# *Explaining the intention to use digital personal data stores: an empirical study*

# Explaining the Intention to Use

# Digital Personal Data Stores: An empirical study


**Abstract**

Recent data leaks such as those involving Dropbox have apparently made Internet users feel less secure than in the past as they face risks when dealing with their digital personal data. However, consumers have increasingly embraced cloud computing empowered Digital Personal Data Stores (DPDSs). To understand this paradox, this study shifts the unit of analysis of DPDSs acceptance from organizations to individuals/consumers and identifies the drivers of adoption of DPDSs (beyond broadly defined cloud computing services). Moreover, it proposes, develops and tests empirically a comprehensive extended version of the Technology Acceptance Model (TAM) in the context of DPDSs, leveraging perceived privacy risks and trust. Using a panel of UK consumers, we find that perceived trust positively influences both usefulness and ease of use. These constructs, in turn, positively affect attitude towards using DPDSs, which ultimately increases the intention to use DPDSs. Privacy risk does not moderate any of the investigated relationships, thus suggesting that trust is a key underlying mechanism enhancing the acceptance of DPDS. Hence, theoretical and managerial implications are discussed.



**Keywords**: Digital Personal Data Stores; Technology Acceptance Model; Personal Data; Privacy Risk; Trust; Empirical study.

## 1. Introduction

Data storing is a human activity dating back at least to the ancient Egypt around 4000 years ago. Since then, and increasingly over the last two centuries, different technologies, devices and media have been developed to record and store data including magnetic tapes, CDs, DVDs, computers' hard-disk drives and solid-state drives.

Today, digital information is stored by means of semiconductor, magnetic, and optical-based systems on digital media in various formats. Interestingly, 2002 represents a kind of watershed year, as it is commonly believed to be the moment in human history when digital storage devices took over analog storage devices. Since then, the capacity of digital stores of information and data has increased exponentially (Hilbert and Lopez, 2011). Currently, the largest share of data is stored on digital storage devices including, e.g., computers' hard disk drives, USB flash drives, microdrives (Park et al., 2008), and increasingly on cloud computing services since the launch of Amazon web services in 2006 and the introduction of Dropbox in 2007.

Over the last 30 years there have been four discernible trends in consumer electronics related to digital data storage: 1) radical improvement of the capacity of consumers' storage devices from Megabytes for floppy and compact disks to Gigabytes for DVDs, HD-DVDs, USB flash drives and compact disks to Terabytes for portable hard drives and hard drives; 2) pervasiveness of data and data storage devices across consumers worldwide; 3) miniaturization of devices (with hard disk drives and solid state drives that have become more diffused for portable computers and mobile applications); 4) ubiquity in data storing by means of  cloud computing that enables storing and accessing data from everywhere. The confluence of the aforementioned trends has led new storage devices to be millions of times more effective and efficient than several of their precursors were and has paved the way for the fourth industrial revolution also known as Industry 4.0 (Mariani and Borghi, 2019; Pillai et al., 2021).

Online data storage, empowered by cloud computing, has meant not only allowing to store huge quantities of data online in a cost effective manner, but also growing security issues as witnessed by extant literature (Singh et al., 2016; Vurukonda and Rao, 2016; Zissis and Mekkas, 2012).

Consequently, while people storing their digital personal data are increasingly looking for effective and efficient digital personal data stores (DPDSs), they are also increasingly concerned about security and privacy risks, issues and threats (Bansal et al., 2010; Singh et al., 2016; Vurukonda and Rao, 2016; Zissis and Mekkas, 2012). Privacy risks are of paramount importance and are defined as an "individual's general tendency to worry about information privacy" (Li 2011, p. 5). In a social and economic context whereby value is co-created, sharing data becomes increasingly relevant. This is the reason why individuals are willing to store and share their data by striking a balance between the usefulness of DPDSs and concerns about the security (Narayanan and Shmatikov, 2009), privacy (Acquisti et al., 2015) and confidentiality (Spiekermann et al., 2015) of their personal digital data.

We know through anecdotal evidence and active users figures published by storage providers on their corporate websites that both offline DPDSs, such as USB flash drives, and online DPDSs, such as cloud computing storage services (the like of Dropbox, Apple iCloud, Google Drive and Microsoft OneDrive), are increasingly adopted by consumers (e.g., Song et al., 2020). However, we do not know much about the drivers of adoption and acceptance of online DPDSs. This is even more surprising given the number of data security issues that many of them have faced over the last decade. For instance, in 2011, a security bug affected all Dropbox accounts that could be accessed without passwords for four hours (Kincaid, 2011), and five years later in August 2016, the email addresses and passwords of about 68 million Dropbox accounts were published online based on a data leak originating in 2012 (Gibbs, 2016; McGoogan, 2016). Extant research in information systems and management has relied on different models to understand the drivers of cloud computing systems acceptance (e.g., Arpaci, 2017; Song et al., 2020). These studies did however not dig in depth about the antecedents of acceptance of cloud-computing empowered digital personal data stores, and mostly confined their attention to parsimonious models neglecting or downplaying the role of trust and privacy risks.

To bridge this research gap, the objective of this work is to address the following focal research question: What are the drivers of users' acceptance and adoption of online Digital Personal Data Stores (despite recent data leaks affecting them in recent times)? By addressing the aforementioned question, this study makes three contributions. First, it shifts the unit of analysis of DPDSs studies from organizations to individuals/consumers. Second, to the best of our knowledge, this is the first study to identify drivers of adoption and acceptance of online DPDSs beyond broadly defined cloud computing services. Third, this is also the first work to propose, develop and test empirically a comprehensive model of online DPDSs acceptance by extending the core TAM antecedents (usefulness, ease of use, attitude, behavioral intention) with additional constructs that have been found to play a role in online services acceptance, such as trust (Almarazroi et al., 2019; Chen et al., 2016) and privacy risks (Acquisti et al., 2015). In line with privacy risks literature at the organizational level (Aguirre et al. 2015, 2016; Li 2011), we argue that trust constitutes a key promotive mechanism (Martin, 2018) through which individuals counteract the potentially negative influence of privacy concerns in relation to DPDS acceptance and adoption.

To make those contributions, we develop an extended version of the Technology Acceptance Model (TAM) and test it on a sample of 214 UK consumers. The paper is organized as follows: Section two reviews the literature revolving around digital data storing services and the TAM, and develops the focal hypotheses. Section three describes the methodology, while the ensuing section illustrates and discusses the findings. Section five draws the conclusions, by discussing both theoretical and practical implications. The fifth section also identifies limitations of the study and a future research agenda.

## 2. Literature review

### 2.1. Data stores and personal data stores

Data storage has always been of paramount importance for organizations and individuals. Organizations have relentlessly stored data about their customers, suppliers and other stakeholders over time, as data can be transformed into analytics and actionable insights (Davenport, 2006, 2014; Davenport et al., 2012; Mariani, 2019; Mariani and Fosso Wamba, 2020). This holds also for individuals who are increasingly using and producing vast amounts of (digital) data through a number of devices such as smartphones and laptops to acquire information and improve their individual decision making.

Data storing involves the storing of information in a storage medium that could be analog (e.g., a phonographic record) or digital (e.g., a solid-state drive of a computer). Opportunities and drawbacks of data storing, as well as of storage media, have become an increasingly popular object of study in computer and information science research (Abdalla and Varol, 2019; Chiarugi et al., 2004; Craig et al., 2004; Park et al., 2008).

The Internet has changed storing from an isolated process to a process empowered by cloud-computing storage services offered by technology giants such as Apple, Dropbox, Google and Microsoft, as well as by a number of smaller firms (Aldiabat et al., 2018; Song et al., 2020; Yang and Lin, 2019). Cloud computing has been found to display effectiveness, ease of implementation and scalability (Varghese and Buyya, 2018). So far, cloud-computing adoption has been mostly examined at the organizational level (Senyo et al., 2018). The research stream revolving around individual level adoption of cloud computing is relatively nascent (Song et al., 2020) and only a few works have dealt with the drivers of individual acceptance (Almarazroi et al., 2019; Arpachi et al., 2017; Chen et al., 2017; Wang, 2016; Song et al., 2020). This is relatively surprising, as the shift to low-cost digital storage media has made storage devices and services increasingly popular for individuals who store their data in cloud-computing empowered digital personal data stores (DPDSs). For the purpose of this study, DPDSs are defined as storage devices and services that allow individuals to store their personal digital data for a wide range of purposes.

While we know through anecdotal evidence that consumers increasingly adopt DPDSs, we do not yet know much about the drivers of adoption and acceptance. Previous studies focusing broadly on cloud computing services acceptance at the individual level (Song et al., 2020) have analyzed different drivers by leveraging a number of models. These include the technology acceptance model (TAM) (Davis, 1986, 1989) and its variations (e.g., Almazroi et al., 2019; Wang, 2016), as well as the Unified Theory of Acceptance and Use of Technology (UTAUT) and its new developments (Ali et al., 2019; Moryson and Moeser, 2016). However, these studies are limited because they have examined specific domains including education (e.g., Arpachi et al., 2017) or healthcare (e.g., Hsieh and Lin, 2018) and relied mostly upon samples of students.

For instance, Wang (2016) partially leveraged the TAM to explore several drivers of adoption, and found that perceived usefulness, perceived ease of use, perceived risk and perceived trust influence positively Chinese users' adoption intention of cloud computing systems. By deploying the UTAUT, Ali et al. (2019) found that effort expectancy, performance expectancy, and social influence had a positive influence on behavioral intention. In another study applying the UTAUT, Song et al. (2020) found that only effort expectancy, performance expectancy, and habit influenced behavioral intention significantly and positively. To summarize, extant studies rely on different models to understand the drivers of cloud computing systems acceptance, and those using the UTAUT do not generally find significant effects of social influence and hedonic motivation on behavioral intention (Song et al., 2020). Those studies using the mere TAM do not dig in depth about the antecedents of acceptance and do not build on an enriched version of the TAM capable to take into account also trust and privacy risks.

To bridge this research gap, this work proposes, develops and tests an extended model of the antecedents of behavioral intention to use DPDSs. To do so, we develop an extended version of the Technology Acceptance Model (TAM) (Davis, 1986, 1989) that we illustrate in the ensuing section. More specifically, in our conceptualization and model we suggest – in line with privacy risks literature at the organizational level (Aguirre et al. 2015, 2016; Li 2011) – that trust constitutes a key promotive mechanism (Martin, 2018) through which individuals counteract privacy concerns' potential of negative influence

In bridging the aforementioned research gap, this study makes three relevant and distinctive contributions. First, it shifts the unit of analysis of digital data storing studies from organizations to individuals/consumers. Second, to the best of our knowledge, this is the first study to identify drivers of adoption and acceptance of online DPDSs beyond broadly defined cloud computing services. Third, and related to the previous point, this is also the first work to test empirically a comprehensive model of online DPDSs acceptance blending some of the TAM drivers with additional constructs/elements that have been found to play a role in cloud computing services acceptance such as trust (Almarazroi et al., 2019; Chen et al., 2016).

