Use of Food Delivery Apps

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The pandemic forced both organizations and consumers to make many adjustments to their daily lives. However, due the technological advances that have been seen in recent years, some tools have become much more widely used. Among them are the food delivery applications (FDAs) that experienced an exponential growth during the pandemic. During the COVID-19 pandemic, the use of food delivery applications (FDAs) has not only met the requirements of businesses but also the demands of customers for convenient food supplies and personal safety concerns since these applications allow customers to effectively and easily order and access their food from several restaurants at convenient times and locations

food delivery app | health belief model | technology readiness | technology acceptance model | continuance intention | COVID-19 pandemic

1. Introduction

The recent pandemic (COVID-19) erupted as a severe infectious disease in late 2019, progressively expanding to rapidly assume a worldwide expansion [1]. Several innovative measures have been presented and proposed to mitigate the situation, such as the use of a protective mask, social distancing and self-isolation, among others, all of them strongly recommended by the World Health Organization [2] and aimed at reducing the risk of disease transmission [1][3]. Given this situation, fewer consumers intend to use many services, such as the traditional restaurant industry, which suffered and suffers dramatically during this pandemic [4].

The negative influence of COVID-19 on supply and demand in the restaurant industry changed people’s consumption habits and accelerated the transformation of restaurant companies from traditional service to online services, to seek to survive the pandemic situation [4][5]. It is in this process that technology, based on a well-known growth of wireless communication technologies and high internet penetration rates, is seen by food service businesses as an important resource for innovation and competitiveness [6].

The rise of digital technologies has led to a reshaping of markets, and the convenience of being able to order food more easily, with vast options to choose from, has enabled consumers to shift to on-demand shopping through websites or apps [7]. In 2019, online food delivery services reached a value of USD 107.4 billion worldwide and are expected to be worth USD 182.3 billion by 2024 [8]. Food delivery services through online apps have become a global trend [9]. This type of application is among the fastest growing sectors of mobile applications [8].

During the COVID-19 pandemic, the use of food delivery applications (FDAs) has not only met the requirements of businesses but also the demands of customers for convenient food supplies and personal safety concerns since these applications allow customers to effectively and easily order and access their food from several restaurants at convenient times and locations [10]. Consequently, the factors that have motivated users to use these same applications continuously during this pandemic situation are essential to understanding online food delivery purchasing behavior and decision-making processes regarding FDA services.

Several theoretical perspectives have been applied to understand the usage behavior of a new technology and research focused on technology acceptance has been reported in the past two decades [11]. Among these, TAM (technology acceptance model) suggested by Davis [12], and TR (technology readiness) suggested by Parasuraman [13] have been popular models, used to study the factors that contribute to the acceptance of a new technology [14]. Perceived ease of use and perceived usefulness are considered the most important constructs of TAM [15] since users' acceptance or rejection of a technology is mainly influenced by them [12]. However, these two constructs are both affected by external variables. Therefore, to better explain users' technology adoption and continued usage of a technology (FDA in researchers' study) it is important to understand the antecedents of perceived usefulness and perceived ease of use. TR has been recognized as an important antecedent of TAM constructs (e.g., [16][17]). TRAM (technology readiness and acceptance model), suggested by Lin et al. [17], is an extended model that combines TAM and TR. Despite the recognized importance of TR as an antecedent of TAM, the application of TRAM to explain the adoption and post-adoption of technologies in the mobile applications arena has been scarce. Some exceptions are the study of Aboelmaged et al. [18] in the context of mobile apps' use for wellness and fitness applications, Ferreira et al. [19] in the context of mobile self-scanning applications, Jin (2020) in the context of brand applications, and Chiu and Cho [20] in the context of health and fitness applications. To the best of researchers' knowledge, no study has applied TRAM in the context of FDAs.

