combined suggest that a relevant number of people have adopted these solutions for the first time and others have reinforced their activity. Based on the discussion above, and since SC implies the use of SNS in the online purchasing process, it becomes relevant to study the possible impact that COVID-19 pandemic may have in SC adoption.

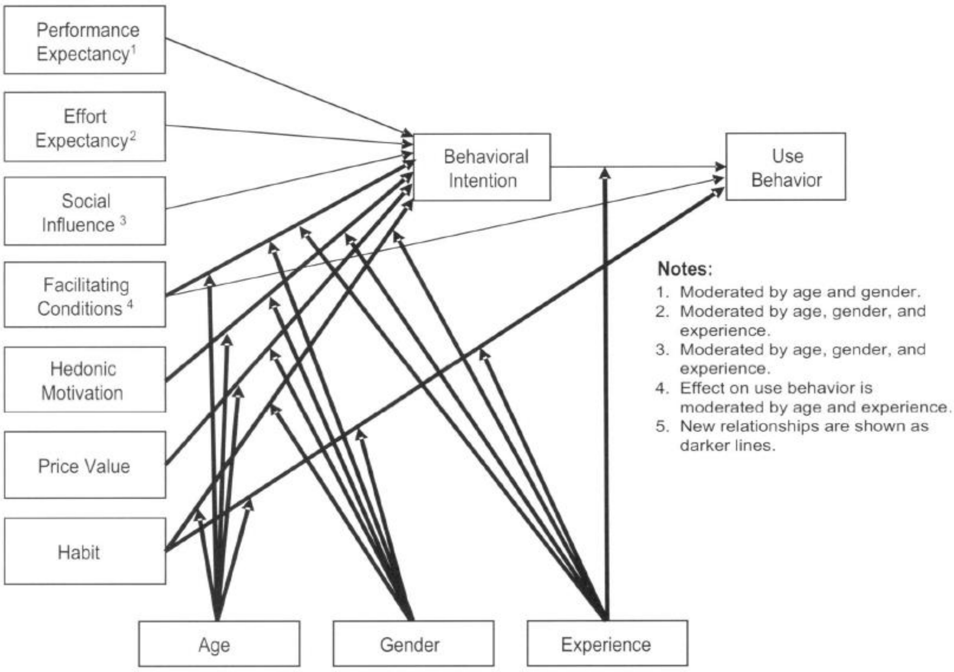
2.4 User Acceptance Models

User Acceptance Models have been developed with the aim to contribute to a better understanding of the factors that influence the adoption of a certain technology. As SC can be considered a subset of electronic commerce (Liang and Turban, 2011; Kim and Park, 2013), which consumers usually associate with technology use, theories explaining technology acceptance might be adapted to the Social Commerce context.

In this sense, some of the most significant theories and models are: a) Theory of Reasoned Action (TRA) used to understand human behavior in a specific context (Fishbein and Ajzen, 1975); b) Theory of Planned Behavior (TPB), an extension of TRA model that adds the Perceived Behavioral Control variable (Ajzen, 1991); c) Technology Acceptance Model (TAM), derived from TRA model, widely cited in the field of technology acceptance (Davis, Bagozzi and Warshaw, 1989); d) TAM2 (Venkatesh and Davis, 2000) review of TAM model with additional variables that predict Behavioral Intention and Use and; e) Social Cognitive Theory (SCT), inspired from social psychology, used to predict behavior based on environmental, personal and behavioral factors (Bandura 1986). The triadic structure of SCT is characterized to have all factors influencing and determining each other (Appendix I). The behavior factor is focused on usage, the personal is related to personality, cognitive or any demographic characteristics of a person, and finally, the environment includes physical and social influences, both external to the individual (Bandura, 1986). In this sense, beliefs and expectations can be created and modified by environmental influences such as the built environment. This becomes particular important to explain the impacts that environmental external factors such as a pandemic may have in behavioral intention.

Another widely used model is the Unified Theory of Acceptance and Use of Technology (UTAUT). Developed by Venkatesh et al. (2003), UTAUT is based on eight different models previously used in the context of information systems: TAM, TRA, TPB, combined TAM and TPB (C-TAM-TPB), Model of PC Utilization (MPCU), Diffusion of Innovation, Motivational Model and SCT. As a result of an extensive analysis, the following key constructs were formulated and added to the UTAUT model: Effort Expectancy (EE), Performance Expectancy (PE), Social Influence (SI), and Facilitating Conditions. Four moderating variables were also considered: experience, gender, age and voluntariness of use (Venkatesh et al. 2003). Despites the wide acceptance of UTAUT, in order to better suit the consumer context, this model was extended to UTAUT2 with the addition of the following constructs: Hedonic Motivation (HM), Price Value (PV), and Habit (HT) (Venkatesh et al., 2012). Moreover, in order to better adapt the model to consumer context, the moderating variable voluntariness of use was not considered. Figure 1 depicts UTAUT2 model.

Figure 1. UTAUT2 model



This extended version resulted in a substantial improvement of the variance explained in Behavioral Intention and technology Use (Venkatesh et al., 2012). Some significant findings of the application of UTAUT2 are summarized as follows: a) Hedonic Motivation is a key determinant of Behavioral Intention; b) both hedonic and utilitarian benefits are significant drivers of technology usage; c) Habit takes an important role in predicting the continued use of technology and d) Facilitating Conditions, moderated by gender and age influences Behavioral Intention (Venkatesh et al., 2012).

3. Research Model and Hypothesis

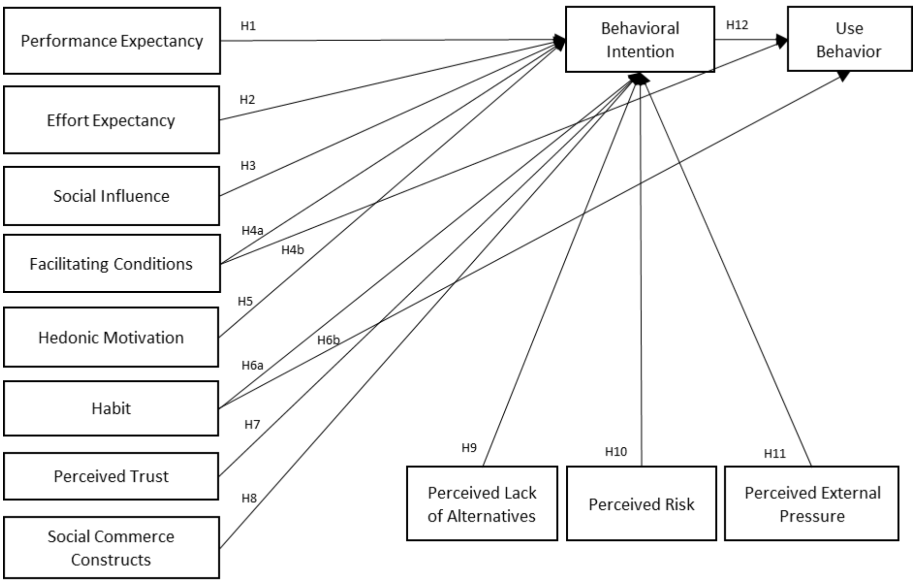
Taking in consideration the literature review, it is assumed that UTAUT2 can be useful to understand the adoption of SC. Furthermore, literature shows that some authors have successfully employed this model to study the SC adoption (Gatautis and Medziausiene, 2014; Sheikh et al., 2017).

However, even though this model is very complete, it needs to be adapted in order to fit the issue at hand. Thus, additional variables that could impact the acceptance of SC were identified and added to the model – Perceived Trust and Social Commerce Constructs. On the other hand, since SC does not entail a financial cost for technology usage, the construct Price Value was not considered.

In light of SCT, environment related constructs were also considered relevant to consider in the model as an attempt to study the pandemic influence in SC acceptance. Hence, the constructs Perceived Lack of Alternatives, Perceived Risk and Perceived External Pressure were added to the model.

The proposed research model depicted in Figure 2. enhances the relationships between the constructs.

Figure 2. Research Model



3.1 Performance Expectancy (PE)

Venkatesh et al., (2012) defines Performance Expectancy (PE) as "the degree to which using a technology will provide benefits to consumers in performing specific activities" (p. 159). Previous studies indicate that Performance Expectancy is an important determinant factor of Behavioral Intention (Davis et al., 1992, Venkatesh et al., 2012). Gan and Wang (2017), argue that utilitarian and hedonic values are crucial for motivating user behavior in social commerce context. Furthermore, when users perceive a website as useful or convenient, they are more likely to be satisfied and therefore to make online purchases (Bhattacherjee, 2012). Features offered on the system website, like the design, easy access and navigation tools can affect the way consumers accept social commerce (Huang and Benyoucef, 2013, Teh and Ahmed, 2012). Taking that in consideration, a positive relationship between Performance Expectancy and Behavioral Intention to accept SC is expected. Thus, the following hypotheses is formulated:

H1: Performance Expectancy positively influences Behavioral Intention to use Social Commerce.

3.2 Effort Expectancy (EE)

According to UTAUT, Effort Expectancy is defined as “the degree of ease associated with consumers’ use of the system” (Venkatesh et al., 2003, p.450). As mentioned by David (1989), the easier a system is to interact with, the more chances the system as to be accepted by the user. Thus, Effort Expectancy was proven to be an important factor impacting intention to use a system (Venkatesh et al., 2012). Similarly, in SC context, the belief that engaging in SC would be free of effort positively affects the its acceptance and consequently increases the intention to make a purchase (Hajli M. 2012, Teh and Ahmed, 2012; Maia et al. 2018). Additionally, Gatautis and Medziausiene (2014), mentioned in their research that the FC impacted positively the intention to use SC.