### 2.2. Technology Acceptance Model (TAM) and digital personal data stores (DPDSs)

In information systems literature and social sciences, several models have been developed to predict and explain the adoption and acceptance of technological and information systems over the last five decades, both at the firm (Oliveira and Martins, 2011) and the individual user level (Shaikh and Karjaluoto, 2015; Venkatesh et al., 2003, 2007). While most of the models draw on Fishbein and Ajzen's (1975) theory of reasoned action (TRA) (Ajzen and Fishbein, 1980; Fishbein and Ajzen, 1975), the theory of planned behavior (TPB) (Ajzen, 1991), theories of human behavior (Triandis, 1977), innovation diffusion theories (Rogers, 1995; Tornatzky and Klein, 1982), social cognitive theories (Bandura, 1986) and motivational theories (Vallerand, 1997), the most dominating model remains the Technology Acceptance Model (TAM). The model was developed in the mid-eighties by Fred Davis and colleagues (Davis, 1986, 1989, 1993; Davis, Bagozzi and Warshaw, 1989) to respond to a real need of IBM to assess the market potential of then emerging technologies such as image processing and multimedia. TAM illustrates and explains how external variables can affect the adoption and acceptance of technological innovations and information systems in work settings. More specifically, in its original formulation, the model captures the causal relationships between a set of external variables, such as system features, involvement in design, and nature of the implementation process, on one hand, and attitude and behavioral intention to use the system on the other hand. In doing so, it focuses on two mediating factors: perceived usefulness and perceived ease of use.

Several scholars in information systems and social sciences have extensively embraced TAM as a model to assess the behavioral intention to use a new technology in order to shed light on issues related to technology user acceptance (e.g., Davis and Venkatesh, 1995; Sjazna, 1994; Taylor and Todd, 1995). While several variations of the TAM model have been developed over time, such as the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003), the key constructs of the model are rather established. They include the behavioral intention (BI) to use a specific technology, which is affected by the attitude (ATT) towards using that technology. In its turn, attitude in influenced by two causal antecedents: 1) perceived ease of use (PEOU) that entails the user’s perception of the degree to which using a technology/system will be effortless; 2) perceived usefulness (PU) that relates to the user's perception of the extent to which using a specific technology/system will improve the user's performance. Overall, the TAM has been described as "a parsimonious and robust model of technology acceptance behaviors" (Gefen et al., 2003: 53).

Interestingly, so far the TAM has been deployed to understand acceptance of many information technologies and systems, including enterprise resource planning systems (ERPs) (Gefen, 2004), smartphones and apps (Shaikh and Karjaluoto, 2015), virtual and augmented reality (Jetter et al. 2018), video games (Wang and Sun, 2016), online shopping platforms (Perea et al., 2004), cloud computing (Pinheiro et al., 2014), and semantic web technology (Kim et al., 2018). However, services for digital personal data storage have been only partially covered by business and management studies dealing with the acceptance and adoption. As clarified in a recent literature review (Song et al., 2020) whose findings were validated by a systematic literature review conducted at the moment of writing in 2020, only very few studies have examined the drivers of individual intention to use cloud computing systems, with most of the studies focusing on organizational adoption. For instance, based on a sample of Chinese users, Wang (2016) found that perceived usefulness, perceived ease of use, and perceived trust influence positively users' adoption intention of cloud computing systems. Surprisingly, in their version of the model, attitude towards use is not present. Chen et al. (2017) conducted a survey of Taiwanese users and found that perceived usefulness and perceived ease of use influence positively attitude, which in its turn influences intention. Moreover, intention is affected positively by subjective norms, perceived behavioral control, and compatibility. Almarazroi et al. (2019) analyzed the role of gender in influencing end users' acceptance of cloud computing in Saudi Arabia and found that trust was a significant determinant of behavioral intention to accept cloud computing for female students, but not for male students.

To summarize, technology acceptance and adoption have been examined in a broad sense in relation to cloud computing services, but not specifically to DPDSs. Moreover, most of the extant studies have focused on organizations, with individual analyses being a minority (Song et al., 2020). In general, existing literature did not analyze in detail the antecedents of acceptance by enriching the TAM to accommodate issues that are of paramount importance for DPDSs and their use in online settings: perceived privacy risks (Li, 2011) and trust (Martin, 2018). Accordingly, this study aims at filling this research gap by developing and testing an enriched version of the TAM in the context of cloud computing empowered digital personal digital data stores (DPDSs). The next section develops the hypotheses of our proposed TAM in the context of DPDSs.

### 2.3. Hypotheses development

*Perceived usefulness*

Within the context of DPDSs, usefulness is associated with specific objectives or tasks (such as data storing), and therefore DPDSs could lose their usefulness when they are removed from their original context (e.g., Osswald et al., 2012). The main focus here is on current and prospective users looking for a service capable to store their digital data, and in this context the usefulness of DPDSs pertains to the capability of the particular digital data store to help users in their storing activities. Therefore, perceived usefulness is assumed to influence users' attitude and intention to use DPDSs for storing digital data. Besides being proposed in the original version of the Technology Acceptance Model (TAM) and its variations, and tested in a number of studies (e.g., Pavlou and Fygenson, 2006), the relationship usefulness – attitude is hypothesized to hold also in the context of DPDSs. Additionally, a significant body of research in technology acceptance has identified a direct significant effect of usefulness on intention (Davis, 1989; King and He, 2006). Hence, the ensuing hypotheses are formulated:

*H1a:* Perceived usefulness of DPDSs positively influences attitude towards using them.

*H1b:* Perceived usefulness of DPDSs positively influences the behavioral intention to use them.

*Perceived ease of use*

Scholars in the wider information systems (e.g., King and He, 2006) and management (Perea et al., 2004) fields have validated the relevance and effect of the ease of use construct within the TAM. Based on the theory underlying the TAM, a system might be considered as more useful if the user perceives that it is easy to use. A vast number of studies offer consistent empirical backing regarding the effect of ease of use on usefulness (e.g., Davis, 1989, 1993; King and He, 2006). Meanwhile, Venkatesh and Davis (2000) have observed that ease of use has shown a less stable effect than usefulness on behavioral intention in existing literature, and generally it has been found that the effect of ease of use on attitude is lower than the effect of usefulness on attitude (Davis, 1989). In the context of this study, perceived ease of use is related to the extent to which an individual believes that using DPDSs will not be onerous and will entail negligible efforts. Storage devices and services are generally believed to facilitate data storage and, in the broadly defined cloud computing services literature, perceived ease of use has been found to produce significant effects on intention to use cloud-computing services. For instance, Wang (2016) found that ease of use has a positive and significant effect on both adoption intention and perceived usefulness in a sample of individual cloud service users in China. In addition, Chen et al. (2017) detected that perceived ease of use influences positively and significantly perceived usefulness and adoption intention in a sample of individual cloud service users in Taiwan. Last, similar effects of ease of use on perceived usefulness and adoption intention were measured by Arpaci (2017) in a study on cloud computing adoption by Turkish students. Consequently, in light of the reviewed literature, we hypothesize that individual users' evaluation of the efforts involved in using a DPDS will have an effect on their attitudes and perceived usefulness.

*H2a:* Perceived ease of use of DPDSs positively influences attitude towards using them.

*H2b:* Perceived ease of use of DPDSs positively influences perceived usefulness of DPDSs.

*Relationship between attitude and behavioral intention*

In the context of data storage, the attitude construct is supposed to be related to using DPDSs. The connection between attitude toward a specific behavior/object and behavioral intention has been discovered and documented in information system user behavior models (e.g., Bagozzi et al., 1992; King and He., 2006; Warshaw and Davis, 1985) as well as in consumer behavior studies and models (e.g., Ajzen, 1991; Loiacono et al., 2007; Ek Styven and Mariani, 2020). Henceforth it has been deeply analyzed in the mainstream IS (Venkatesh *et al.*, 2003) and marketing (Pavlou and Fygenson, 2006) bodies of literature. In the context of cloud-computing services adoption, attitude has been found to positively influence the behavioral intention to adopt those systems in a sample of individual cloud service users in Taiwan (Chen et al., 2017). Another study on Turkish students has revealed that attitude has a positive effect on continued use of cloud computing services (Arpaci, 2017). Accordingly, we hypothesize:

*H3:* Attitude towards using DPDSs positively influences the behavioral intention to use them.

*Trust*

In the information systems literature, trust has been found to play a critical role in the context of transactional information systems that imply the transmission of sensitive and personal data and information (see Aguirre et al. 2015; Li, 2011). More specifically, a large body of literature has found that trust plays a central role in the relationship between information privacy concerns and willingness to disclose information (Aguirre et al. 2015; Li 2011; Luo 2002). Indeed, on one hand users of information systems express privacy concerns that can be defined as individual tendencies to worry about information privacy (Li, 2011). On the other hand, they are willing to disclose information if this allows them to get more personalized and tailored services (Pavlou, 2003).

In management and especially marketing science, it has been found that trust can affect online consumer behavior (Gefen, 2000; Gefen and Straub, 2002; Jarvenpaa et al., 1999). For instance, in their study of electronic government (e-government) technologies adoption, Venkatesh et al. (2011) discuss the role of trust and its influence in the Hong-Kong citizens' adoption of, and loyalty towards, e-government technologies. In his study of e-commerce, Pavlou (2003) found that trust (conjointly with perceived risk) is an antecedent of behavioral intention to transact, as it contributes to reduce transaction-related uncertainty and also influences perceived usefulness and perceived ease of use, as well as perceived risk. Furthermore, trust in mobile payment solutions has been found to enhance the perceived usefulness of mobile payment technology (Dahlberg et al., 2003).

Trust permeates social and economic transactions in both offline and online settings but is even more pronounced on digital platforms and ecosystems (Nambisan, 2017; Wathen and Burkell, 2002), as individuals increasingly store their personal data and information in online DPDSs, which are typically enabled by cloud-computing technologies. In our conceptualization, we argue that trust constitutes a key promotive mechanism (Martin, 2018) through which individuals counteract the potentially negative influence of privacy concerns in relation to DPDSs acceptance and adoption. More specifically, in the broader literature revolving around cloud computing systems adoption by individuals, only one study has examined the effect of trust and the results reveal that it positively influence adoption of cloud computing systems in a sample of Chinese users (Wang, 2016).