Concurrently, active customer participation is an essential attribute of service in an e-service context and a crucial element for open innovation [21]. Thus, the implementation of TAMs in service contexts cannot be dissociated from high customer involvement to explain consumer adoption of technology [22]. It is therefore important to identify and qualify the psychological processes of perceived value of a technology and structure a model that incorporates individual difference variables such as technological readiness, self-efficacy, and perceived threat.

The health belief model (HBM) is used to directly explain perceived usefulness and indirectly the continued use of apps [23] from the individual perspective. HBM is used to predict health behavior more generally [24]. The basic assumption of HBM is that individuals will have a preventive attitude towards their health if they feel vulnerable to illness [25]. Wahyuni and Nurbojatmiko [26] in their study show that individuals' concerns about their own health also influence their intentions to use e-services.

2. Food Delivery Apps (FDAs)

Among the most popular mobile applications that have been recently developed by service organizations/companies are mobile food ordering applications [10]. These can be defined as mobile applications that smartphone users download and use as an innovative and convenient channel to access restaurants, view food menus, place orders, and make payments without any physical interaction with restaurant staff [5][27]. Technology has helped and driven food service businesses to keep up with the changes in the industry [6]. Smartphones allow for real-time connection/connectivity with mobile applications, and have greatly increased the popularity of food delivery applications, which has also led to much greater competition in these markets [28]. Mobile applications are seen as an additional means by companies to attract new customers and to influence the existing ones to continue and increase their loyalty [27]. The increasing use of smartphones has also led to many changes in people's dining cultures and food delivery apps are among the most innovative changes in the contemporary restaurant market [29]. During the pandemic, many traditional food delivery services switched platforms and new companies entered the business and began using FDAs to maintain themselves or utilize the opportunity to transition to the digital platform [30].

3. Health Belief Model (HBM)

The HBM was initially developed by Hochbaum [31] to help predict individuals' behavioral reactions to disease. This model is one of the most notable public health frameworks for understanding why individuals may or may not act upon a threat to either their personal or community health [32]. Like many public health behavior models, this model conceptualizes the determinants of behavior [33]. According to the HBM, the dimensions of perceived susceptibility, perceived severity, perceived benefits, perceived barriers, action cues, and self-efficacy can be used to explain whether a person takes action to prevent, track, or improve their health behaviors [34][35]. Beliefs are influenced by each person's background and comprise their impression of perceived threat, perceived benefits and barriers to taking action, and their perceived ability to take action (i.e., perceived self-efficacy) [36]. Additionally, according to the HBM, the perception of the threat of disease is measured by the perception of susceptibility and severity; the perception of benefits and the perception of barriers, together with the perception of self-efficacy, promote the development of health behaviors among the population affected by a given disease [37]. The perception of susceptibility refers to the beliefs of being vulnerable to the disease, while the perception of severity refers to beliefs concerning the negative effects of disease contraction, i.e., the severity of the risk [38]. The perception of benefits refers to the existence of a way to reduce the incidence or severity of the disease, while the perception of barriers refers to the higher costs versus the benefits of the action [39].

The two dimensions of perceived threat, perceived susceptibility and perceived severity [40], have been widely adopted to explain different behaviors such as technology adoption (e.g., [41][42][43]), fear of travel (e.g., [44]), organic food choices [45], among others. Recent studies also adopted these dimensions to explain customer intention to use online food delivery services during COVID-19 [46][47].

3.1. Perceived Threat

Perceived threat has been recognized as a core component to understand a variety of preventive health behaviors, such as those related to COVID-19 [47]. The two dimensions of perceived threat (perceived severity and perceived susceptibility) are also among the various measurements that have been widely used to determine people's perceptions of a disease [46]. The perception of susceptibility refers to the belief of being vulnerable to the disease, while the perception of severity refers to belief concerning the negative effects of disease contraction, i.e., the severity of the risk [38]. According to the HBM, an individual is considered more likely to take appropriate action if the perceived threat of disease is high. In turn, the perceived threat will be higher if the perceived severity is higher —that is, the disease is considered to be a serious problem.