Based on these findings, the following hypothesis is formulated:

H2: Effort Expectancy positively influences Behavioral Intention to use Social Commerce.

3.3 Social Influence (SI)

In UTAUT2, Social Influence can be defined as “the extent to which consumers perceive that important others (e.g., family and friends) believe they should use a particular technology” (Venkatesh et al., 2012, p.159). In other words, Social Influence means individuals may change attitudes or behaviors as a result of interactions with others. In both UTAUT and UTAUT2, this construct is recognized as a direct determinant of Behavioral Intention (Venkatesh et al., 2003, 2012). Lu (2014), argue that the social environment that consumers are exposed to in social media platforms have impact on the intention toward a technology. Furthermore, prior research in SC context report that Social Influence is positively related to the intention to use social commerce (Gatautis and Medziausiene, 2014; Liang and Turban, 2011). Therefore, the following hypothesis is proposed:

H3: Social Influence positively influences Behavioral Intention to use Social Commerce.

3.4 Facilitating Conditions (FC)

Venkatesh et al., (2003) defines Facilitating Conditions as “consumers’ perceptions about the resources and support available to use a system.” (Venkatesh et al., 2003, p.453). Venkatesh et al. (2012) consider that intention to use a system is likely to be higher if the individual has access to a “favorable set of Facilitating Conditions” (p. 162). Gatautis and Medziausiene (2014), argue that facilitating conditions contribute towards social commerce acceptance. Additionally, Sheikh et al., (2017) mention that the purchase behavior trough social media is directly impacted by this construct. Hence, the following hypothesis is suggested:

H4a: Facilitating Conditions positively influences Behavioral Intention to use Social Commerce.

H4b: Facilitating Conditions positively influences Use Behavior of Social Commerce.

3.5 Hedonic Motivation (HM)

Hedonic Motivation can be defined as “the fun or pleasure derived from using a certain technology” (Venkatesh et al., 2012, p. 161). Hedonic Motivation, frequently conceptualized as Perceived Enjoyment, has been proved to influence technology acceptance and use directly (Heijden 2004, Venkatesh et al., 2012). According to Shin (2012), people adopting social commerce tend to seek for entertainment in order to facilitate the online purchasing process. Although shopping itself may not be considered enjoyable to all consumers, previous research has shown that consumers enjoy shopping activity itself (Arnold and Reynolds, 2003). This can be particularly true to SC, since consumers actively interact with others in shopping activities. Additionally, Chen et al., (2017) verified that consumers make online purchases through social media primarily for hedonic reasons and their intention to continue visiting social commerce sites is strongly determined by its hedonic value. Hence, the following hypothesis is formulated:

H5: Hedonic Motivation positively influences Behavioral Intention to use Social Commerce.

3.6 Habit (HT)

In UTAUT2, Habit can be conceptualized in two similar ways: for Limayem et al. (2007) Habit arises from prior experiences, being learning crucial for people to perform behaviors automatically. For Kim and Malhotra (2005), Habit is equal to automaticity. In UTAUT2, Habit is operationalized accordingly to Limayem et al. (2007) definition. Prior research confirmed Habit as direct determinant in intention and/or use behavior (Venkatesh et al., 2012; Gefen 2003), reinforcing its influence on technology acceptance. According to Turel and Serenko (2012), it is common for people to develop habits on social websites that provide them with hedonic experiences. Farivar et al., (2017), argue that as SC users repeat the use behavior of visiting SNSs and purchase online, an automatic response tend to replace rational thoughts. Thus, purchasing intentions may automatically happen without considering possible risky factors. Furthermore, Sheikh et al., (2017) mention that Habit is a key determinant of the intention and use of social media to make online purchases. Therefore, the following hypothesis are proposed:

H6a: Habit positively influences Behavioral Intention to use Social Commerce.

H6b: Habit positively influences Use Behavior of Social Commerce.

3.7 Perceived Trust

Trust can be defined as the individuals' willingness to depend on the beliefs of benevolence and integrity Gefen et al. (2003). According to the authors, trust is an important determinant of consumer's behavioral intention and actual behavior. The uncertainty inherent to the online environment, makes trust a critical factor to engage in EC. The lack of face-to-face interaction with the seller may accentuate the sense of insecurity and thus the perceived trust of consumers can be decisive to make online transactions (Gefen et al., 2003; Turban and Lee, 2001; Pavlou 2003). In this line, due to the uncertainty present in the SC environment, trust has been studied as an important predictor of users' behavior. In this line, several studies shown that users' intention to engage in social commerce websites depends on trust (The and Ahmed, 2012; Hajli, 2012;

Shin, 2013). Additionally, Hajli (2014) mentioned that trust has a significant effect on intention to buy in e-commerce sites and Kim and Park (2013) indicated that users who trust social commerce sites are more likely to purchase on these platforms. In line with these findings, this research suggests that Perceived Trust have a positive impact in the intention to use SC. Therefore, the following hypothesis is formulated:

H7: Perceived Trust positively influences Behavior Intention to use Social Commerce.

3.8 Social Commerce Constructs (SCCs)

According to Hajli (2015), Social Commerce Constructs are social platforms that empower consumers to generate content. They can be categorized as ratings and reviews, communities, forums, recommendations and referrals (Hajli, 2015). In the SC environment, consumers can easily post product reviews and ratings that would be beneficial for other potential customers. Additionally, considering recommendations and referrals, as customers cannot experience the products or services in an online context, consumers tend to rely more other consumers' experiences such as their product recommendations (Senecal and Nantel, 2004). Online communities and forums can facilitate the social interaction of customers. Members of online communities join different group activities and support other members through their social interactions in the platform (Hajli, 2015). Moreover, as stated by Wang and Hajli (2015), SNSs motivate users to share information with others and participate in forums. According to Hajli (2014), one of the main reasons why SC plays its critical role via SCCs is the social influence that consumers may exposed to in this environment. Consumer communications in SNSs can endorse a brand positively and affect consumers' behavior.

Since SCCs are likely to play an important role on social commerce intention, the following hypotheses is formulated:

H8: Social Commerce Constructs positively influence Behavior Intention to use Social Commerce.

3.9 Perceived Risk

Sweeney et al., (1999) defined risk as an expectation of loss. Perceived risk (PR) is commonly associated as an uncertainty feeling regarding possible negative consequences of using a product or service (Featherman and Pavlou, 2003). Hence, the greater the probability of loss, the greater the perceived risk (Mitchell, 1999). Considerable research has examined the impact of risk on technology acceptance; however, most studies address risk with financial or security concerns (Featherman, 2001, Featherman and Pavlou, 2003). Risk varies according each context challenges. In the COVID-19 pandemic context, Perceived Risk is associated to the perception of health risks that people can be exposed to. The World Health Organization has established preventive measures to combat the virus spreading, such as physical distancing and avoidance of spaces that are crowded or involve close contact (WHO, 2019). Hence, there might be a higher risk of contracting the virus in public places like malls and supermarkets, consumers may consider alternatives in order to satisfy their shopping needs. In this line, a risk subjacent in using SC may also exist. Hence, the following hypothesis is proposed:

H9. Perceived Risk has a negative effect on Behavioral intention to use Social Commerce.

3.10 Perceived Lack of Alternatives

Jones et al., (2000) defines the attractiveness of alternatives as the consumer perceptions regarding which viable competing alternatives are available in the marketplace. Salem and Nor (2020) studied the impact of the COVID-19 pandemic in the adoption of EC. Based on the authors' findings, the Perceived Lack of Alternatives is the extent to which viable competing alternative is available to shopping and it has a direct impact in the intention to adopt the system. In order to control the COVID-19 pandemic, imposed restrictions to traditional shopping were imposed by the government what indicates fewer available options for consumers. Therefore, Perceived Lack of Alternatives may positively impact the intention to adopt SC. Thus, this study proposes the following hypothesis:

H10. Perceived Lack of Alternatives positively influences Behavioral Intention to use Social Commerce.

3.11 Perceived External Pressure

Technology adoption can be influenced by the pressure exerted on one by its environment or external circumstances. External Pressure can be defined as the degree to which an industry or business influence the adoption of a new technology (Premkumar et al., 1997). Salem and Nor, (2020) adapted the concept of external pressure to the EC context with the aim to study potential impacts that the COVID-19 pandemic may have had in EC adoption. In line with this research, in the context of this study it is stated that Perceived External Pressure is related to the consumers' perception of pressure imposed by government and/or stakeholders concerning the adoption of SC. The COVID-19 pandemic forced people to change their buying behavior and thus, the following hypothesis is proposed:

H11. Perceived External Pressure positively influences Behavioral Intention to use social commerce.

3.12 Behavioral Intention

Behavioral Intention (BI) is considered a measure of strength of an individual's intention to satisfy a specific behavior that can foretell the usage behavior of a technology (Davis et al., 1989; Fishbein & Ajzen, 1975). As this study aims to assess the acceptance of consumers to use SC, this construct is relevant. In line with UTAUT2, the Behavioral Intention is an antecedent of the Use construct (Venkatesh et al., 2012). Taking this in consideration, the same reasoning can be applied in the SC context. Hence, the following hypothesis is formulated:

H12. Behavioral Intention positively influences Use Behavior of Social Commerce.

4. Methodological Approach

4.1 Data Collection

As mentioned before, the present research aims to study the factors influencing SC adoption, taking in consideration the COVID-19 pandemic context. For that, a conceptual model was developed being a quantitative approach appropriate to validate it.