We hypothesize, in line with extant and scant literature revolving around cloud computing adoption (Wang, 2016), that the extent to which prospective users trust DPDSs will influence positively the extent to which they perceive DPDSs as useful and easy to use.

*H4a:* Perceived trust in DPDSs positively influences perceived usefulness of DPDSs.

*H4b:* Perceived trust in DPDSs positively influences perceived ease of use of DPDSs.

*Perceived privacy risk and moderation effects*

Perceived risks emerge in relation to uncertainty. Following the lead of Bensaou and Venkataman (1996), risks relate to both behavioral and environmental uncertainty. Behavioral uncertainty stems mainly from the possibility that DPDSs might be affected by private information leaks and DPDSs managers might retain data and share them with advertisers. This is the case of Google that, besides operating the online DPDS Google Drive, is also one of the two leaders in digital advertising with its product Google Ads. As such, behavioral uncertainty might entail mostly *privacy risk* due to the possibility for DPDSs providers to disclose personal information. Privacy risk is tightly related to privacy concern that can be defined as an "individual's general tendency to worry about information privacy" (Li, 2011, p. 5). In the broad research stream revolving around cloud computing acceptance, it has been found that privacy risk negatively affects cloud computing adoption (Shin, 2013; Shin et al., 2014) and in some cases does not exert any effect in acceptance intention (e.g., Wang, 2016).

On the other hand, environmental uncertainty is related to the very same weaknesses of a technology. Even though DPDSs providers typically design, implement and update strategies, policies and practices to enhance security (including authentication, encryption, etc.), there could be the possibility that third parties may subtract or steal personal data and information.

Therefore, environmental uncertainty in this context might entail substantial privacy risks due to data theft.

As Featherman et al. (2010) and Krishen et al. (2017) point out, consumers' concern for information privacy online is one of the most important issues of the information age. Generally, perceived risk concerns the belief of suffering a loss while carrying out a specific activity (e.g., Pavlou, 2003), which in our case is storing digital data on DPDSs. *Perceived privacy risk* is in this context defined as "a consumer's subjective evaluative assessment of potential losses to the privacy of confidential personally identifying information" (Featherman et al., 2010, p. 220).

Previous studies in the context of cloud computing adoption have found that perceived privacy risks negatively affect cloud computing adoption (Shin, 2013; Shin et al., 2014) and in some cases do not exert any effect in acceptance intention (e.g., Wang, 2016). Building on this literature, we expect that perceived privacy risks would negatively moderate the core relationships of the TAM model; namely the effect of usefulness on attitude, the effect of ease of use on attitude, and the effect of usefulness on behavioral intention. Indeed, if potential users' subjective evaluation of the potential losses to the privacy of confidential personally identifying information are relevant, we would expect this to attenuate the relationships between usefulness/ease of use and attitude, as well as the relationship between usefulness and behavioral intention. Accordingly, we hypothesize that:

*H5a:* Perceived privacy risk negatively moderates the relationship between perceived usefulness of DPDSs and attitude towards using them.

*H5b:* Perceived privacy risk negatively moderates the relationship between perceived ease of use of DPDSs and attitude towards using them.

*H5c:* Perceived privacy risk negatively moderates the relationship between perceived usefulness of DPDSs and behavioral intention to use them.

*Hypothesized model*

To summarize our hypothesized relationships, perceived trust, usefulness, and ease of use are hypothesized to influence users' attitude and behavioral intention to use DPDSs for storing activities (see Fig. 1). In its turn and in line with the underlying theories of the TAM such as the TRA (Ajzen, 1991), attitude is hypothesized to influence directly behavioral intention to use DPDSs. Perceived privacy risk is then hypothesized to have negative moderating influences on some of these relationships, as indicated by the dashed arrows in the figure~~ outlined above~~.

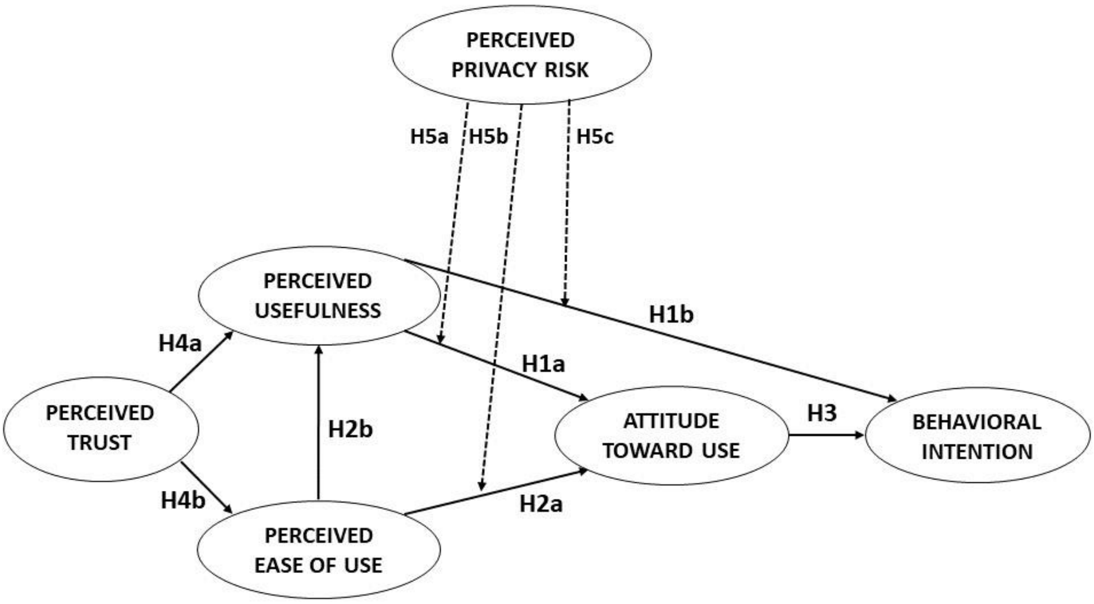


**Fig. 1.** Proposed research model

## 3. Method

### 3.1 Instrument design

In line with previous research on TAM (Venkatesh et al., 2003), this study adopts a survey research design. To increase reliability and content validity, we utilized existing constructs from previous TAM studies and adapted the items slightly to fit the empirical context of the study. Specifically, we adopted scales from Venkatesh and Davis (2000) to measure perceived ease of use (four items) and behavioral intention (two items). An eight-item scale was used to capture perceived usefulness based on Venkatesh and Davis (1996; 2000) and Gefen et al. (2003). Perceived trust was measured with four items adapted from Gefen (2000) and Pikkarainen et al. (2004). Finally, attitude toward use was captured using five items adapted from studies by Mariani et al. (2019) and Yang and Yoo (2004), who drew their measures from earlier studies on TAM (Davis, 1989; Venkatesh et al., 2003). The items for all constructs, except for attitude toward use, were measured with seven-point Likert type scales, with anchors ranging from "strongly disagree" (1) to "strongly agree" (7). For the attitude construct, we used a seven-point semantic differential scale. All items in the model are listed in the Appendix.

In addition to the above, the questionnaire also included four items adapted from Pavlou et al. (2007) to capture the perceived privacy risk construct, which was included for the purpose of moderation tests (Hayes, 2018). Moreover, a screening question, ranging from "Never" to "Almost always", was placed in the beginning of the questionnaire to ensure that all respondents had some experience of using DPDS within the last three years. Two open follow-up questions also asked respondents to indicate which DPDSs they had used, and which one of these they preferred to use. Moreover, respondents were asked if they had ever paid for the DPDSs that they had used. Finally, some background questions covering respondents' gender, age, and main occupation were included for descriptive purposes.

Before launching the survey, we conducted a pilot study with students and academics within the UK and France, including 57 participants in total. Principle component analysis (PCA) was applied to validate the survey items. The results showed that all constructs loaded accordingly and as expected. Overall, the researchers assessed that the scales used allowed us to effectively capture the constructs of the proposed research model. Hence, we retained all items in the questionnaire and proceeded to the main study.

### 3.2 Data collection and sample

To remain consistent with the majority of the population who responded to the pilot study, the target population of the main study was people living in the UK. An anonymous online survey was developed on the web platform Qualtrics and distributed to collect data from men and women between 16 and 65 years who are members of online consumer panels in the UK. The set-up of the survey ensured that a census representative sample was achieved in terms of gender, age, and region of residence, with a wide coverage of users of consumer electronics.

The survey was introduced by explaining the aim of the study and participants were instructed to think about "Digital Personal Data Stores" and how they use them to store and share their personal (digital) data. Examples were cited in the survey to facilitate the practical understanding of DPDSs: Dropbox, OneDrive, Google Drive, Hub of All Things, Apple iCloud, Databox, and Digime. Respondents first answered a screening question: "In the last three years, how often have you used digital online digital personal data stores?" Those who responded "Never" were screened out ($n$=69), while respondents who chose one of the other response options were re-directed to the survey for them to complete.

After the screen-out and further removal of 24 incomplete or dubious responses, 214 responses remained for analysis. Slightly more than half (52.8%) of the respondents were female and 47.2 percent male. The majority of the sample (63.6%) was younger than 41, with the most common age category being 31-40 years (35.5%). In terms of occupation, 77.1 percent were working, while the rest were either unemployed, students, or other. Only ten percent of the respondents indicated that they had "seldom" used digital personal data stores in the last three years, while 30.8 percent answered "sometimes", 38.8 percent "often", and 20.1 percent "almost always". The most commonly preferred DPDS was Dropbox, which was mentioned by 34.1 percent of the respondents, followed by iCloud (29.1%) and OneDrive (20.5%). The majority of the respondents (89.3%) indicated that they had never paid for their most preferred DPDS.

### 3.3 Measurement validation

No missing values remained in the sample after removing incomplete responses. Furthermore, assessment of univariate and multivariate normality showed that skewness and kurtosis values were within accepted ranges for all items (skewness -1 to 1, kurtosis -1.5 to 1.5) (Hair et al., 2010, 2014).

Construct validity and reliability was tested through confirmatory factor analysis (CFA), using IBM SPSS Amos 25. This resulted in the stepwise removal of three items (PT1, PU8, and ATT2) due to high modification indices and standardized residual covariances. After dropping these items, fit indices of the measurement model were satisfactory with $X^2$=305.97 (df 160), $X^2$/df=1.91, CFI=.963, TLI=.956, and RMSEA=.065 (cf. Hair et al., 2010). All factor loadings were significant and well above .70, a common rule of thumb for convergent validity (Hair et al., 2010). The Appendix shows the loadings of all items included in the final measurement model.