3.2. Perceived Self-Efficacy

Perceived self-efficacy can be defined as the belief that one has the ability to overcome a given challenge [33].

In the health management literature, self-efficacy can be seen as a significant determinant of preventive health behaviors [48]. Venkatesh et al. [11] explain self-efficacy as the ability of individuals to perform a given task. In the context of technology adoption, self-efficacy thus refers to users' confidence in their ability to use a technology and serves as a determinant of perceived ease of use [11]. Perceived self-efficacy is considered to be an important precursor to the adoption of new technologies [49], being especially relevant in the use of mobile devices and, although they offer advantages, they also increase challenges, compared to computers. Contemporary studies have shown that self-efficacy affects behavioral intention to adopt apps, e-government system, and e-portfolios, among other things, both directly and indirectly ([15][50]). In the present study self-efficacy was analyzed in relation to technology adoption, and not integrated into the HBM.

4. Models Related to Technology Acceptance

4.1. TAM

The literature has used several theoretical frameworks to explain the adoption and use of technologies. The technology acceptance model (TAM), developed by Davis [12], is now one of the most widely used models to explain the acceptance of new technologies [51], and is recognized as a valid and robust model [52]. TAM suggests that when a user encounters a new technology, there are several factors that affect how they accept and use it, and it has been used in both consumer and organizational contexts to explain the factors that affect the acceptance of a particular technology [53]. TAM has also been widely applied to examine individual technology adoption behaviors across different populations and types of innovative technologies [54], such as e-portfolios [10], and m-commerce [55], among others. This is also useful in explaining what influences an individual's intention to use mobile technologies [56] and smartphones [22]. Fishbein and Ajzen [57] suggest that behavior can be predicted based on the intention to perform it and that this intention is driven, in part, by attitudes toward it. Some studies applied TAM to examine individuals' usage and behavior in the context of applications (e.g., [58]). These studies demonstrated that TAM was an appropriate theoretical framework to explain individuals' intentions to use apps.

Among the wide adoption in all fields of technology acceptance studies, TAM [12] has also been used to predict consumers' acceptance of technology in relation to health ([59]). According to TAM, perceived usefulness and perceived ease of use are the two main determinants of technology use [60]. While TAM has proven useful [61], additional constructs believed to have enhanced TAM have resulted in a variety of extended models, such as TAM2 and TAM3 [11][62]. It is also important to note that while TAM is instrumental in the initial acceptance of the new technology, more and more researchers have emphasized that the success of the new technology should not be limited to that same initial acceptance, but supported by continued use [63]. For example, Bhattacherjee [64] suggests continuance intention as a variable of technology acceptance, and thus, in order to include continuance intention, research on technology acceptance has been expanded.

4.2. TRAM

Several studies have applied the technology acceptance model (TAM) as a theoretical basis to analyze individuals' intentions to use applications (e.g., [29][58]). However, some have argued that this model may not be sufficient to explain individuals' technology adoption behavior, as the main variables of TAM measure utilitarian aspects of technology use, i.e., ease of use and usefulness (e.g., [17]). Thus, several authors suggest an integration of additional factors in order to extend TAM to better explain individuals' psychological processes in their behavior regarding technology adoption (e.g., [17][19]).

TRAM combines the general personality constructs of TR with the specific model of TAM, thus determining how individuals' technology-related beliefs may affect their perceptions of interacting with, experiencing, and using new technologies [16]. The integration of TR and TAM can provide a deeper understanding of the psychological process involved in application adoption behavior [20]. Since Lin et al. [17] introduced TRAM, several researchers have conducted studies to examine users' technology adoption behavior in a wide range of settings, such as m-services [65] and mobile self-scanning applications [19].