Based on the literature review, a questionnaire was elaborated using Google Forms platform. The study population was the Portuguese population with experience with SNSs. An age group was not defined, which allowed a higher diversity of responses. In order to follow Podsakoff et al. (2003) recommendations, there was an effort to develop the questionnaire as understandable as possible. Moreover, to assess its adequacy, a pre-test with an initial version of the questionnaire was completed by seven people. Consequently, feedback from the respondents were took in consideration and adjustments to the wording were made to make some questions clearer. The questionnaire was divulged on Facebook, LinkedIn, Instagram and WhatsApp, what leads to a non-probabilistic sampling, reaching a snowball effect. The answers were collected from to 5 to 14 October 2020. Since all the requested questions were mandatory to be answered, all the responses were considered and there were no missing values.

The questionnaire was divided into three different sections. As the Social Commerce concept may be unknown for some people, a cover page was elaborated to explain the concept. The confidentiality of participants collected data was also ensured.

The first section was designed to obtain data related socio-demographic variables. The respondents age, gender, qualifications and experience with SNSs and SC were assessed.

The second section was related to the conceptual model, being composed of a range of statements meant to test each of its constructs. As the original model was written in English, and once the questionnaire was applied in Portugal, to make it clear these statements were translated to Portuguese. In order to validate the translation, the backtranslation method was applied. The questionnaire was translated to Portuguese by the author and a college with a very high knowledge of English language. After that, the original English version was compared to the translated one by a third person. This enabled a more reliable information.

Finally, the third section was related to the COVID-19 pandemic. In here, questions regarding the model constructs were assessed as well as the frequency of usage of SC before and after the pandemic, in order to answer the second research question.

For all questions respondents were asked to rate the statements on a five-point Likert Scale (with exception of age, gender and qualifications). A summary of the model statements can be found on Appendix II.

4.2 Data Analysis

The Structural Equation Modeling (SEM) was considered suitable to proceed with the data analysis. There are two different SEM techniques: partial least squares-based SEM (PLS-SEM) and covariance-based SEM (CB-SEM). The first method is based on an iterative approach that aims to maximize the explained variance of endogenous constructs, being more appropriate for exploratory research. In contrast, CB-SEM is primarily used to confirm theories by determining how well a model can estimate a covariance matrix for a sample set (Hair et al., 2017). In the present study, PLS-SEM was utilized. This method provides numerous advantages to researchers working with SEM and has received considerable attention in management information systems discipline (Ringle et al., 2012). Moreover, according this method is recommended in an early stage of theoretical development, allowing reflective and formative measurement models. Additionally, it has the capability of working with nonnormal data and small sample sizes (Hair et al., 2017). In order to perform the structural equation modeling based on partial least squares, SPSS Statistics (v20) and Smart PLS 3.0 software were utilized. First, a measurement model (used to assess the associations between the indicator variables and corresponding constructs) and a structural model (which illustrate the relationships between the constructs) were specified.

5. Analysis of Results

5.1 Preliminary Data Analysis

The collected data was checked for any missing values and none were found. With the aim to examine response patterns, standard deviation was calculated for all the data pertaining to the model's constructs. As result, one observation was found to have a standard deviation of zero, which means that one person marked the same response for all the items of the questionnaire. This suggest that the respondent may have not been totally engaged with the questionnaire, so the observation was removed. Since all the items of the questionnaire were measured on a Likert scale, no outliers had been observed.

Hence, the final sample has 209 valid responses. Analyzing the collected data, 87 respondents (41.6%) were male and 122 (58.4%) were female. The age group between 25 and 34 years old were the most representative one with 51.7% of respondents. Regarding the academic background, 163 respondents (77.6%) have higher education with 34.3% holding bachelor's degree. Considering a five-point Likert scale, all respondents have been shown to be familiarized with Social Network Sites (mean of 4), with no one reporting one (no experience). The degree of experience with Social Commerce was in average 3.5, showing that the sample has adequate experience to answer to this questionnaire.

Table 1. Descriptive statistics (n=209)

Characteristics	Frequency	(%)
Gender		
Masculine	87	41.6%
Feminine	122	58.4%
Age groups		
< 18	3	1.4%
18-24	45	21.4%
25-34	108	51.4%
35-44	14	6.7%
45-54	27	12.9%
55-64	10	4.8%
65 or above	2	1.0%
Academic degree		
1st/2nd/3rd cycles of basic education	5	2.4%
High School	29	13.8%
Technological/professional/other courses	12	5.7%
Licentiate's degree (Licenciatura)	72	34.3%
Bachelor's degree (Bacharelato)	5	2.4%
Postgraduate studies	21	10.0%
Master's degree	63	30.0%
Doctorate	2	1.0%

Experience	Mean
Social Networking Sites	4
Social Commerce	3.5

Measured in a five-point Likert scale
(1=No experience; 5=Very experienced)

5.2 Operationalizing the model

5.2.1 Measurement Model

The measurement model represents the relationships between constructs and their corresponding indicators (Hair et al, 2017). The developed model is composed by twelve reflective constructs (PE, EE, SI, FC, HM, HT, PT, SCC, PR, PLA, PEP and BI) and a single-item construct (UB) (Appendix III). The assessment of the reflective measurement model includes: the indicators reliability, internal consistency reliability, convergent validity, and discriminant validity (Hair et al, 2017).

According to the authors, indicators with outer loadings above the threshold value of 0.70, suggest sufficient levels of reliability. Taking that in consideration, one item in the model raised concern, with an outer loading of 0.637 – "SCCfriendsugg". According to Hair et al (2017), a removal of an indicator should be considered if: a) its outer loading value is between 0.40 and 0.70 b) its' removal from the model increases the Composite Reliability (CR)[1] and the Average Variance Extracted (AVE)[2] levels above threshold. After verifying these conditions, the indicator mentioned was removed from the model in order to improve its quality.

To guarantee a good reliability and internal consistency, Cronbach's Alpha criterion (based on the intercorrelations of the indicator variables), and Composite Reliability must have values higher than 0.7 (Hair et al, 2017). As shown in Table 2, all Cronbach's Alpha and Composite Reliability values are above 0.7, what guarantees the reliability and consistency of the model.

Table 2. Reliability measurement of reflective variables (n =209)

Measurement Item	**Cronbach's Alpha (α)**	**Composite Reliability**	**AVE**
Behavioral Intention	0.909	0.943	0.847
Effort Expectancy	0.885	0.929	0.813
Facilitating Conditions	0.843	0.906	0.764
Hedonic Motivation	0.932	0.957	0.881
Habit	0.931	0.956	0.879
Performance Expectancy	0.88	0.918	0.736
Perceived External Pressure	0.865	0.937	0.881
Perceived Lack of Alternatives	0.869	0.919	0.792
Perceived Risk	0.753	0.858	0.668
Perceived Trust	0.849	0.899	0.689
Social Commerce Constructs	0.797	0.881	0.712
Social Influence	0.898	0.936	0.83

Regarding the assessment of validity, the convergent validity and discriminant validity must be examined. According to Hair et al., (2017), convergent validity is the extent to which an indicator is positively correlated with alternative indicators of the same construct. AVE values should be equal to or greater than 0.5, to indicate a satisfactory convergent validity. That would mean that in average, the latent variables are able to explain more than half of the variance of its indicators. As seen in Table 2, all constructs have AVE values above 0.5 what assurances the model's convergent validity.

[1] Measure of reliability that considers the different outer loadings of the indicator variables (Hair et al., 2017).
[2] The mean value of the squared loadings of indicator variables associated with the construct (Hair et al., 2017).

To conclude the assessment of the measurement model, the discriminant validity must be examined. According to Hair et al, (2017), the most commonly used criteria for this assessment are: Cross-Loadings and Fornell-Larcker.

Regarding Cross-Loadings, the objective is to verify that an indicator's outer loading on the associated construct is greater than its cross-loadings, on other constructs. As seen in Appendix IV, this criterion was met. The Fornell–Larcker criterion compares the squared root of AVE with the latent variable correlations. The squared root of AVE of each latent variable should be bigger than the latent variable's highest correlation with any other latent variable. As it is possible to verify in Table 3, all values are according to the requirement.

Table 3. Fornell–Larcker criterion (n= 209)

	BI	EE	FC	HM	HT	PE	PEP	PLA	PR	PT	SCC	SI
BI	**0.92**											
EE	0.598	**0.901**										
FC	0.39	0.713	**0.874**									
HM	0.794	0.63	0.479	**0.938**								
HT	0.815	0.609	0.424	0.782	**0.937**							
PE	0.748	0.643	0.419	0.725	0.711	**0.858**						
PEP	0.559	0.339	0.186	0.543	0.511	0.497	**0.939**					
PLA	0.59	0.319	0.177	0.549	0.536	0.502	0.741	**0.89**				
PR	0.377	0.359	0.35	0.376	0.371	0.337	0.344	0.393	**0.817**			
PT	0.553	0.355	0.201	0.601	0.623	0.478	0.374	0.393	0.262	**0.83**		
SCC	0.613	0.554	0.432	0.625	0.564	0.6	0.344	0.307	0.387	0.484	**0.844**	
SI	0.694	0.578	0.354	0.621	0.692	0.757	0.485	0.478	0.261	0.497	0.501	**0.911**

Notes: Values in diagonal represent AVE; values off-diagonal represent squared correlation.
BI - Behavioral Intention; EE - Effort Expectancy; FC - Facilitating Conditions; HM - Hedonic Motivation; HT - Habit; PE - Performance Expectancy; PEP - Perceived External Pressure; PLA - Perceived Lack of Alternatives; PR - Perceived Risk; PT - Perceived Trust; SCC - Social Commerce Constructs; SI - Social Influence

All the evaluation criteria have been met, what provides support for the reliability and validity of the model.