Moreover, following Fornell and Larcker (1981), we checked that the average variance extracted (AVE) was higher than .50 for all constructs and that the correlation between each pair of constructs was less than the square root of the AVE for each construct. All of these criteria were met. Finally, internal consistency of the scales was assessed by computing composite reliability (CR) and Cronbach's alpha. These values well exceeded the commonly suggested threshold of .70 for all five constructs (Hair et al., 2010). Table 1 shows the results of these analyses.

**Table 1.** Inter-construct correlation matrix

| Construct | α | CR | AVE | PT | PEOU | PU | ATT | BI |
|---|---|---|---|---|---|---|---|---|

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Perceived Trust (PT)** | .887 | .898 | .748 | **.865** | | | | |
| **Perceived Ease of Use (PEOU)** | .914 | .915 | .729 | .772 | **.854** | | | |
| **Perceived Usefulness (PU)** | .937 | .930 | .689 | .705 | .775 | **.830** | | |
| **Attitude towards Use (ATT)** | .930 | .930 | .768 | .753 | .654 | .610 | **.876** | |
| **Behavioral Intention (BI)** | .931 | .931 | .871 | .557 | .665 | .645 | .588 | **.933** |

Note: The values on the diagonal represent the square root of AVE (in bold).

### 3.4 Data analysis

Based on the satisfactory results of the measurement model, we proceeded to estimating the full model and testing the hypotheses. Using IBM SPSS Amos 25, we applied structural equation modeling (SEM) with maximum likelihood estimation (ML), which is considered a relatively robust method for most uses (Iacobucci, 2010). With cross-sectional survey data being used for the estimation, we cannot claim causality, but the aim is to test the hypothesized relationships and feasible influences among the model's constructs (cf. Bagozzi and Yi, 2012). According to Hair et al. (2010) and Iacobucci (2010), very large samples are not required for structural equation models if certain criteria are fulfilled, such as normally distributed data, no more than five constructs in the model, high item communalities, and reliable measures. As our model meets these criteria, the sample size was considered adequate to run the structural model as well as the moderation tests.

## 4. Findings

### 4.1 Structural model and main hypotheses tests

The structural model was evaluated to measure the explanatory power and predictive relevance of the proposed research model, using the full sample ($n$=214). Model fit was adequate with $\chi^2$/df=2.17 ($p$<.001), CFI=.951, TLI=.943, and RMSEA=.074. Overall, the squared multiple correlations (analogous to $R^2$) indicate that the model can explain 63.4 percent of the variance of perceived usefulness, 61.8 percent of perceived ease of use, 48.4 percent of attitude toward use, and 48.6 percent of behavioral intention to use digital personal data stores.

Path coefficients and significance levels were assessed with regard to the hypotheses. First, the assumptions of direct positive relationships between perceived usefulness of DPDSs and Internet users' attitude (Beta=.216, t=2.20, $p<0.05$) and intentions (Beta=0.463, t=6.06, $p<0.001$) underlying hypotheses H1a and H1b were supported. This adds to models that tried to identify the drivers of acceptance of cloud computing systems and did not consider attitude (e.g., Wang, 2016).

Second, in line with most of the TAM work (Davis, 1989), also hypotheses H2a and H2b were supported as perceived ease of use of DPDSs positively influence Internet users' attitude (Beta=.513, t=5.11, $p<0.001$) and perceived usefulness (Beta=0.593, t=6.43, $p<0.001$). This is also in line with some of the extant studies on acceptance of cloud computing systems (e.g., Chen et al., 2017).

Third, consistently with literature documenting the relationship between attitudes and behavioral intentions in technology settings (Bagozzi et al., 1992; King and He, 2006), the findings reveal that Internet users' attitude towards using DPDSs positively influences behavioral intention (Beta=0.308, t=4.15, $p<0.01$), thus supporting H3. This finding corroborates a study by Arpaci (2017), whose critical dependent variable was continuance intention rather than acceptance intention.

Fourth, perceived trust in DPDSs displayed a statistically positive effect on usefulness (Beta=0.241, t=2.75, $p<0.01$) and ease of use (Beta=0.786, t=13.41, $p<0.00$), thus lending support to H4a and H4b. This adds also to previous studies examining in a broad way individual acceptance of cloud computing services (e.g., Song et al., 2020). The results of all hypothesis tests are summarized in Table 2 together with the results of the moderation hypotheses tests, which are described in the following section.

### 4.2 Moderation hypotheses tests

The hypothesized moderation effects (Hayes, 2018) of perceived privacy risk were evaluated by conducting a multigroup analysis in Amos. The internal consistency of the perceived risk construct was first assessed by checking Cronbach's alpha (.921) and item-total correlations (.773 to .851) of the scale. As the construct was found to be internally reliable, we created a summated averaged factor for perceived risk. Then, a median split of the sample was conducted, with respondents exactly on the median value left out to create two more distinctive groups (median=5.0, *n*=22). The "lower risk" group (median <5.0) then consisted of 89 respondents and the "high risk" group (median >5.0) contained 103 respondents.

In the multigroup analysis, each investigated path was constrained to be equal in both groups; i.e. at one degree of freedom. Overall fit of the unconstrained multigroup model was adequate, with $\chi^2$/df=1.85, CFI=.924, TLI=.911, and RMSEA=.067. A significant change in $\chi^2$ under the path constraint indicates that the path coefficients in fact are different and thus that a moderating influence exists. However, as Table 2 shows, while the path coefficients to some extent differ between the lower and high-risk groups, none of these differences was significant.

**Table 2.** Results of hypothesis tests

| **Hypothesis** | **Path** | **Coefficient** | ***t*** | ***p*** |
|---|---|---|---|---|
| H1a | PU → ATT | .216 | 2.20 | * |
| H1b | PU → BI | .463 | 6.06 | *** |
| H2a | PEOU → ATT | .513 | 5.11 | *** |
| H2b | PEOU → PU | .593 | 6.43 | *** |
| H3 | ATT → BI | .308 | 4.15 | *** |

| | | | | | |
|---|---|---|---|---|---|
| H4a | PT → PU | .241 | 2.75 | ** | |
| H4b | PT → PEOU | .786 | 13.41 | *** | |
| | | **Lower risk** | **High risk** | **Δ$X^2$** | ***p*** |
| H5a | PU → ATT | .129 (n.s.) | .305* | 1.146 | .284 |
| H5b | PEOU → ATT | .659*** | .374** | .883 | .347 |
| H5c | PU → BI | .535*** | .496*** | .007 | .934 |

Note: ***) $p<.001$, **) $p<.01$, *) $p<.05$, n.s.) Non-significant ($p>.05$)

Thus, the empirical data do not support hypotheses 5a-c, which proposed that perceived privacy risk would negatively moderate the relationships between perceived usefulness and attitude, perceived ease of use and attitude, and perceived usefulness and intention to use DPDS. One of the reasons why perceived risk seems not to have a significant influence on any of the traditional relationships of the TAM might be attributed to the context. In e-commerce settings, where most of the extant studies have been conducted, consumers have to face more forms of *behavioral uncertainty* that entail economic risk (related to monetary losses), personal risk (related to unsafe products and services), seller performance risk (related to imperfect monitoring) and privacy risk (related to the disclosure of private consumer information) (Pavlou, 2003). However, in the context of DPDSs analyzed, behavioral risk might be less relevant, especially because the highest share of users might have a free rather than a premium version of DPDSs (this is the case of our UK sample where 89.3% of the respondents indicated that they did not pay for their most preferred DPDS). As such, the absence of any monetary transaction might generate lower perceived behavioral uncertainty overall, which also reduces the influence of perceived privacy. Regarding *environmental uncertainty*, privacy risk might be less influential because apparently the DPDSs providers appear trustworthy and reliable in the minds of Internet users. In other words, we found that trust constitutes a key antecedent of usefulness and ease of use through which individuals counteract privacy risks' potential negative influence in relation to DPDS acceptance and adoption.

### 4.3 Summary of model results

Figure 2 summarizes and visualizes the results of the structural model, including the standardized path estimates of the hypothesized relationships, while the dashed arrows show the non-significant moderating influences. Overall, as discussed above, the proposed moderating influences (H5a-5c) were found to be non-significant, while all the other hypothesized relationships were statistically significant. Therefore, the proposed enriched version of TAM can be supposed to capture and explain effectively Internet users' intention to use digital personal data stores for storing their digital data. In the examined setting, perceived usefulness, perceived ease of use, and trust influence meaningfully and significantly attitudes toward use, whereas perceived usefulness constitutes the most influential driver of behavioral intention.

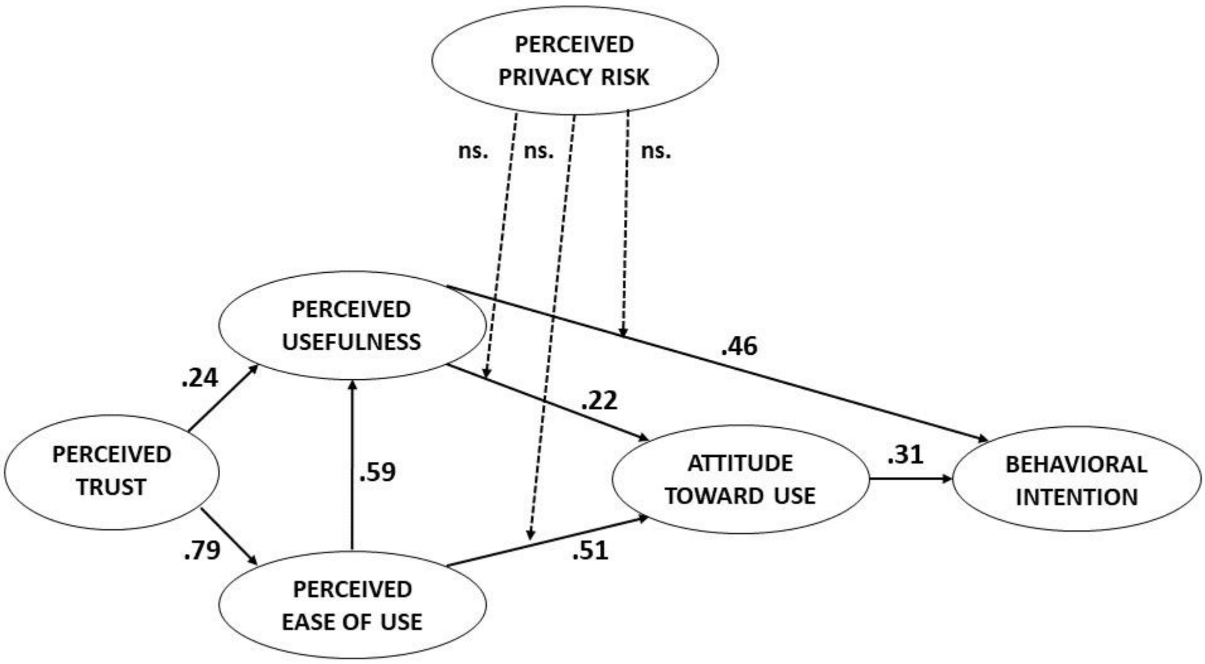


**Fig. 2.** Structural model results

## 5. Discussion and Conclusions

### *5.1 Discussion of findings*

This study has contributed to fill a relevant research gap regarding the antecedents of the intention to use online digital personal data stores (DPDSs). More precisely, we made three different and distinctive contributions as we (1) identified conceptually and examined the drivers of Internet users' behavioral intention to use DPDSs, (2) proposed an enriched and extended version of the Technology Acceptance Model for DPDSs, and (3) tested it on a sample of UK Internet users. Therefore, the study is distinctive for three main reasons. First, consistently with recent calls for more research on cloud computing systems at the individual level (see for instance Senyo et al., 2018; Song et al., 2020), it shifts the unit of analysis of digital data storing acceptance and adoption studies from organizations to individuals. Second, to the best of our knowledge, this is the first study to identify drivers of adoption and acceptance of online DPDSs beyond broadly defined cloud computing services (Song et al., 2020). Third, and related to the previous point, this is also the first work to test empirically a comprehensive model of online DPDSs acceptance blending some of the TAM drivers with additional constructs that have been found to play a critical role in cloud computing services acceptance, such as trust (Almarazroi et al., 2019; Chen et al., 2016).