4.3. Technology Readiness (TR)

Technology readiness (TR) was defined by Parasuraman ([13], p. 308) as being “the propensity of people to embrace and use new technologies to achieve goals in home life and work”. The same author argues that technology readiness is divided into four components. The first two are related to positive feelings, i.e., optimism (belief that technology will bring efficiency, control, benefits, and flexibility) and innovation (being a pioneer in testing innovative technology-based services or products). The other two are related to negative feelings, i.e., discomfort (reflects the individual's perception of lack of control and confidence in using the technology) and insecurity (fear that the technology-based service, product or process may not work in an accurate and reliable way).

The four dimensions of TR are independent of each other and are associated with an individual's behavioral disposition and general thoughts and feelings toward technology [66]. TR can be considered as an overall state of mind arising from mental and inhibiting factors that jointly determine a person's tendency to use new technologies [67]. If an individual has a higher level of TR then their rate of adoption of new technologies is higher. In addition, the individual exhibits more intensive use of technology and greater ease in using it [68].

4.4. Continuance Intention

The number of studies on the intention to continue using information systems (IS) has grown rapidly in recent years and now covers several contexts such as the intention to continue in m-services, in applications, and in m-commerce, among others [69]. Although most of the previous research on these systems is strongly focused on the initial acceptance, it is now sought to investigate the direct effects on the continuity intention of mobile applications, since it is considered essential for the long-term viability of an IS [64].

Kim and Kang [70] argue that ongoing IS usage may specifically reflect users' behavioral patterns toward a target IS/m-service. Bhattacherjee et al. [64] also indicate that while the initial adoption of an IS/IT is an important advance for IS/IT success, users' continued use, rather than initial acceptance, is the determining factor of the long-term sustainability and ultimate success of IS/IT. It becomes evident that the intention of continued use is strongly associated with user behaviors (i.e., a behavior that an individual can decide whether to perform or not) [71]. Bhattacherjee [72] was one of the first researchers to distinguish between technology acceptance and continuance of use behavior. Bhattacherjee [72] further defines continuance intention to use as an individual's intention to continue to use an information system. In their literature review, Nabavi et al. [73] also described it as a user's decision to continue using a specific IT that an individual has already used.

Designing strategies to continuously attract the user is one of the most critical phenomena in the IT world [74]. Similarly, other authors have postulated that continuous usage is more important than initial usage, as it is argued that the cost to develop a new customer can be up to five times more than the cost to maintain an existing customer (e.g., [72]).

5. Proposed Model and Development of Hypotheses

Due to COVID-19, people believe that their health is at risk and thus may formulate a higher perception of usefulness regarding applications, to prevent and thus reduce the likelihood of COVID-19 infection [41]. The adoption of technology was considered as a behavior to promote, protect, or maintain one's own health [75]. Therefore, this technology adoption can be explained by the HBM, since it suggests that people's beliefs about health problems, perceived benefits, and perceived barriers to action, as well as self-efficacy, explain the involvement or lack thereof in health promotion behavior by individuals [34]. The perception of health threat refers to people's awareness and care, as well as the potential consequences. Previous studies developed in the health care context found contradictory results regarding the influence of perceived threat, which involves perceived susceptibility and severity, on perceived usefulness. For example, Dou et al. [76] found a strong relationship between perceived threat and perceived usefulness while Kim and Park [60] found lack of a significant relationship. However, more recent studies developed in the context of COVID-19 found a positive significant effect of perceived susceptibility and severity on perceived usefulness of mobile-based payments [41] and e-wallet systems [42].

Technological self-efficacy is the personal belief that a person has the adequate and accurate skills and abilities to succeed when dealing with a technology-related task [77]. Based on Luarn and Lin's [78] study on mobile services, the current research focuses on whether individuals believe that they have the necessary knowledge, skills or ability to use food delivery applications (FDAs). Thus, perceived self-efficacy is defined as the judgment of one's ability to use food delivery applications. Self-efficacy has been adapted for the purpose of being incorporated into technology adoption models (e.g., [15][49]). This implies that consumers of mobile services are more likely to pursue activities within their perceived areas of competence, self-efficacy being an important factor in understanding individual responses to new technologies [79]. This variable has figured in studies developed in different contexts such as e-shopping [80], mobile banking [10], use of e-portfolios [15], food delivery services [46], use of electronic wallets [42], and mHealth services [44], among others.