5.2.2 Structural Model

After verifying that the measurement model estimation requirements were met, the next step addresses the assessment of the structural model. The structural model, or inner model, describes the relationships between the latent variables. According to Hair et al., (2017) the key criteria for assessing the inner model are: collinearity issues, the path coefficients, the coefficient of determination (R^2), f^2 effect size, and the cross-validated redundancy (Q^2). To assess the model, the bootstrapping technique was applied to generate 5000 samples from 209 cases.

Given the following criteria, in first place, we should examine the structural model for potential collinearity issues. According to Hair et al (2017), if the VIF values of all sets of predictor constructs are above 5, there might be collinearity issues. As verified in Table 4, all VIF values are below 5, therefore no concerns were raised concerning collinearity and we can proceed with the analysis.

Table 4. Collinearity Statistics (VIF)

Construct	**Behavioral Intention**	**Use Behavior**
Behavioral Intention		3.003
Effort Expectancy	3.136	
Facilitating Conditions	2.204	1.228
Hedonic Motivation	3.777	
Habit	3.552	3.102
Performance Expectancy	3.483	
Perceived External Pressure	2.411	
Perceived Lack of Alternatives	2.593	
Perceived Risk	1.387	
Perceived Trust	1.863	
Social Commerce Constructs	2.003	
Social Influence	2.796	

In order to assess the significance and relevance of the structural model relationships, the path coefficients and significance levels are examined. The path coefficients vary between −1 and +1, with higher absolute values suggesting stronger predictive relationships between the constructs (Hair et al, 2017).

As shown in Table 5, some path coefficients values are very low what represents weak relationships: Effort Expectancy → Behavioral Intention (0.039); Social Influence → Behavioral Intention (0.092); Facilitating Conditions linked to both Behavioral Intention (-0.057) and Use Behavior (-0.055); Perceived External Pressure → Behavioral Intention (0.020); Perceived Risk → Behavioral Intention (0.005) and finally Perceived Trust → Behavioral Intention (-0.031). Hence, assuming a 5% significance level, we can verify that the hypothesis H2, H3, H4a, H4b, H7, H9, and H11, were not supported. On the other hand, all the remain hypotheses are statistically significant.

Table 5. Structural model results and hypotheses testing

#	Relationships	Path Coefficients	p values	Supported
H1	Performance Expectancy → Behavioral Intention	0.127	0.046	**Yes**
H2	Effort Expectancy → Behavioral Intention	0.039	0.581	No
H3	Social Influence → Behavioral Intention	0.092	0.203	No
H4a	Facilitating Conditions → Behavioral Intention	-0.057	0.286	No
H4b	Facilitating Conditions → Use Behavior	-0.055	0.222	No
H5	Hedonic Motivation → Behavioral Intention	0.241	0.001	**Yes**
H6a	Habit → Behavioral Intention	0.352	0	**Yes**
H6b	Habit → Use Behavior	0.235	0.007	**Yes**
H7	Perceived Trust → Behavioral Intention	-0.031	0.478	No
H8	Social Commerce Constructs → Behavioral Intention	0.114	0.038	**Yes**
H9	Perceived Risk → Behavioral Intention	0.005	0.901	No
H10	Perceived Lack of Alternatives → Behavioral Intention	0.119	0.01	**Yes**
H11	Perceived External Pressure → Behavioral Intention	0.020	0.701	No
H12	Behavioral Intention → Use Behavior	0.638	0	**Yes**

The coefficient of determination (R^2) is a measure of the model's predictive power, representing amount of variance in the endogenous constructs explained by the exogenous constructs associated (Hair et al, 2017). R^2 values of 0.75, 0.50, or 0.25 for endogenous constructs can be considered substantial, moderate or weak, respectively. As shown in Table 6, the R^2 value for BI (0.774) is considered substantial. That means that all the exogenous variables used in the study accounts for 77.4% of variation in the in BI. Similarly, the R^2 value for UB (0.671) is moderate, what means that about 67.1% of variation in UB is explained by the exogenous variables associated with the construct. Therefore, we can conclude that the model is capable to explain the variation of the endogenous variables.

Table 6. R^2

	R^2	R^2 (Adj.)
Behavioral Intention	0.774	0.759
Use Behavior	0.671	0.667

With the aim to verify the effect-size of the exogenous constructs in explaining R^2 on the endogenous constructs, the f^2 effect size is assessed. Values of 0.02, 0.15

and 0.35, represent small, medium, and large effects on the endogenous constructs. Values of less than 0.02 indicate that there is no effect (Hair et al, 2017). In this study, the variables with stronger effect sizes are Habit, with a medium effect size on BI (0.155) and Behavioral Intention with a large effect size on UB (0.412). All the remain constructs have weak effects (Appendix V).

The last criterion to be examined is the Stone-Geisser's Q^2. The Q^2 values are estimated by the blindfolding procedure[3] and indicate the model's predictive relevance. The reflective endogenous latent variables should have Q^2 values larger than zero to have a meaningful power (Hair et al, 2017). As seen in Appendix VI, the Q^2 values of UB (0.650) and BI (0.637) support the model's predictive relevance. The final assessment addresses the q^2 effect sizes. However, since SmartPLS software does not provide this information these values had to computed manually. Results of 0.02, 0.15, and 0.35 indicate that an exogenous construct has a small, medium, or large predictive relevance, respectively, for an endogenous variable (Hair et al, 2017). Analyzing the results, the construct Habit has the largest predictive relevance. Appendix VII summarizes the results of the q^2 effect sizes of all the relationships in the model.

5.3 The pandemic impact on Social Commerce usage

In order to answer the second research question (the impact of COVID-19 pandemic on SC usage), two questions regarding the frequency of use of SC (before and during the pandemic) were added in the questionnaire. Respondents were asked to rate the frequency of use of SC in a five-point Likert scale, from "never" to "daily", considering both occasions. Since the population in study is the same in both situations (before and during the pandemic) and it is aimed to make a comparison between them, the t-test statistics is appropriate. To proceed with the analysis and obtain the descriptive statistics, Microsoft Excel was used (Appendix VIII). Table 6 summarizes the results. The difference in the use of SC during the pandemic (mean=2.77) and before the pandemic (mean=2.35) suggest being significant. In fact, according to the

[3] Resampling technique that deletes and predicts every data point of the indicators, in the reflective measurement model of endogenous variables (Hair et al., 2017).

t-test statistics, the difference between the frequency of use of SC during the pandemic and the usage of SC before the pandemic is significative. Therefore, it is possible to conclude that the COVID-19 pandemic has increased the frequency of use of SC.

Table 7. Summary of descriptive and t-test statistics

	N	Min	Max	Mean	t	Sig (2-tailed)
Frequency of use of SC during COVID-19 pandemic (UB1)	209	1	5	2.77	7.502	0.00
Frequency of use of SC before COVID-19 pandemic (UB2)	209	1	5	2.35		

6. Discussion

The aim of this research is to identify the antecedents for the SC acceptance and adoption, taking in consideration additional constructs to better suit the SC context as well as some related to COVID-19 pandemic. In accordance to Venkatesh et al. (2012) findings, some of the original constructs from UTAUT2 impacting Behavioral Intention and Use behaved as expected. The main factor impacting directly Use is Behavioral Intention, succeeded by Habit. Regarding Behavioral Intention, the key determinants are, in order of relevance: Habit, Hedonic Motivation, Perceived Lack of Alternatives, Social Commerce Constructs and Performance Expectancy.

From the results mentioned above, we can conclude that Habit plays an important role in SC acceptance and adoption, being considered the highest factor impacting Behavioral Intention (β=0.352; $p<0.000$) and Use (β=0.235; $p<0.007$). These results are aligned with previews research (Venkatesh et al., 2012) that refer to Habit has having a direct effect on behavioral intention and/or the use of a technology. Considering that in this research context, SC implies using SNSs to make online purchases, it is assumed that greater chances of online purchase intentions and actual purchasing behavior exist if consumers usage of SNSs is superior. These findings are in accordance to prior studies developed in the SC context (Sheikh et al., 2017; Farivar et al., 2017). Taking in consideration that Habit is a factor that can both negatively or positively impact Behavioral Intention and Use Behavior (Venkatesh et al., 2012), companies engaged in SC should consider develop a frequent/committed relationship with customers in SNSs in order to encourage them to make online purchases, leading to an automatic behavior.

As suggested by Limayem et al. (2007), websites may encourage a frequent usage through incentive mechanisms for their members.

Hedonic Motivation is considered the second most important determinant of Behavioral Intention ($\beta=0.241$; $p<0.001$). This indicates that respondents consider entertainment and enjoyment an important factor when using SC. These findings are consistent with UTAUT2 model, with HM considered an important factor in determining BI (Venkatesh et al., 2012). Also, according to previous studies, perceived enjoyment is considered an important factor impacting the intention to use SC (Chen et al., 2017; Shin, 2012). Similarly, Sheikh et al., (2017) emphasized the importance of HM in accepting SC. Confirming those findings, this study reinforces that the hedonic characteristics of SC and the perceived enjoyment that users have by using SNSs to make online purchases, influence the intention to use SC significantly.