By comparing our findings with previous technology acceptance studies conducted in other settings, our work displays interesting results. Many of the major effects typically examined in TAM studies hold also in the context under analysis, especially in relation to the constructs of perceived usefulness, perceived ease of use, and behavioral intention. This clearly testifies to the high levels of reliability and validity of the TAM scales (Davis and Venkatesh, 1996). We add to the literature on cloud computing systems adoption as, in contrast to previous studies (e.g., Wang, 2016), we detect an important mediation effect of attitude between perceived usefulness/ease of use on one hand, and behavioral intention using DPDSs on the other hand. Moreover, we find that trust plays a key role in promoting acceptance of cloud computing empowered DPDSs. This adds also to previous studies that broadly examined individual acceptance of cloud computing services (e.g., Song et al., 2020).

Consistently with TAM-related literature (Davis, 1989; Venkatesh and Davis, 2000), and with only a portion of the literature adopting TAM in explaining the predictors of cloud computing adoption (Wang, 2016), the study reveals that perceived usefulness is the factor that plays the most relevant role in influencing behavioral intention to use DPDSs. As such, Internet users might increasingly deploy DPDSs for digital data storing given that they would find them useful for their personal and professional activities. Therefore, DPDSs appear to serve mainly a utilitarian purpose. This result seems compatible with other studies, which however have found perceived control as the most influential driver of intention (Chen et al., 2017); even higher than usefulness.

The study therefore reveals that extrinsic motivations (Davis et al., 1992) (i.e., utilitarian value represented by perceived usefulness) are of paramount importance in the context under analysis to predict users' intention to use DPDSs. This result reinforces recent literature (e.g., Song et al., 2020) that has explored acceptance of cloud computing systems and found that hedonic motivation – within an UTAUT model specification – did not influence behavioral intention to use cloud-computing systems. By leveraging a different model (and enriched version of the TAM versus the basic UTAUT), we are able not only to explain a high share of variance (48.6%) but also to corroborate the idea that the utilitarian value associated to DPDSs, similarly to the utilitarian value associated with cloud computing services in a broader sense, can make a difference. That said, this result could also be due to cultural factors (Mariani, Borghi and Okumus, 2020; Mariani and Matarazzo, 2020). Indeed, the studied sample consists of subjects from an individualistic culture (i.e., the UK) that in other studies adopting TAM (e.g., Mariani et al., 2019) has been found to emphasize utilitarian value more than hedonic value.

Ease of use was found to be critical in influencing both perceived usefulness and, to a lesser extent, attitude. This finding is consistent with extant literature that has identified a clear positive effect of ease of use on usefulness (e.g., Davis, 1989, 1993; King and He, 2006). In line with Venkatesh and Davis (2000), we observed that the effect of ease of use on attitude displays a lower magnitude than the effect of usefulness on attitude (Davis, 1989). This result is also in line with a study adopting TAM to measure the intention to accept cloud-computing systems (Chen et al., 2017). Accordingly, it is apparent that individuals believe that using DPDSs will not entail major efforts.

In addition, attitude towards using was found to influence behavioral intention to use DPDSs, which is in line with extant TAM literature suggesting that attitude plays a mediating role between perceived usefulness and ease of use on one hand and behavioral intention on the other hand. This result is compatible with the TRA and with the enrichment that social psychologists have proposed over time (Bagozzi et al., 1992; Bagozzi, 2007). However, one study adopting a technology acceptance model to predict the use of cloud computing systems has found that attitude does not work as a mediator (Wang et al., 2016). This might be explained theoretically by reflecting on the different versions of the TAM that have been developed over time (Davis and Venkatesh, 1996) and also by the difference of the settings examined (i.e., adoption of cloud computing in China vs. adoption of DPDSs in the UK).

In line with extant literature, this study found trust to positively influence both ease of use (Pavlou, 2003) and perceived usefulness (Gefen, 2000; Pavlou, 2003; Dahlberg et al., 2003), with the effect on ease of use being stronger than the effect on perceived usefulness. This result informs the theoretical debate on the drivers of adoption of cloud computing empowered DPDSs. Accordingly, we add to those few modelling attempts that have found trust to play a significant role in the acceptance of cloud computing systems by organizations (Stieninger et al., 2018). This study indicates that trust plays a critical role also at the individual level and in relation to individual acceptance of DPDSs, as it enhances and trumps usefulness and ease of use.

Privacy risk seems to lack significant moderation influences, as it did not affect any of the tested relationships; i.e., neither the effects of perceived usefulness and ease of use on attitude, nor the effect of perceived usefulness on behavioral intention. This is a potentially interesting finding, as it seems to indicate that in the context of the DPDSs analyzed, behavioral risk might not be as relevant as in online retailing contexts. A likely explanation is that the majority of users has activated a free subscription rather than a premium one with the DPDS (this seems to be the case in our representative UK sample). Alternatively, if they use DPDSs for business, then their companies/employers are paying for the premium versions. As such, the absence of any monetary transaction might generate lower perceived behavioral uncertainty overall. This is consistent with research that has found that monetary transactions increase perceived behavioral uncertainty (Pavlou, 2003) and adds to the nascent research stream revolving around cloud computing adoption that has not touched the theme of behavioral uncertainty (e.g., Song et al., 2020). Regarding *environmental uncertainty*, the influence of perceived privacy risk might be limited for two reasons: first, the DPDSs providers - notably technology companies such as Google, Dropbox, Apple and Microsoft offering cloud computing services - appear trustworthy and reliable in the minds of Internet users, due to their brand value and corporate reputation (Swilley and Goldsmith, 2007). Second, age might help explain the results as the majority of the respondents was younger than 41 and extant studies have highlighted that attitudes towards privacy can be related to age (Elvy, 2017). As such, our findings are consistent with a study conducted by the Global Alliance of Data Driven Marketing Association suggesting that younger consumers globally are less concerned by data privacy compared to older age groups across many main markets all over the world (GDMA 2018). This result complements previous studies revolving around cloud-computing services acceptance, which found that perceived risk has a non-significant direct effect on acceptance intention (Wang, 2016) and that security risks have a non-significant influence on attitude (Chen et al., 2017).

Overall, this study generates several theoretical and practical implications that are discussed below.

### *5.2 Theoretical implications*

This study contributes to the information technology adoption literature by extending the research scope to cloud-computing empowered digital personal data storage platforms. Thus, it contributes to advance also the wider research stream around the acceptance of cloud computing systems (e.g., Chen et al., 2017; Song et al., 2020). More specifically, it identifies several relevant antecedents of Internet users' decisions to use DPDSs to store their digital data. Several of the identified antecedents entail traditional TAM-related constructs such as perceived usefulness, perceived ease of use, and attitude that have been analyzed also in a few studies adopting TAM to analyze acceptance of cloud computing services (see Chen et al., 2017). Beyond those constructs, we have found also that perceived trust plays a significant role in the context under analysis. This is certainly an important enrichment of the wider research stream investigating the acceptance of cloud computing systems by individuals (e.g., Chen et al., 2017; Song et al., 2020). As such, this work seems to support the relevance of extrinsic motivational factors such as usefulness and perceived ease of use (Bagozzi et al., 1992; Teo et al., 1999), thus indicating that DPDSs and their underlying digital platforms are mainly perceived as means to fulfill a highly functional need. This finding resonates also with the results of research that has deployed other IT acceptance models such as the Unified Theory of

Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003) where the effect of performance expectancy, effort expectancy, and social influence on behavioral intention are measured. In that comprehensive model, the most influential driver of behavioral intention is performance expectancy, which is a construct close to usefulness in the original version of the TAM. Interestingly, this finding is also consistent with recent literature (e.g., Song et al., 2020) that has explored acceptance of cloud computing systems and found that hedonic motivation - within a UTAUT model specification – did not influence significantly behavioral intention to use cloud computing systems. By leveraging a different model - an enriched version of the TAM versus the basic UTAUT deployed by Song et al. (2020) - we demonstrate cross-model robustness of the idea that the utilitarian value associated to DPDSs, similarly to the utilitarian value associated with cloud computing services, can make a difference for acceptance.

On the other hand, and despite the apparent decline in Internet users' confidence in the security of digital platforms along with mounting concerns about privacy risks (Acquisti et al., 2015; Pearson, 2002; Strand, 2014), this study did not detect any significant moderating effect of perceived risk. This finding seems to be in contrast with a few studies (Lee, 2009; Pavlou, 2003) that have found perceived risk to affect behavioral measures in e-commerce contexts. However, most of the DPDSs commonly adopted are available for free through free subscription and most of the users tend to adopt the free rather than the premium version for personal purposes, whereas they might use also the premium version for free when using DPDS in their working activities as employees. As such, our findings are consistent with research that has showed that risk becomes less relevant or even irrelevant when technology users are given free access to an application or given free trials (Lu et al., 2005; Tan, 1999). Accordingly, the free access versions of most of the DPDSs, very much like the warranties and money back guarantees on online product sales, influence risk perceptions (Schiffman and Kanuk, 1987; Shimp andBearden, 1982) by acting as risk relievers (Akaah and Korgaonkar, 1988; Derbaix,

1983) and increasing trust. Our findings seem to complement recent literature revolving around cloud computing acceptance that found no direct effects of risk on adoption intention (Wang, 2016) and on attitudes (Chen et al., 2017).