Self-efficacy plays an important role in the context of technology and IS use (Ahmed et al. 2010) and internet self-efficacy (ISE) in the context of internet technology [4]. Self-efficacy affects user behavior towards using a technology, as individuals with high levels of self-efficacy will be confident in their capability to overcome any difficulties when using the technology [15]. Regarding computer usage, “the higher the individual’s computer self-efficacy, the higher his/her use of computers” ([49], p. 196). A sense of self-efficacy may increase the likelihood that users will evaluate the technology as easy to use [76]. Previous studies developed in different contexts such as mobile commerce, mobile banking, e-portfolios, smartphone health apps, among others, associate higher levels of self-efficacy and perceived ease of use (e.g., [42][71][78]).

Regarding the relationship between self-efficacy and perceived usefulness, the literature presents more contradictory results. Although some studies have found a non-significant effect between these two variables (e.g., [60]) or a negative significant effect (e.g., [15]), several studies in fact found a positive significant effect (e.g., [42][60][71][80]). A recent study developed in the context of mobile technologies’ usage, more specifically, the usage of mobile wallets while dining out in a restaurant, also found a strong association between mobile self-efficacy and mobile usefulness and ease of use [81].

There are few studies assessing the link between TR and TAM, compared to the number of studies applying the TAM model. A high TR may result from previous experience with the same technology which, in turn, may increase ease of use and perceived usefulness [82]. It is expected that technology readiness has a direct positive effect on perceived usefulness, since individuals with higher innovativeness and higher optimism towards technological innovations should be more able to see the utility related to their adoption [17]. Previous studies that linked technology readiness to TAM constructs in various technology adoption contexts, for example self-service technologies [83], online stock trading systems [17], mobile self-scanning applications [19], and m-commerce [84], among others, found a positive and significant relationship between it and perceived usefulness and perceived ease of use. Moreover, Jin [85] also confirmed a positive and a negative effect of positive technology readiness and negative technology readiness, respectively, on perceived usefulness and perceived ease of use.

Previous studies have also linked technology readiness to users’ behavioral intentions in various technology adoption contexts such as self-service technologies [86], online stock trading systems [17], and self-checkout services using smartphones [87], among others. Regarding the relationship between these two variables, the literature reports several results. Some studies found a positive direct effect (e.g., [86]), others support indirect effects through other variables such as perceived usefulness and ease of use [17], and others indicated lack of significant relationship (e.g., [87]). Blut and Wang [16] in their meta-analysis about TR constructs and its impact on technology usage found an indirect effect of technology readiness on usage intention via TAM mediators (ease of use and usefulness).

TAM is a representative model used to explain and predict individuals' adoption of information technology. Several studies have used this model as well its extensions to explain the process of information technology acceptance, such as studies of e-service, service mobile apps, information technology systems, and internet-based services, among others (e.g., [11][15][19]), further indicating that behavioral intentions to use a given technology are determined, in part, by users' perceived ease of use (PEOU) and perceived usefulness (PU). According to TAM, PEOU is a determinant of PU [11][12]. When individuals have perceived ease of use of technology, they are more likely to believe that the technology is useful and helpful for a specific purpose. Venkatesh ([11], p. 343) stated that "the easier a technology is to use, the more useful it may be". Once individuals perceive ease in using a technology and it has perceived usefulness, individuals will adopt and accept it for a specific purpose [20].

The literature further indicates that PEOU and PU appear to be particularly vital measures of users' intention to use a particular system [12]. A great deal of research on TAM demonstrates that these two factors have a joint impact on the use and acceptance of a wide variety of technologies (e.g., [65][86]). Users will always want to continue using a particular application that can help them improve their productivity [64][72].