Performance Expectancy also impacts positively Behavioral Intention ($\beta=0.127$; $p<0.046$). These results are congruent with the reported by Venkatesh et al., (2012), stating that utilitarian characteristics influence the use of a technology. Also, in SC context, Sheikh et al., (2017) mentioned that PE is directly related to behavioral intention to use SC. Even though SC is highly valued by its hedonic characteristics, these results show that consumers give importance to the utilitarian characteristics. As PE relates to the system functions/features, our findings suggest that issues regarding the online purchasing process such as the payment methodology or even the redirection functionality to other external commercial websites, may decrease the intention to use SC.

The extended variable Social Commerce Constructs is also statistically significant regarding Behavioral Intention ($\beta=0.114$; $p<0.038$). This result is consistent with Hajli (2015) and Sheikh et al. (2017) findings. This suggests that not only communities and forums that promote social interactions are valued by consumers, but also reviews, ratings and recommendations of products are taken into consideration before making the online purchasing decision. Therefore, online businesses should invest in the development of online communities that promote a positive word of mouth from customers in order to increase their intention to make online purchases.

With regard to COVID-19 pandemic constructs, Perceived Lack of Alternatives is the only factor impacting Behavioral Intention ($\beta=0.119$; $p<0.01$). These results corroborate

Salem M. and Khalid N.'s (2020) findings, where it is mentioned that the perceived lack of alternatives to shop, that consumers experience during the pandemic, will highly influence the intention to adopt e-commerce. This can be explained by the restrictions imposed by the government in order to contain the virus spreading. Constraints like curfew, the reduced working hours and even the shutting down of commercial establishments lead consumers to arrange alternative ways to fulfill their shopping needs. Therefore, Social Commerce can be considered as an alternative to traditional shopping. In this line, Perceived Lack of Alternatives is considered significant to accept SC.

Finally, Behavioral Intention influence on Use showed a strong statistical significance (p=0.000). Taking in consideration that the model under study is in its most based on UTAUT2, this result was expected. The intention to use SC highly determines its usage.

There were also several hypotheses rejected by this study. The hypotheses H2 (Effort Expectancy → Behavioral Intention), H3 (Social Influence → Behavioral Intention), H4a (Facilitating Conditions → Behavioral Intention), H4b (Facilitating Conditions → Use Behavior), H7 (Perceived Trust → Behavioral Intention), H9 (Perceived Risk → Behavioral Intention) and H11(Perceived External Pressure → Behavioral Intention) were rejected due to their statistical insignificance.

Effort Expectancy can be conceptualized as the perceived ease of use of a certain technology. Our results contradict prior research (Sheikh et al., 2017; Gatautis and Medziausiene, 2014) that have shown the influence of this variable in intention to engage in SC. One possible explanation for this result can be current usual use of SNSs on user’s daily basis. Since users are highly familiarized with these technologies, it is supposed that they have the expertise and capacity to understand how SNSs work which leads to a devaluation of this factors' relevance in determining the intention to use SC. Moreover, Facilitating Conditions were also not considered determinant in the intention to use and in the actual usage of SC. This result is in accordance to Sheikh et al., (2017) findings that posit that FC does not affect consumers’ intention to buy in social media websites. Assuming the fact that the respondents have experience with SNSs, they might consider having the necessary resources and knowledge to use SC. In this sense, the expected support from companies involved in SC is not considered relevant in the intention and adoption of SC.

Social Influence was also rejected, indicating that people tend to use SC whether it is recommended by people whose opinions are valued, or not. One of the reasons could also be the sample characteristics

Surprisingly, Perceived Trust and Social Influence were not considered determinants of SC intention. In contrast to several studies (The and Ahmed, 2012; Hajli, 2012; Shin, 2013; Kim and Park, 2013) trust does not seem to have importance in the intention to engage in SC.

Considering the pandemic context, the constructs Perceived Risk and Perceived External Pressure were also found not to be relevant in the intention to adopt SC and in regard to Perceived Risk, our study reveals that it does not have a significant impact in SC intention. These results are in line with Salem M. and Khalid N. (2020) findings, that studied this variable in the EC context. Even though a lot of consumers shifted their shopping behavior to online means, Perceived External Pressure was not a significative factor in the intention to adopt SC which may indicate that the pressure enforced by the government and stakeholders (e.g., retailers) was not considered a determinant factor of SC acceptance in this study. These results as well are in accordance to Salem and Khalid (2020) research.

Finally, respondents were asked to measure the frequency of use of SC before and during the pandemic. Comparing the results, this study reinforces that the COVID-19 pandemic has increased the frequency of usage of SC. One of the possible reasons for this behavior ought to be the Perceived Lack of Alternatives, proved to be a determinant factor in the intention to adopt Social Commerce, as previously verified.

7. Conclusion, Limitations and Future work

7.1 Conclusion

The present research verified the applicability of the UTAUT2 model in the SC context, suggesting that some of the Venkatesh et al. (2012) constructs for determining Behavioral Intention and Behavioral Use of a technology provide a useful insight for the investigation of the adoption of SC. According to this study results, Habit plays an important role in SC acceptance and adoption, highlighting the importance of fomenting a committed relationship with customers in SNSs, in order to improve the intention and usage of SC. Moreover, the variables Hedonic Motivation and Performance Expectancy also impact directly the intention to use SNSs in the online purchasing process. As SC can be considered a hedonic and utilitarian system, these results reinforce the assumption that consumers expect to enjoy making online purchases in SNSs as well as find the system user friendly and useful. Additionally, Social Commerce Constructs showed a substantial impact in the intention to use SC, with communities, forums, ratings and reviews being valued by consumers before making the online purchasing decision.

A significant finding of this study is the role Perceived Lack of Alternatives plays in influencing Behavioral Intention to use SC. Due to the pandemic context, the restrictions imposed by the governments in order to contain the spreading of the virus, have a huge influence in consumer behavior, attracting more customers to purchase in SNSs. As consumers are purchasing more in online contexts, this transition to SC may result in a trend that increases the use of these systems. In fact, this research proved that the SC usage increased in terms of frequency, when comparing the period before and during the COVID-19 pandemic.

The lack of a significant relationships between Effort Expectancy, Social Influence, Facilitating Conditions and Perceived Trust suggest that these variables don't impact the intention to engage in SC. Furthermore, in contrast to the literature review, a widely studied construct – Perceived Trust, didn't show significative impacts in SC acceptance. One of the possible causes for this result may have been the sample characteristics, mostly composed by the age-group 18 – 34. Considering the pandemic context, Perceived Risk and Perceived External Pressure variables were considered not determinant in the intention to adopt SC. As the field in question is recent, this research contributes to enrich the literature being built to understand SC. In this way, this study supports the scientific knowledge regarding the acceptance of a technology by the user in a SC context and helps to understand the impact that the pandemic may had had in this systems' adoption.

7.2 Limitations and Future work

One of the main purposes of this research was to understand the relationships between the variables applied in the extended UTAUT2 model, in the Social Commerce context. In this line, the absence of the UTAUT2 moderators (gender, age, experience) could be considered a limitation to this research. The sample may be more diversified, since the majority of this study' inquiries had ages between 18 – 34 years. In order to achieve a more comprehensive understanding of UTAUT2 application on SC context, a thoroughly version of this analysis should be performed. To better adapt the model to the SC context, other constructs could be considered. However, considering that this study is the pioneer in extending the UTAUT2 model with SC and pandemic related constructs in Portugal, this does not refute the validity of the results. In this sense, further research regarding the pandemic impact in SC may also be performed. While this study analyzed the impact that the COVID-19 pandemic had in SC adoption and frequency of use, deeper research can be developed in this field by assessing the way different brands developed their SC strategies and their efforts to cope with the ever-changing demands in this field.

References

ACEPI (2020a). Pandemia acelerou transformação digital em Portugal com reação notável das empresas. [online] portugaldigitalsummit.pt. Available at: https://portugaldigitalsummit.pt/pt/noticias/pandemia-acelerou-transformacao-digital-em-portugal-com-reacao-notavel-das-empresas/ [Accessed 13 Nov. 2020].

Ajzen, I. (1991). The theory of planned behavior. Organizational Behavior and Human Decision Processes, 50(2), pp.179–211.

Arnold, M.J. and Reynolds, K.E. (2003). Hedonic shopping motivations. Journal of Retailing, 79(2), pp.77–95.

Bandura, A. (1989). Social Cognitive Theory. Encyclopedia of Management Theory.

Bhattacherjee, A. (2012). Scholar Commons Social Science Research: Principles, Methods, and Practices. [online] Available at: https://scholarcommons.usf.edu/cgi/viewcontent.cgi?article=1002&context=oa_textbooks.

Boyd, D.M. and Ellison, N.B. (2007). Social Network Sites: Definition, History, and Scholarship. Journal of Computer-Mediated Communication, [online] 13(1), pp.210–230. Available at: https://onlinelibrary.wiley.com/doi/full/10.1111/j.1083-6101.2007.00393.x.

Business Wire (2020). TBRC E-Commerce Market Outlook 2020-2030: COVID-19 Implications and Growth. [online] www.businesswire.com. Available at: https://www.businesswire.com/news/home/20200615005360/en/e-Commerce-Market-Outlook-2020-2030-COVID-19-Implications-and-Growth---ResearchAndMarkets.com [Accessed 7 Nov. 2020].

Chen, W.-K., Chang, D.-S. and Chen, C.-C. (2017). The Role of Utilitarian and Hedonic Values on Users' Continued Usage and Purchase Intention in a Social Commerce Environment. Journal of Economics and Management, 13(2), pp.193–220.