Overall, and despite contradictory findings related to the effect (weakly significant or not) of perceived risk in the TAM literature and technology acceptance literature related to cloud computing (Senyo et al., 2018; Song et al., 2020), embedding perceived risk into TAM has been found to increase only marginally the predictive validity of the model (Featherman, 2001). This study seems to corroborate that empirical observation. Finally, this study has contributed to shed light on the drivers of DPDSs adoption that might be relevant to understand DPDSs adoption, not only for researchers but also for digital platform developers and managers as well as digital entrepreneurs.

### *5.3 Practical implications*

A number of practical implications stem from this study, including implications for 1) digital data storage hardware and software developers; 2) managers and marketers of online DPDSs; 3) incumbent firms and technology entrepreneurs interested in developing and fine-tuning business models leveraging digital personal data streams.

First, as far as digital data storage hardware and software developers are concerned, the enriched version of the TAM developed and tested might help professionals working as IT and computer science researchers and developers to understand how Internet users evaluate online DPDSs and digital storage platforms such as Dropbox, Google Drive, Microsoft OneDrive, Apple iCloud, the HAT, Digime, Databox, and many others. In more detail, this study offers a first yet important synopsis and explanation of the cognitive factors determining Internet users' decisions to adopt and accept DPDSs. Consequently, both hardware and software developers should learn more about these factors in their attempts to design and develop solutions that might increase users' adoption of digital data stores. More specifically, software developers realize that online DPDSs are currently mostly about cloud-based Software as a Service (SaaS) platforms that should be able to operate with different operating systems (e.g., proprietary and open OSs) and devices (e.g., desktop and mobile devices) to allow users to perceive high levels of usefulness over time. Moreover, while DPDSs look rather independent from each other as their providers (e.g., Google, Dropbox, Apple, etc.) are competing to attract users, companies should strike a balance between offering inter-operable systems (such as the storing services of Dropbox) that allow wider scope in terms of inter-operability vs. closed systems (such as the services of Apple iCloud) that empower only the customers that utilize a specific OS.

Secondly, managers and marketers of online DPDSs and other online file hosting services are encouraged to keep on investing to create the highest levels of utilitarian value for their users. More specifically, usefulness might be improved by enhancing the capability of storing data in terms of type of data, volume and storage time, ability to accomplish the necessary tasks to store data, and time needed to undertake the tasks related to data storage. Overall, usefulness seems a leading indicator of users' intention to use and is therefore the strategic area where firms should invest to improve their DPDSs. In its turn, usefulness is positively influenced by ease of use: as such, DPDSs providers are strongly encouraged to further invest in simplifying their platforms to guarantee better usage. The popularity of DPDSs such as Dropbox, Google Drive and Apple iCloud in the context under examination is certainly the byproduct of a constant attention to reduce the users' efforts in learning how to use the digital stores proficiently. Interestingly, we observe that users trust the ability of DPDSs to protect their personal data and their overall security. This is in spite of the severe data security and data breaches issues that have affected several DPDSs over the last decade (Gibbs, 2016; Kincaid, 2011; McGoogan, 2016) and very loose privacy policies that allow DPDSs to get a worldwide license to use, host, store, reproduce, modify and create derivative works, communicate, publish, publicly perform and distribute the content for the limited purpose of operating, promoting and improving the providers' services (Patel, 2012). Hence, this suggests that end users are willing to take some risks in terms of their data security and privacy in exchange of the functionality and usefulness of DPDSs.

Third, incumbent firms and technology entrepreneurs interested in developing and fine-tuning business models leveraging digital personal data streams should be very careful when it comes to monetization strategies. Indeed, our study shows that perceived risk plays a minor if not negligible role in DPDSs acceptance and usage. As such, offering free basic subscriptions for a limited amount of storage space typically in the order of a few Gigabytes (e.g., 2 GB and up to 18 GB for referrals for Dropbox, 15 GB for Google Drive, 5 GB for Apple iCloud, 5 GB and up to 10 GB for referrals for Dropbox) seems a suitable strategy to acquire and maintain a satisfied user base. Free basic subscriptions seem to work as risk relievers (Akaah and Korgaonkar, 1988; Derbaix, 1983) and this might become increasingly relevant in the near future, considering increasing concerns about privacy and private information leaks (Acquisti et al., 2015) brought about by recent scandals such as those involving Cambridge Analytica and Dropbox.

Digital entrepreneurs interested in developing digital platforms allowing both DPDSs providers and customers to monetize on personal digital data like the Hub of All Things (HAT) can further invest to enhance usefulness and ease of use. This can ~~might~~ trigger the evolution of a new ecosystem of DPDSs (Nambisan, 2017) with the power to generate multiple monetization mechanisms involving both platform providers and users who can trade their data in exchange of benefits and monetary rewards.

### *5.4 Limitations and future research*

This work exhibits some limitations. First, the model proposed was empirically tested in a specific country, the UK, renowned for high Internet penetration rates (World Bank, 2019) and tech-savvy Internet users. Replicating and validating the empirical study in other countries (for example countries with lower penetration of DPDSs or countries where the utilitarian value is less relevant) might be potentially interesting to improve the generalizability of the results. While the findings offer strong support of established relationships and effects in the wider IS adoption and acceptance literature (Davis, 1986, 1989; Venkatesh et al., 2003), and in some cases in relation to the cloud-computing acceptance research stream (e.g., Song et al., 2020), it would be interesting to conduct comparative studies that might reveal if the magnitude of the effects would change across different countries, cultures and geographical contexts. In line with Adams et al. (1992), replication studies corroborating TAM findings in different contexts are always of paramount importance.

Second, privacy issues could be explored further, also based on behavioral economics literature revolving around privacy in online settings (e.g., Acquisti et al., 2015). Such studies could triangulate in more detail consumer demographics and consumer behaviors that might affect the willingness to pay for the storage services and consumers' perceived value of the services.

Third, while we focus on a parsimonious model of technology acceptance, there might be additional factors that influence DPDSs adoption. For instance, social influence (Deutsch and Gerard, 1955) might play a role (Mariani et al., 2021), as adoption is a function of network effects as well. As such, future research might shed light on the role of social influence as a construct capturing network effects and their related positive externalities on technology acceptance.

Last, in this specific study - the first to deal specifically with DPDSs and among the few dealing with cloud computing services for personal storing purposes - we have purposefully focused on a few facets of usefulness mainly related to storage. However, DPDSs serve also another important function, which is “sharing data”. Given that “data sharing” is the object of a parallel ongoing study conducted by the research team, we envision that integrating the findings of this study with the findings of the other might allow to gain a more comprehensive and granular view of the phenomenon analyzed.

## References


Abdalla, P. A., and Varol, A. (2019). Advantages to Disadvantages of Cloud Computing for Small-Sized Business. In 2019 7th International Symposium on Digital Forensics and Security (ISDFS), *IEEE*, 1-6.

Acquisti, A. Brandimarte, L. and Loewenstein, G. (2015). Privacy and human behavior in the age of information, *Science*, 347 (6221), 509-514.

Adams, D. A., Nelson, R. R. and Todd, P. A. (1992). Perceived Usefulness, Ease of Use, and Usage of Information Technology: A Replication, *MIS Quarterly*, 16 (2), 227-247.

Aguirre, E., Mahr, D., Grewal, D., de Ruyter, K. and Wetzels, M. (2015). Unravelling the personalization paradox: the effect of information collection and trustbuilding strategies on online advertisement effectiveness, *Journal of Retailing*, 91(1), 34-49.

Aguirre, E., Roggeveen, A.L., Grewal, D. and Wetzels, M. (2016). The personalization-privacy paradox: implications for new media, *Journal of Consumer Marketing*, 33(2), 98-110.

Aldiabat K., Rashid A.S.K., Talafha H., and Karajeh A. (2018). The extent of smartphones users to adopt the use of cloud storage, *Journal of Computer Science*, 14 (12), 1588-1598.

Ali, U., Mehmood, A., Majeed, M. F., Muhammad, S., Khan, M. K., Song, H., et al. (2019). Innovative citizen's services through Public Cloud in Pakistan: User's privacy concerns and impacts on adoption. *Mobile Networks and Applications*, 24(1), 47–68.

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

Ajzen, I. and Fishbein, M. (1980). *Understanding Attitudes and Predicting Social Behaviour*, Englewood Cliffs, NJ: Prentice-Hall.

Akaah, I.P. and Korgaonkar, P. (1988). A conjoint investigation of the relative importance of risk relievers in direct marketing, *Journal of Advertising Research*, 28 (4), 38-44.

Almarazroi, A. A., Kabbar, E., Naser, M., and Shen, H. (2019). Gender effect on cloud computing services adoption by university studenst: Case study of Saudi Arabia. *International Journal of Innovation*, 7(1), 155‑177.

Angst C.M. and Agarwal, R. (2009). Adoption of electronic health records in the presence of privacy concerns: The elaboration likelihood model and individual persuasion, *MIS Quarterly*, 33 (2), 339-370.

Arpaci, I. (2017). Antecedents and consequences of cloud computing adoption in education to achieve knowledge management. *Computers in Human Behavior*, 70, 382–390.

Bagozzi, R.P. (2007). The legacy of the technology acceptance model and a proposal for a paradigm shift, *Journal of the Association for Information Systems*, 8, 244-254.

Bagozzi R.P., Davis F.D.D. and Warshaw P.R. (1992). Development and Test of a Theory of Technological Learning and Usage, *Human Relations*, 45 (7), 659-686.

Bagozzi, R.P. and Yi, Y. (2012). Specification, evaluation, and interpretation of structural equation models. *Journal of the Academy of Marketing Science*, 40 (1), 8–34.

Bandura, A. (1986). *Social Foundations of Thought and Action: A Social Cognitive Theory*, Prentice Hall, Englewood Cliffs, NJ.

Bansal G, Zahedi F.M. and Gefen D. (2010). The impact of personal dispositions on information sensitivity, privacy concern and trust in disclosing health information online, *Decision Support Systems*, 49 (2), 138-150.

Bensaou, M. and Venkataman, N. (1996). Inter-organizational relationships and information technology: A conceptual synthesis and a research framework, *European Journal of Information Systems*, 5, 84–91.

Brodkin, J. (2008). Gartner: Seven cloud-computing security risks. *Infoworld*, 2008, 1-3.

Cecez-Kecmanovic, D., Galliers, R. D., Henfridsson, O., Newell, S. and Vidgen, R. (2014). The sociomateriality of information systems: Current status, future directions, *MIS Quarterly*, 38 (3), 809–830.