Users need to feel that a particular application (e.g., FDAs) is easy enough to use to motivate them to use it [38]. The theory of reasoned action (TRA) [57], a theory that gave rise to the development of TAM by [12], states that perceived usefulness and perceived ease of use can influence user's attitudes and intention to use. Thus, PEOU and PU are expected to be positively related to the intention to continue using applications. Moreover, a recent study developed in the context of online food delivery services confirms a strong positive effect of both perceived ease of use and usefulness on continuance intention [46].

According to TAM, perceived ease of use is hypothesized to be a determinant of perceived usefulness. Several empirical studies have also supported this relationship for a wide variety of technologies (e.g., [15][38]). A recent study developed by Roh and Park [88] in the context of O2O food delivery services also found a strong effect of perceived ease of use on usefulness. When an individual realizes that few resources are needed to learn a new mobile technology, he/she may perceive the technology as being useful, which leads to its continued use.

Figure 1 presents the conceptual and hypotheses.

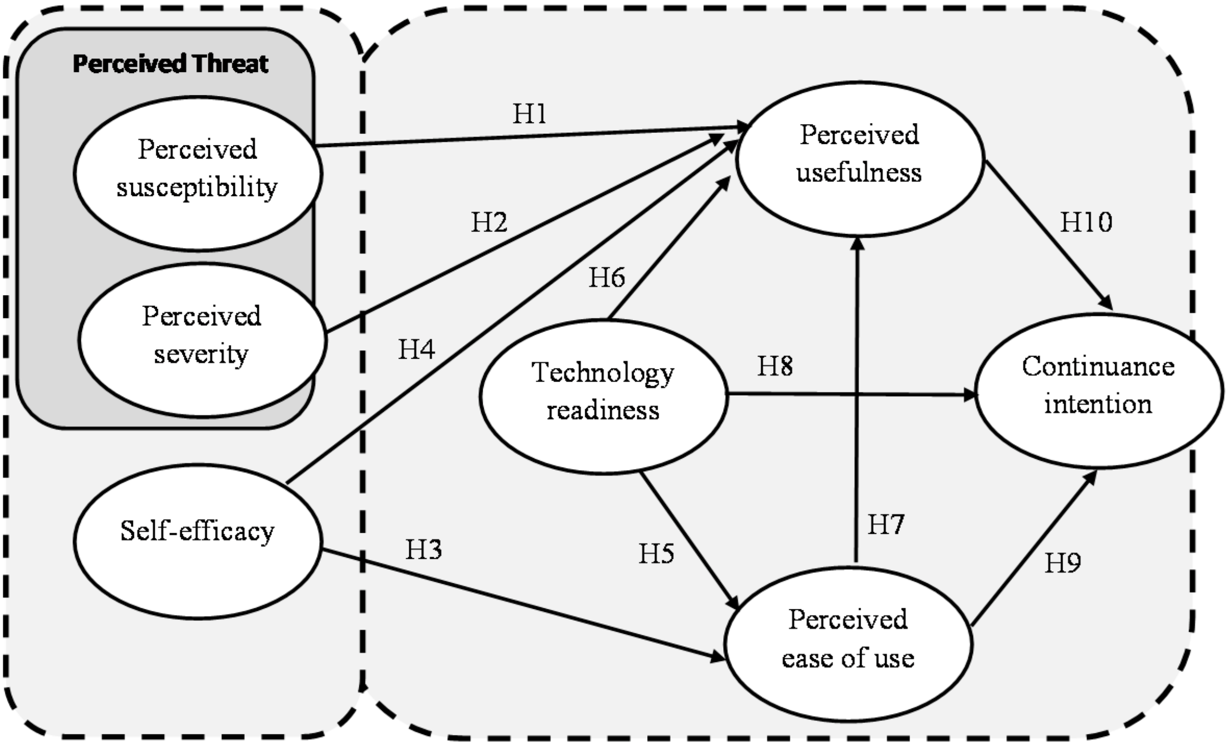

Figure 1. Conceptual model and hypotheses.

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