Curty, R.G. and Zhang, P. (2011). Social commerce: Looking back and forward. Proceedings of the American Society for Information Science and Technology, 48(1), pp.1–10.

Davis, F.D., Bagozzi, R.P. and Warshaw, P.R. (1989). User Acceptance of Computer Technology: A Comparison of Two Theoretical Models. Management Science, 35(8), pp.982–1003.

Davis, F.D., Bagozzi, R.P. and Warshaw, P.R. (1992). Extrinsic and Intrinsic Motivation to Use Computers in the Workplace1. Journal of Applied Social Psychology, 22(14), pp.1111–1132.

Facebook (2020a). Introducing Facebook Shops, a New Online Shopping Experience. [online] Facebook for Business. Available at:

https://www.facebook.com/business/news/announcing-facebook-shops [Accessed 13 Nov. 2020].

Facebook (2020b). Keeping Our Services Stable and Reliable During the COVID-19 Outbreak. [online] About Facebook. Available at: https://about.fb.com/news/2020/03/keeping-our-apps-stable-during-covid-19/ [Accessed 10 Nov. 2020].

Farivar, S., Turel, O. and Yuan, Y. (2017). A trust-risk perspective on social commerce use: an examination of the biasing role of habit. Internet Research, 27(3), pp.586–607.

Featherman, M. (2001). Extending the Technology Acceptance Model by Inclusion of Perceived Risk. AMCIS 2001 Proceedings.

Featherman, M.S. and Pavlou, P.A. (2003). Predicting e-services adoption: a perceived risk facets perspective. International Journal of Human-Computer Studies, 59(4), pp.451–474.

Fishbein, M. and Ajzen, I. (1975). Belief, attitude, intention, and behavior : an introduction to theory and research. Reading, Mass.: Addison-Wesley Pub. Co.

Gan, C. and Wang, W. (2017). The influence of perceived value on purchase intention in social commerce context. Internet Research, 27(4), pp.772–785.

Gatautis, R. and Medziausiene, A. (2014). Factors Affecting Social Commerce Acceptance in Lithuania. Procedia - Social and Behavioral Sciences, 110, pp.1235–1242.

Gefen, D. (2003). TAM or Just Plain Habit. Journal of Organizational and End User Computing, 15(3), pp.1–13.

Gefen, Karahanna and Straub (2003). Trust and TAM in Online Shopping: An Integrated Model. MIS Quarterly, 27(1), p.51.

GSMA (2020e). The Mobile Economy 2020. pp.11–17.

Hajli, M. (2012). Social Commerce Adoption Model. In: UK Academy for Information Systems Conference Proceedings 2012.

Hajli, M.N. (2014). The role of social support on relationship quality and social commerce. Technological Forecasting and Social Change, 87, pp.17–27.

Hajli, N. (2015). Social commerce constructs and consumer's intention to buy. International Journal of Information Management, 35(2), pp.183–191.

Heidjen, H.V.D. (2004). User Acceptance of Hedonic Information Systems. MIS Quarterly, [online] 28(4), pp.695–704. Available at: https://www.jstor.org/stable/25148660.

Hollenbeck, C.R. and Kaikati, A.M. (2012). Consumers’ use of brands to reflect their actual and ideal selves on Facebook. International Journal of Research in Marketing, 29(4), pp.395–405.

Huang, Z. and Benyoucef, M. (2013). From e-commerce to social commerce: A close look at design features. Electronic Commerce Research and Applications, 12(4), pp.246–259.

Instagram (2020a). Introducing Shops on Instagram: A New Online Shopping Experience. [online] Instagram for Business. Available at: https://business.instagram.com/blog/introducing-shops-on-instagram?locale=pt_BR [Accessed 10 Nov. 2020].

Jones, M.A., Mothersbaugh, D.L. and Beatty, S.E. (2000). Switching barriers and repurchase intentions in services. Journal of Retailing, 76(2), pp.259–274.

Kim, S. and Park, H. (2013). Effects of various characteristics of social commerce (s-commerce) on consumers’ trust and trust performance. International Journal of Information Management, 33(2), pp.318–332.

Kim, S.S. and Malhotra, N.K. (2005). A Longitudinal Model of Continued IS Use: An Integrative View of Four Mechanisms Underlying Postadoption Phenomena. Management Science, 51(5), pp.741–755.

Kim, Y.A. and Srivastava, J. (2007). Impact of social influence in e-commerce decision making. Proceedings of the ninth international conference on Electronic commerce - ICEC ’07.

Kuss, D. and Griffiths, M. (2017). Social Networking Sites and Addiction: Ten Lessons Learned. International Journal of Environmental Research and Public Health, 14(3), p.311.

Kuss, D.J. and Griffiths, M.D. (2011). Online social networking and addiction--a review of the psychological literature. International journal of environmental research and public health, 8(9), pp.3528–52.

Liang, T.-P. and Turban, E. (2011). Introduction to the Special Issue Social Commerce: A Research Framework for Social Commerce. International Journal of Electronic Commerce, 16(2), pp.5–14.

Limayem, M., Hirt, S.G. and Cheung, C.M.K. (2007). How Habit Limits the Predictive Power of Intention: The Case of Information Systems Continuance. MIS Quarterly, 31(4), p.705.

Lu, J. (2014). Are personal innovativeness and social influence critical to continue with mobile commerce? Internet Research, 24(2), pp.134–159.

Maia, C., Lunardi, G., Longaray, A. and Munhoz, P. (2018). Factors and characteristics that influence consumers’ participation in social commerce. Revista de Gestão, 25(2), pp.194–211.

Martins, C., Oliveira, T. and Popovič, A. (2014). Understanding the Internet banking adoption: A unified theory of acceptance and use of technology and perceived risk application. International Journal of Information Management, 34(1), pp.1–13.

McKinsey & Company (2020). A global view of how consumer behavior is changing amid COVID-19 | McKinsey. [online] www.mckinsey.com. Available at: https://www.mckinsey.com/business-functions/marketing-and-sales/our-insights/a-global-view-of-how-consumer-behavior-is-changing-amid-covid-19 [Accessed 11 Nov. 2020].

Mitchell, V. (1999). Consumer perceived risk: conceptualisations and models. European Journal of Marketing, 33(1/2), pp.163–195.

OECD (2020g). Connecting Businesses and Consumers During COVID-19: Trade in Parcels. [online] OECD. Available at: http://www.oecd.org/coronavirus/policy-responses/connecting-businesses-and-consumers-during-covid-19-trade-in-parcels-d18de131 [Accessed 2 Nov. 2020].

Pavlou, P.A. (2003). Consumer Acceptance of Electronic Commerce: Integrating Trust and Risk with the Technology Acceptance Model. International Journal of Electronic Commerce, 7(3), pp.101–134.

Podsakoff, P.M., MacKenzie, S.B., Lee, J.-Y. and Podsakoff, N.P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. Journal of Applied Psychology, 88(5), pp.879–903.

Premkumar, G., Ramamurthy, K. and Crum, M. (1997). Determinants of EDI adoption in the transportation industry. European Journal of Information Systems, 6(2), pp.107–121.

Ringle, Sarstedt and Straub (2012). Editor's Comments: A Critical Look at the Use of PLS-SEM in "MIS Quarterly." MIS Quarterly, 36(1), p.iii.

Rundmo, T. (1999). Perceived risk, health and consumer behaviour. Journal of Risk Research, 2(3), pp.187–200.

Salem, M.A. and Nor, K.M. (2020). The Effect Of COVID-19 On Consumer Behaviour In Saudi Arabia: Switching From Brick And Mortar Stores To E-Commerce. ResearchGate.

Sarker, P., Kizgin, H., Rana, N.P. and Dwivedi, Y.K. (2019). Review of Theoretical Models and Limitations of Social Commerce Adoption Literature. Lecture Notes in Computer Science, pp.3–12.

Senecal, S. and Nantel, J. (2004). The influence of online product recommendations on consumers' online choices. Journal of Retailing, 80(2), pp.159–169.

Sharma, S., Menard, P. and Mutchler, L.A. (2017). Who to Trust? Applying Trust to Social Commerce. Journal of Computer Information Systems, 59(1), pp.32–42.

Sheikh, Z., Islam, T., Rana, S., Hameed, Z. and Saeed, U. (2017). Acceptance of social commerce framework in Saudi Arabia. Telematics and Informatics, 34(8), pp.1693–1708.

Shin, D.-H. (2013). User experience in social commerce: in friends we trust. Behaviour & Information Technology, 32(1), pp.52–67.

Statista (2020a). Number of social media users worldwide 2010-2021. [online] Statista. Available at: https://www.statista.com/statistics/278414/number-of-worldwide-social-network-users/.

Statista (2020b). Facebook users worldwide 2018 | Statista. [online] Statista. Available at: https://www.statista.com/statistics/264810/number-of-monthly-active-facebook-users-worldwide/.

Statista (2020c). Global social media ranking 2020 statistic. [online] Statista. Available at: https://www.statista.com/statistics/272014/global-social-networks-ranked-by-number-of-users/ [Accessed 11 Nov. 2020].

Sweeney, J.C., Soutar, G.N. and Johnson, L.W. (1999). The role of perceived risk in the quality-value relationship: A study in a retail environment. Journal of Retailing, 75(1), pp.77–105.

Teh, P.-L. and Ahmed, P.K. (2012). Understanding Social Commerce Adoption: An Extension of the Technology Acceptance Model. In: IEE International Conference on Management of Innovation & Technology (ICMIT).

Turban, E. and Lee, M.K.O. (2001). A Trust Model for Consumer Internet Shopping. International Journal of Electronic Commerce, 6(1), pp.75–91.