Chen, S.L., Chen, J.H., Chang, S.C. (2017). Understanding the Antecedents of Individuals Intention of Using Cloud Services, *Journal of Economics and Management*, 13 (2), 139-166.

Chiarugi, F., Trypakis, D. and Spanakis, E G. (2004). Problems and solutions for storing and sharing data from medical devices in eHealth applications. In *2nd OpenECG Workshop*, 65-69.

Cialdini, R.B. (2001). *Influence: Science and practice* (4th ed.). Boston: Allyn & Bacon.

Craig, R., Cortens, J. P. and Beavis, R. C. (2004). Open source system for analyzing, validating, and storing protein identification data, *Journal of proteome research*, 3(6), 1234-1242.

Davenport, T.H. (2014). How strategists use "big data" to support internal business decisions, discovery and production, *Strategy & Leadership*, 42(4), 45-50.

Davenport, T.H., Barth, P., Bean, R. (2012). How "Big Data is different", *MIT Sloan Management Review*, Fall 2012. Retrieved from: https://sloanreview.mit.edu/article/how-big-data-is-different/

Davenport, T.H. (2006). Competing on Analytics, *Harvard Business Review*, 84/1 (January 2006), 98-107.

Davis, F. D. (1986). A technology acceptance model for empirically testing new end-user information systems: theory and results, Doctoral dissertation, Sloan School of Management, Massachusetts Institute of Technology, Amherst, MA.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology, *MIS quarterly*, 13 (3), 319-340.

Davis, F.D. (1993). User acceptance of information technology: system characteristics , user perceptions and behavioral impacts, *International Journal of Man – Machine Studies,* 38 , 475-487 .

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), 982-1003.

Davis, F. D., Bagozzi, R. P. and Warshaw, P. R. (1992). Extrinsic and intrinsic motivation to use computers in the workplace, *Journal of applied social psychology,* 22 (14), 1111-1132.

Davis, F. D. and Venkatesh, V. (1995). Measuring user acceptance of emerging information technologies : an assessment of possible method biases. *Proceedings of the 2 8 th Annual Hawaii International Conference on System Sciences*. pp. 729 – 736 . Los Alamitos : IEEE Computer Society Press.

Davis, F. D. and Venkatesh, V. (1996). A critical assessment of potential measurement biases in the technology acceptance model. *International Journal of Human-Computer Studies*, 45, 19-45.

Deutsch, M. and Gerard, H.B. (1955). A study of normative and informational social influences upon individual judgment, *Journal of Abnormal and Social Psychology*. 51 (3), 629–636.

Dahlberg, T., Mallat, N. and Öörni, A. (2003). Trust enhanced technology acceptance modelconsumer acceptance of mobile payment solutions: Tentative evidence. *Stockholm Mobility Roundtable*, 22 (1).

Derbaix, C. (1983). Perceived risk and risk relievers: an empirical investigation, *Journal of Economic Psychology*, 3, 19-38.

Ek Styvén M., Mariani M.M. (2020). Understanding the intention to buy secondhand clothing on sharing economy platforms: The influence of sustainability, distance from the consumption system, and economic motivations, *Psychology and Marketing*, 37(5), 724-739.

Elvy, S. (2017). Paying for privacy and the personal data economy. *Columbia Law Review*, 117(6), 1369-1459.

Featherman, M. S., Miyazaki, A. D. and Sprott, D. E. (2010). Reducing online privacy risk to facilitate e-service adoption: the influence of perceived ease of use and corporate credibility. *Journal of Services Marketing*, 24(3), 219–229

Featherman, M. (2001). Extending the Technology Acceptance Model by Inclusion of Perceived Risk, *AMCIS 2001 Proceedings*. 148. http://aisel.aisnet.org/amcis2001/148

Fishbein, M. and Ajzen, I. (1975). *Belief, attitude, intention and behavior: An introduction to theory and research*. Reading, MA Addison-Wesley.

Fornell, C. and Larcker, D. F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error, *Journal of Marketing Research*, 18 (1), 39-50.

Franke, N. and Schreier, M. (2008). Product uniqueness as a driver of customer utility in mass customization, *Marketing Letters*, 19 (2), 93-107.

GDMA (2018). *Global data privacy: What the consumer really thinks*. May. https://dma.org.uk/uploads/misc/5b0522b113a23-global-data-privacy-report---final-2_5b0522b11396e.pdf

Gefen, D. (2004). What makes an ERP implementation relationship worthwhile: linking trust mechanisms and ERP usefulness, *Journal of Management Information Systems* 21(1), 263–288.

Gefen, D., Karahanna, E. and Detmar, W. (2003). Trust and TAM in Online Shopping: An Integrated Model, *MIS Quarterly*, 27(1), 51-90.

Gefen, D. and Straub, D.W. (2002). Managing user trust in e-services. *e-Service Journal*, 2 (2): 7-24.

Gefen, D. (2000). E-commerce: the role of familiarity and trust, *Omega*, 28(6), 725-737.

Gibbs, Samuel (2016). Dropbox hack leads to leaking of 68m user passwords on the internet, *The Guardian*. *Guardian Media Group*, August 31, 2016. Retrieved December 19, 2019. https://www.theguardian.com/technology/2016/aug/31/dropbox-hack-passwords-68m-data-breach

Hair, J., Black, W., Babin, B., Anderson, R., (2014). *Multivariate data analysis*, Harlow, England: Pearson.

Hair, J. F., Black, W. C., Babin, B. J. and Anderson, R. E. (2010), *Multivariate data analysis: A global perspective*, Pearson Education, Upper Saddle River, N.J.

Hayes, A., 2018. *Introduction to mediation, moderation and conditional process analysis: A regression-based approach*, New York: Guildford Press.

Hilbert, M. and López, P. (2011). The World's Technological Capacity to Store, Communicate, and Compute Information. Science, 332 (6025), 60–65.

Hsieh, P. J., and Lin, W. S. (2018). Explaining resistance to system usage in the PharmaCloud: A view of the dual-factor model. *Information & Management*, 55, 51‑63.

Iacobucci, D. (2010), Structural equations modeling: Fit Indices, sample size, and advanced topics, *Journal of Consumer Psychology*, 20 (1), 90-98.

Jarvenpaa, S.L., Tractinsky, N. and Vitale, M. (1999). Consumer trust in an Internet store. *Information Technology and Management*, 1 (12), 45–71.

Jetter J., Eimecke J. and Rese A. (2018). Augmented reality tools for industrial applications: What are potential key performance indicators and who benefits? *Computers in Human Behavior*, 87, 18-33.

Kincaid, J. (2011). Dropbox Security Bug Made Passwords Optional For Four Hours. TechCrunch. AOL, June 20, 2011. Retrieved December 17, 2019. https://techcrunch.com/2011/06/20/dropbox-security-bug-made-passwords-optional-for-four-hours/

King W.R. and He J. (2006). A meta-analysis of the technology acceptance model, *Information and Management*, 43 (6), 740-755.

Kim D.J., Hebeler J., Yoon V. and Davis F. (2018). Exploring Determinants of Semantic Web Technology Adoption from IT Professionals' Perspective: Industry Competition, Organization Innovativeness, and Data Management Capability, *Computers in Human Behavior*, 86, 18-33.

Krishen, A.S., Raschke, R.L., Close, A.G. and Kachroo, P. (2017). A Power-Responsibility Equilibrium Framework for Fairness : Understanding Consumers ' Implicit Privacy Concerns for Location-Based Services, *Journal of Business Research*, 73, 20–29.

Lee, M-C (2009). Factors influencing the adoption of internet banking: An integration of TAM and TPB with perceived risk and perceived benefit, *Electronic Commerce Research and Applications*, 8(3), 130-141.

Li, Y. (2011). Empirical Studies on Online Information Privacy Concerns: Literature Review and an Integrative Framework, *Communications of the Association for Information Systems*, 28, Article 28

Loiacono E.T., Watson R.T. and Goodhue D.L. (2007), WebQual: An instrument for consumer evaluation of web sites, *International Journal of Electronic Commerce*, 11 (3), 51-87.

Lu, H., Hsu, C. and Hsu, H. (2005), An empirical study of the effect of perceived risk upon intention to use online applications, *Information Management & Computer Security*, 13 (2), 106-120.

Luo, X. (2002). Trust production and privacy concerns on the Internet: A framework based on relationship marketing and social exchange theory. *Industrial Marketing Management* 31(2), 111-118.

Mariani, M. M., and Fosso Wamba, S. (2020). Exploring how consumer goods companies innovate in the digital age: The role of big data analytics companies. *Journal of Business Research*, 121, 338-352.

Mariani, M., and Borghi, M. (2019). Industry 4.0: A bibliometric review of its managerial intellectual structure and potential evolution in the service industries. *Technological Forecasting and Social Change*, 149, 119752.

Mariani M.M., Ek Styven M., Nataraajan R. (2021). Social comparison orientation and frequency: A study on international travel bloggers, *Journal of Business Research*, 123, 232-240.

Mariani M.M., Borghi M., Okumus F. (2020). Unravelling the effects of cultural differences in the online appraisal of hospitality and tourism services, *International Journal of Hospitality Management*, 90, 102606.

Mariani M.M., Matarazzo M. (2020). Does cultural distance affect online review ratings? Measuring international customers' satisfaction with services leveraging digital platforms and big data, *Journal of Management and Governance*, doi: 10.1007/s10997-020-09531-z

Mariani, M.M., Ek Styven, M. and Ayeh, J. (2019). Using Facebook for travel decision-making: An international study of antecedents, *International Journal of Contemporary Hospitality Management*, 31 (2), 1021-1044.

Mariani, M. (2019). Big data and analytics in tourism and hospitality: a perspective article. *Tourism Review*, 75(1), 299-303.

Martin, K. (2018). The penalty for privacy violations: How privacy violations impact trust online. *Journal of Business Research*, 82, 103-116.

McGoogan, C. (2016). Dropbox hackers stole 68 million passwords - check if you're affected and how to protect yourself, August 31, 2016, *The Daily Telegraph*. Telegraph Media Group. Retrieved December 18, 2019, https://www.telegraph.co.uk/technology/2016/08/31/dropbox-hackers-stole-70-million-passwords-and-email-addresses/

Moon, J.-W. and Kim, Y.-G. (2001). Extending the TAM for a World-Wide-Web context, *Information & Management*, 38(4), 217-230.

Moryson, H., and Moeser, G. (2016). Consumer adoption of cloud computing services in Germany: Investigation of moderating effects by applying an UTAUT model. *International Journal of Marketing Studies*, 8(1), 14‐32.