Turban, E., Outland, J., King, D., Lee, J.K., Liang, T.-P. and Turban, D.C. (2018). Electronic Commerce 2018. Springer Texts in Business and Economics. Cham: Springer International Publishing.

Turel, O. and Serenko, A. (2012). The benefits and dangers of enjoyment with social networking websites. European Journal of Information Systems, 21(5), pp.512–528.

United Nations (2020). Digital Divide 'a Matter of Life and Death' amid COVID-19 Crisis. [online] www.un.org. Available at: https://www.un.org/press/en/2020/sgsm20118.doc.htm [Accessed 5 Nov. 2020].

Venkatesh, V. and Davis, F.D. (2000). A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies. Management Science, 46(2), pp.186–204.

Venkatesh, V., Morris, M.G., Davis, G.B. and Davis, F.D. (2003). User Acceptance of Information Technology: Toward a Unified View. MIS Quarterly, 27(3), pp.425–478.

Venkatesh, V., Thong, J.Y.L. and Xu, X. (2012). Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology. MIS Quarterly, 36(1), p.157.

Wang, C. and Zhang, P. (2012). The Evolution of Social Commerce: The People, Management, Technology, and Information Dimensions. Communications of the Association for Information Systems, 31.

Wang, Y. and Hajli, N. (2015). Co-Creating Brand Value through Social Commerce. Advances in Marketing, Customer Relationship Management, and E-Services, pp.17–34.

WHO (2019). Advice for Public. [online] Who.int. Available at: https://www.who.int/emergencies/diseases/novel-coronavirus-2019/advice-for-public.

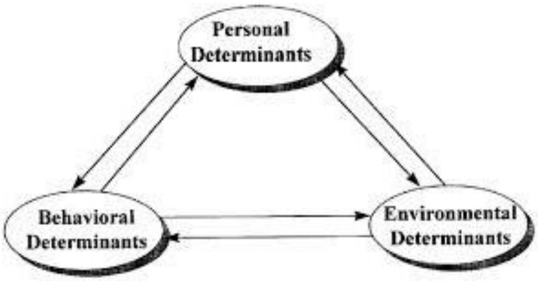
WIGAND, R.T. (1997). Electronic Commerce: Definition, Theory, and Context. The Information Society, 13(1), pp.1–16.

Wigand, R.T., Benjamin, R.I. and Birkland, J.L.H. (2008). Web 2. 0 and beyond: Implications for Electronic Commerce. Proceedings of the 10th international conference on Electronic commerce - ICEC ’08, 7.

Yadav, M.S., de Valck, K., Hennig-Thurau, T., Hoffman, D.L. and Spann, M. (2013). Social Commerce: A Contingency Framework for Assessing Marketing Potential. Journal of Interactive Marketing, 27(4), pp.311–323.

Appendixes

Appendix i. SCT - Triadic reciprocal causation model



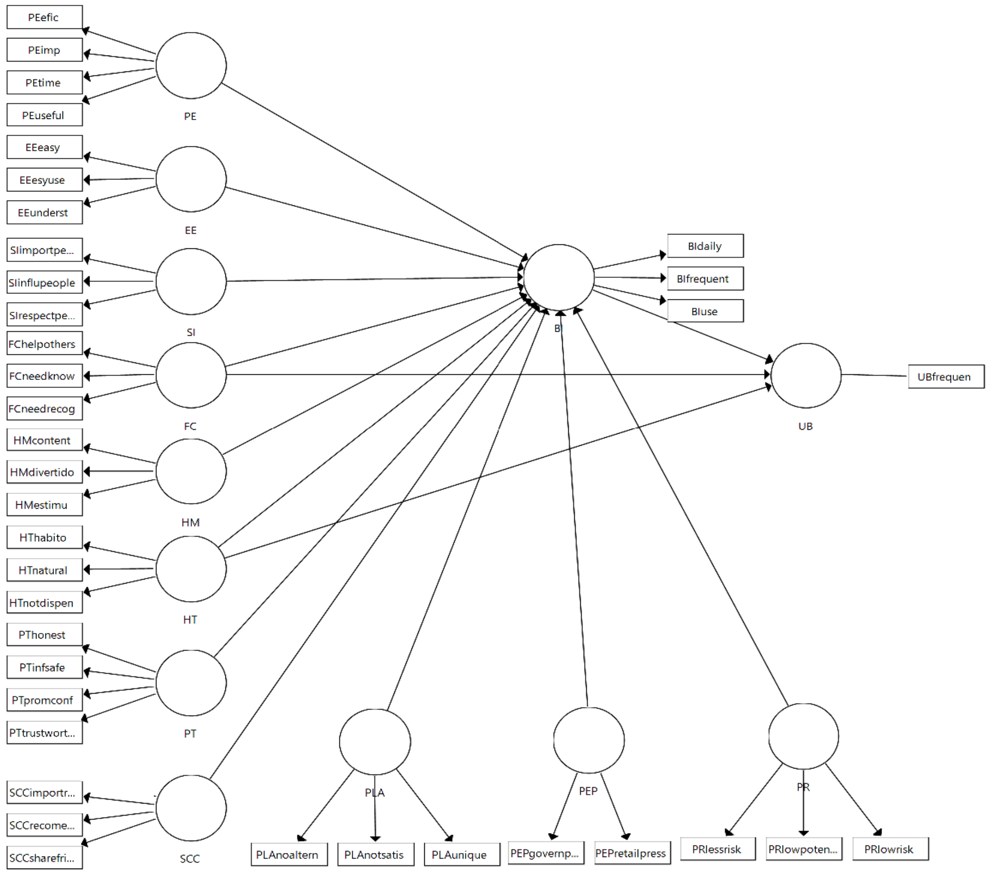
Appendix ii. Model Statements

Construct	ID	Items	Scale	
Respondent profile	AGE	Age	Years	
	GENDER	Gender	Female; Male	
	QUA	Qualifications	-	
	EXP1	Experience with Social Networking Sites	Five-point Likert scale	
	EXP2	Experience with Social Commerce	Five-point Likert scale	
Construct	**ID**	**Items**	**Scale**	**Reference**
Perceived Expectancy (PE)	PE1	I find Social Networking Sites useful in making online purchases.	Five-point Likert scale	Venkatesh et al., (2012)
	PE2	Using Social Networking Sites increase my chances of achieving things that are important to me in making online purchases.		
	PE3	I can save time when I use Social Networking Sites for online purchases.		
	PE4	Using Social Networking Sites would enhance my effectiveness in making of online purchases.		
Effort Expectancy (EE)	EE1	Learning how to use Social Networking Sites for online purchases is easy for me.	Five-point Likert scale	Venkatesh et al., (2012)
	EE2	My interaction with Social Networking Sites for online purchases is clear and understandable.		Venkatesh et al., (2012)
	EE3	I find Social Networking Sites for online purchases easy to use.		Momani et al., (2018)
Social Influence (SI)	SI1	People who are important to me think that I should use Social Networking Sites for online purchases.	Five-point Likert scale	Venkatesh et al., (2012)
	SI2	People who influence my behavior think that I should use Social Networking Sites for online purchases.		
	SI3	People whose opinions I value, support the use of Social Networking Sites for online purchases.		
Facilitating Conditions (FC)	FC1	I have the resources necessary to use Social Networking Sites for online purchases.	Five-point Likert scale	Venkatesh et al., (2012)
	FC2	I have the knowledge necessary to use Social Networking Sites for online purchases.		
	FC3	I can get help from others when I have difficulties using Social Networking Sites for online purchases.		
Hedonic Motivation (HM)	HM1	Using Social Networking Sites for online purchases is fun.	Five-point Likert scale	Venkatesh et al., (2003)
	HM2	Using Social Networking Sites for online purchases is enjoyable.		

	HM3	Using social networking sites for online purchases is very entertaining.		
Habit (HT)	HT1	The use of Social Networking Sites for online purchases has become a habit for me.	Five-point Likert scale	Venkatesh et al., (2012)
	HT2	I am addicted to using Social Networking Sites for online purchases.		
	HT3	Using Social Networking Sites for online purchases has become natural for me.		
	HT4	I must use Social Networking Sites for online purchases.		
Perceive Trust (PT)	PT1	Promises made by Social Networking Sites are likely to be reliable.	Five-point Likert scale	Hajli (2015)
	PT2	Social Networking Sites (such as Facebook, Instagram) are trustworthy.		
	PT3	I do not doubt the honesty of Social Networking Sites.		
	PT4	Social Networking Sites give me an impression that they keep my privacy information safe.		
Social Commerce Constructs (SCC)	SCC1 (dropped)	I will ask my friends on Social Networking Sites to provide me with their suggestions before I go shopping.	Five-point Likert scale	Hajli (2015)
	SCC2	I am willing to recommend a product that is worth buying to my friends on the on my favorite Social Networking Site.		
	SCC3	I am willing to share my own shopping experience with my friends on Social Networking Site through ratings and reviews.		
	SCC4	I would like to use people's online recommendations to buy a product/services.		
Perceived Risk (PR)	PR1	In general, using Social Networking Sites for online purchases involves low risk of being infected by COVID-19.	Five-point Likert scale	Salem and Nor, (2020)
	PR2	There would be a low potential for infection with using Social Networking Sites for online purchases during COVID-19 pandemic.		
	PR3	There would not be too much uncertainty associated with using Social Networking Sites for online purchases during COVID-19 pandemic.		
Perceived Lack of Alternatives (PLA)	PLA1	I use Social Networking Sites for online purchases because there are no good alternatives.	Five-point Likert scale	Salem and Nor, (2020)
	PLA2	Among the available alternatives for online purchases, Social Networking Sites are the only good choice.		
	PLA3	There are not many other choices that would be satisfactory compared to Social Networking Sites for online purchases.		
Perceived External Pressure (PEP)	PEP1	The measures took by government in response to COVID-19 pandemic are pressuring me to adopt social commerce.	Five-point Likert scale	Salem and Nor, (2020)
	PEP2	The goods and services retailers are pressuring me to adopt social commerce during COVID-19 pandemic.		
Behavioral Intention (BI)	BI1	I intend to use Social Networking Sites for online purchases in the future.	Five-point Likert scale	Venkatesh et al., (2012)
	BI2	I plan to use Social Networking Sites for online purchases frequently.		
	BI3	I intend to use Social Networking Sites for online purchases in my daily life.		
Use Behavior (UB)	UB1	How often do you use Social Networking Sites to make online purchases?	Five-point Likert scale (1=Never; 5=Daily)	Venkatesh et al., (2012)
	UB2*	How often did you use Social Networking Sites to make online purchases before COVID-19 pandemic?	Five-point Likert scale (1=Never; 5=Daily)	Elaborated by the author

Five-point Likert scale (1 = strongly disagree, 5 = strongly agree).
*Not considered in the research model

Appendix iii. Path model (Smart PLS results)



Appendix iv. Cross-loadings

Indicator	BI	EE	FC	HM	HT	PE	PEP	PLA	PR	PT	SCC	SI
BIdaily	**0.912**	0.517	0.299	0.702	0.734	0.676	0.532	0.558	0.347	0.55	0.509	0.647
BIfrequent	**0.959**	0.565	0.373	0.741	0.787	0.703	0.544	0.592	0.347	0.529	0.577	0.654
BIuse	**0.888**	0.571	0.41	0.751	0.729	0.687	0.464	0.475	0.346	0.444	0.609	0.613
EEeasy	0.494	**0.901**	0.667	0.533	0.533	0.533	0.258	0.216	0.275	0.282	0.458	0.493
EEesyuse	0.537	**0.899**	0.662	0.581	0.529	0.555	0.327	0.302	0.372	0.372	0.499	0.513
EEunderst	0.58	**0.905**	0.605	0.586	0.582	0.643	0.327	0.337	0.319	0.304	0.535	0.552
FChelpothers	0.294	0.497	**0.773**	0.368	0.297	0.337	0.205	0.197	0.253	0.167	0.308	0.291
FCneedknow	0.381	0.714	**0.933**	0.44	0.435	0.4	0.155	0.143	0.34	0.191	0.433	0.346
FCneedrecog	0.342	0.637	**0.907**	0.443	0.365	0.36	0.14	0.137	0.318	0.168	0.38	0.289
HMcontent	0.745	0.565	0.428	**0.954**	0.756	0.669	0.512	0.538	0.357	0.572	0.587	0.579
HMdivertido	0.759	0.656	0.516	**0.923**	0.716	0.71	0.472	0.491	0.332	0.524	0.613	0.615
HMestimu	0.729	0.55	0.402	**0.938**	0.729	0.661	0.545	0.517	0.371	0.598	0.559	0.554
HThabito	0.776	0.582	0.396	0.727	**0.954**	0.685	0.499	0.512	0.349	0.601	0.512	0.672
HTnatural	0.799	0.616	0.446	0.745	**0.955**	0.693	0.484	0.516	0.38	0.606	0.553	0.656
HTnotdispen	0.714	0.512	0.345	0.728	**0.903**	0.62	0.454	0.479	0.311	0.542	0.521	0.619
PEefic	0.637	0.562	0.361	0.613	0.666	**0.869**	0.443	0.414	0.271	0.404	0.477	0.732
PEimp	0.643	0.561	0.347	0.669	0.586	**0.882**	0.421	0.424	0.301	0.451	0.578	0.61
PEtime	0.616	0.492	0.297	0.582	0.61	**0.829**	0.465	0.49	0.286	0.392	0.414	0.703
PEuseful	0.668	0.588	0.428	0.621	0.58	**0.849**	0.378	0.397	0.297	0.391	0.583	0.557
PEPgovernpress	0.551	0.337	0.156	0.548	0.497	0.474	**0.945**	0.709	0.355	0.39	0.324	0.459
PEPretailpress	0.495	0.297	0.195	0.467	0.461	0.458	**0.932**	0.681	0.287	0.309	0.321	0.451
PLAnoaltern	0.553	0.341	0.179	0.511	0.494	0.492	0.663	**0.878**	0.402	0.349	0.332	0.442
PLAnotsatis	0.533	0.315	0.229	0.527	0.506	0.457	0.663	**0.895**	0.314	0.363	0.255	0.465
PLAunique	0.483	0.185	0.054	0.419	0.425	0.382	0.652	**0.896**	0.327	0.335	0.226	0.361
PRlessrisk	0.341	0.307	0.321	0.379	0.334	0.365	0.324	0.426	**0.814**	0.199	0.328	0.235
PRlowpotenpand	0.282	0.271	0.244	0.237	0.272	0.24	0.296	0.261	**0.814**	0.155	0.249	0.173
PRlowrisk	0.294	0.298	0.286	0.292	0.297	0.206	0.218	0.257	**0.824**	0.289	0.368	0.228
PThonest	0.465	0.286	0.142	0.448	0.506	0.374	0.28	0.312	0.177	**0.845**	0.378	0.417
PTinfsafe	0.425	0.193	0.053	0.456	0.448	0.331	0.308	0.349	0.213	**0.773**	0.362	0.366
PTpromconf	0.481	0.304	0.158	0.545	0.567	0.438	0.388	0.349	0.211	**0.836**	0.412	0.451
PTtrustworthy	0.463	0.388	0.305	0.543	0.54	0.438	0.265	0.296	0.271	**0.864**	0.454	0.414
SCCimportrecomend	0.446	0.455	0.404	0.441	0.408	0.444	0.252	0.217	0.425	0.305	**0.767**	0.347
SCCrecomendfriends	0.554	0.495	0.367	0.594	0.526	0.565	0.272	0.258	0.268	0.47	**0.879**	0.49
SCCsharefriends	0.544	0.454	0.335	0.537	0.486	0.503	0.343	0.298	0.31	0.436	**0.881**	0.422
SIimportpeople	0.682	0.556	0.308	0.59	0.68	0.712	0.497	0.499	0.265	0.503	0.445	**0.916**
SIinflupeople	0.625	0.535	0.355	0.562	0.628	0.681	0.389	0.387	0.216	0.46	0.477	**0.916**
SIrespectpeople	0.582	0.483	0.305	0.544	0.577	0.673	0.434	0.413	0.231	0.389	0.449	**0.901**

BI - Behavioral Intention; EE - Effort Expectancy; FC - Facilitating Conditions; HM - Hedonic Motivation; HT - Habit; PE - Performance Expectancy; PEP - Perceived External Pressure; PLA - Perceived Lack of Alternatives; PR - Perceived Risk; PT - Perceived Trust; SCC - Social Commerce Constructs; SI - Social Influence

Appendix v. f^2

Construct	Behavioral Intention	Use Behavior
Behavioral Intention		0.412
Effort Expectancy	0.002	
Facilitating Conditions	0.007	0.008
Hedonic Motivation	0.068	
Habit	0.155	0.054
Performance Expectancy	0.02	
Perceived External Pressure	0.001	
Percieved Lack of Alternatives	0.024	
Perceived Risk	0.00	
Perceived Trust	0.002	
Social Commerce Constructs	0.029	
Social Influence	0.013	

Appendix vi. Q^2

	Q^2 (=1-SSE/SSO)
Behavioral Intention	0.637
Use Behavior	0.65

Appendix vii. q^2 effects

Predictor	Endogenous	Q^2 included	Q^2 excluded	Predictive Relevance (q^2)
EE	BI	0.637	0.638	-0.003
FC	BI	0.637	0.636	0.003
HM	BI	0.637	0.626	0.030
HT	BI	0.637	0.609	0.077
PE	BI	0.637	0.634	0.008
PEP	BI	0.637	0.639	-0.006
PLA	BI	0.637	0.632	0.014
PR	BI	0.637	0.637	0.000
PT	BI	0.637	0.639	-0.006
SCC	BI	0.637	0.633	0.011
SI	BI	0.637	0.636	0.003
HT	UB	0.65	0.639	0.031
FC	UB	0.65	0.655	-0.014

Notes: $q^2 = (Q^2_{\text{included}} - Q^2_{\text{excluded}}) / (1 - Q^2_{\text{included}})$
q^2 values of 0.02, 0.15, and 0.35 indicate a small, medium, or large predictive relevance.
BI - Behavioral Intention; EE - Effort Expectancy; FC - Facilitating Conditions; HM - Hedonic Motivation; HT - Habit; PE - Performance Expectancy; PEP - Perceived External Pressure; PLA - Perceived Lack of Alternatives; PR - Perceived Risk; PT - Perceived Trust; SCC - Social Commerce Constructs; SI - Social Influence

Appendix viii. t-test statistics

	Ubfrequent	Ubfrequentbefpand
Mean	2.770	2.349
Variance	1.235	1.152
Observations	209	209
Pearson Correlation	0.725	
Hypothesized Mean Difference	0	
df	208	
t Stat	7.502	
P(T<=t) one-tail	0.00	
t Critical one-tail	1.652	
P(T<=t) two-tail	0.00	
t Critical two-tail	1.971	