Nambisan, S. (2017). Digital Entrepreneurship: Toward a Digital Technology Perspective of Entrepreneurship, *Entrepreneurship Theory and Practice*, 41(6), 1029-1055.

Narayanan, A. and Shmatikov, V. (2009). De-anonymizing social networks. *IEEE symposium on security and privacy* (pp. 173–187).

Nowak, G. J. and Phelps, J. (1992). Understanding Privacy Concerns: An Assessment of Consumers' Information Related Knowledge and Beliefs. *Journal of Direct Marketing*, 6 (4), 28–39.

Oliveira, T. and Martins, M.F. (2011). Literature review of information technology adoption models at firm level. *Electronic Journal of Information Systems Evaluation*, 14(1), 110-121.

Osswald S., Wurhofer D., Trösterer S., Beck E. and Tscheligi M. (2012). Predicting information technology usage in the car: Towards a car technology acceptance model, *AutomotiveUI 2012 - 4th International Conference on Automotive User Interfaces and Interactive Vehicular Applications*, In-cooperation with ACM SIGCHI – Proceedings, 51-58.

Park, K. T., Kang, M., Kim, D., Hwang, S. W., Choi, B. Y., Lee, Y. T., ... and Kim, K. (2008). A zeroing cell-to-cell interference page architecture with temporary LSB storing and parallel MSB program scheme for MLC NAND flash memories. *IEEE Journal of Solid-State Circuits*, 43(4), 919-928.

Patel, N. (2012). Is Google Drive worse for privacy than iCloud, Skydrive, and Dropbox?, The Verge, Apr 25, 2012. Retreived January 15, 2020, https://www.theverge.com/2012/4/25/2973849/google-drive-terms-privacy-data-skydrive-dropbox-icloud

Pavlou, P. A. and Fygenson, M. (2006). Understanding and Predicting Electronic Commerce Adoption: An Extension of the Theory of Planned Behavior, *MIS Quarterly*, 30 (1), 115-143.

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), 101-134.

Pearson, S. (2002). Trusted computing platforms, the next security solution. HP Labs. https://www.hpl.hp.com/techreports/2002/HPL-2002-221.pdf, retrieved on the 2nd of December 2019.

Perea Y Monsuwé T., Dellaert B.G.C. and De Ruyter K. (2004). What drives consumers to shop online? A literature review, *International Journal of Service Industry Management*, 15 (1), 102-121.

Pillai, R., Sivathanu, B., Mariani, M., Rana, N.P., Yang, B., Dwivedi, Y.K. (2021). Adoption of AI-empowered Industrial Robots in Auto Component Manufacturing Companies. Production Planning & Control, http://dx.doi.org/10.1080/09537287.2021.1882689

Pinheiro P., Aparicio M. and Costa C. (2014) Adoption of cloud computing systems, *ACM International Conference Proceeding Series*, 127-131.

Rogers, E. (1995). *Diffusion of Innovations*, Free Press, New York.

Senyo, P. K., Addae, E., and Boatenga, R. (2018). Cloud computing research: A review of research themes, frameworks, methods and future research directions, *International Journal of Information Management*, 38(1), 128‑139.

Shaikh A.A. and Karjaluoto H. (2015). Mobile banking adoption: A literature review, *Telematics and Informatics*, 32 (1), 129-142.

Shimp, T.A. and Bearden, W.O. (1982). Warranty and other extrinsic cue effectson consumers' risk perceptions, *Journal of Consumer Research*, 9, 38-46.

Shin, D.H. (2013). User centric cloud service model in public sectors: Policy implications of cloud services. *Government Information Quarterly*, 30(2), 194–203.

Shin, J., Jo, M., and Lee, J., et al. (2014). Strategic management of cloud computing services: Focusing on consumer adoption behavior. *IEEE Transactions on Engineering Management*, 61(3), 419–427.

Singh, S., Jeong, Y. S., and Park, J. H. (2016). A survey on cloud computing security: Issues, threats, and solutions. *Journal of Network and Computer Applications*, 75, 200-222.

Sjazna, B. (1994). Software evaluation and choice predictive validation of the technology acceptance instrument, *MIS Quarterly*, 18, 319-324 .

Song C.-H., Kim S.W., and Sohn Y.-W. (2020). Acceptance of public cloud storage services in South Korea: A multi-group analysis, *International Journal of Information Management*, 51, April, 102035.

Spiekermann, S., Acquisti, A. Böhme, R. and Hui, KL (2015). The challenges of personal data markets and privacy, *Electronic markets*, 25 (2), 161-167.

Stieninger M., Nedbal D., Wetzlinger W., Wagner G., and Erskine M.A. (2018). Factors influencing the organizational adoption of cloud computing: A survey among cloud workers, *International Journal of Information Systems and Project Management*, 6(1). 5-23.

Strand, C. (2014). Challenging confidence in cyber-security. *Computer Fraud & Security*, 12, 12-15.

Swilley E. and Goldsmith R.E. (2007). Assessing the impact of corporate credibility and technology acceptance on online shopping, *International Journal of Electronic Marketing and Retailing*, 1(3), 199-216.

Taylor, S. and Todd, P. A. (1995). Understanding Information Technology Usage: A Test of Competing Models, *Information Systems Research*, (6), 144-176.

Teo, T.S.H., Lim, V.K.G. and Lai, R.Y.C. (1999). Intrinsic and extrinsic motivation in internet usage. *Omega International Journal of Management Science*, 27 (1), 25-37.

Terry (1994). The determinants of coping: the role of stable and situational factors. *Journal of Personality and social psychology*, 66 (5), 895-910.

Tornatzky, L. G. and Klein, K. J. (1982). Innovation Characteristics and Innovation Adoption-Imple- mentation: A Meta-Analysis of Findings, *Transactions on Engineering Management*, 29 (1), 28-45.

Triandis, H.C. (1977). *Interpersonal Behavior*, Brooke/ Cole, Monterey, CA.

Vallerand, R. J. (1997). Toward a Hierarchical Model of Intrinsic and Extrinsic Motivation. In *Advances in Experimental Social Psychology* (29), M. Zanna (ed.), Academic Press, New York, pp. 271-360

Varghese, B., and Buyya, R. (2018). Next generation cloud computing: New trends and research directions. *Future Generation Computer Systems*, 79(3), 849‑861.

Venkatesh, V. (2000). Determinants of perceived ease of use: Integrating control, intrinsic motivation, and emotion into the technology acceptance model, *Information systems research,* 11 (4), 342-365.

Venkatesh, V. and Davis, F.D. (1996). A model of the antecedents of perceived ease of use: Development and test, *Decision Sciences,* 27 (3), 451-477.

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

Venkatesh, V. and Morris, M.G. (2000). Why don't men ever stop to ask for directions? Gender, social influence, and their role in technology acceptance and usage behavior, *MIS Quarterly*, 24(1), 115–139.

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), 425-478.

Venkatesh V., Thong J.Y.L., Chan F.K.Y., Hu P.J.-H. and Brown S.A. (2011). Extending the two-stage information systems continuance model: Incorporating UTAUT predictors and the role of context, *Information Systems Journal*, 21(6), 527-555.

Vurukonda, N., and Rao, B. T. (2016). A study on data storage security issues in cloud computing. *Procedia Computer Science*, 92, 128‑135.

Warshaw P.R. and Davis F.D. (1985). The accuracy of behavioral intention versus behavioral expectation for predicting behavioral goals, *Journal of Psychology: Interdisciplinary and Applied*, 119 (6), 599-602.

Wang J. (2016). Critical factors for personal cloud storage adoption in China, *Journal of Data and Information Science*, 1(2), 60-74.

Wang, Q. and Sun, X. (2016). Investigating gameplay intention of the elderly using an extended technology acceptance model (ETAM), *Technological Forecasting & Social Change,* 107, 59-68.

Wathen, C.N. and Burkell, J. (2002). Believe it or not: factors influencing credibility on the web, *Journal of the American Society for Information Science and Technology,* 53 (2), 134-144.

Xu H, Dinev T, Smith HJ and Hart P (2008). Examining the formation of individual's information privacy concerns: Toward an integrative view. *Proc. 29 th Annual Internat. Conf. Inform. Systems (ICIS 2008)*, Paris , France (AIS, Atlanta).

Yang, H.D. and Yoo, Y. (2004). It's all about attitude: revisiting the technology acceptance model. *Decision Support Systems,* 38 (1), 19–31.

Zissis, D., and Lekkas, D. (2012). Addressing cloud computing security issues. *Future Generation computer systems*, 28(3), 583-592.

**Appendix: Items in Model**

Factor loadings in parentheses (all loadings significant at $p<.001$).

**BI: Behavioral Intention** (Adapted from Venkatesh and Davis, 2000)

1. Assuming I had access to a digital personal data store (DPDS), I intend to use it. (.942)
2. Given that I had access to a DPDS, I predict that I would use it. (.924)

**PU: Perceived Usefulness** (Adapted from Venkatesh and Davis, 1996; 2000, and Gefen et al., 2003)

1. Digital personal data stores (DPDSs) are useful for storing my personal data. (.817)
2. DPDSs improve my overall performance in storing my personal data (my capability to store data in terms of type of data, volume, and time). (.834)
3. DPDSs enables me to store my personal data how I want to. (.870)
4. DPDSs enhance my effectiveness in storing my personal data (my ability to accomplish the necessary tasks to store data). (.898)
5. DPDSs makes it easier to store my personal data. (.845)
6. DPDSs increase my productivity in storing my personal data (the time I need to do the tasks related to storing data). (.799)
7. DPDSs make it easier for me to gain insights from my personal data. (.722)
8. I find DPDSs to be useful in my day-to-day life.*

**PEOU: Perceived Ease of Use** (Adapted from Venkatesh and Davis, 2000)

1. My interaction with digital personal data stores (DPDSs) is clear and understandable. (.824)
2. Interacting with DPDSs does not require a lot of my mental effort. (.763)

3. I find DPDSs to be easy to use. (.897)
4. I find it easy to get DPDSs to do what I want them to do. (.922)

**PT: Perceived Trust** (Adapted from Gefen, 2000, and Pikkarainen et al., 2004)

1. Using a digital personal data store (DPDS) is secure.*
2. I trust in the ability of a DPDS to protect my personal data. (.908)
3. I am not worried about the security of a DPDS. (.740)
4. I believe that DPDSs are trustworthy. (.934)

**ATT: Attitude toward Use** (Adapted from Mariani et al., 2019, and Yang and Yoo, 2004)

Generally, using a digital personal data store (DPDS) to store my personal data is…

1. Bad – Good. (.869)
2. Unpleasant – Pleasant.*
3. Negative – Positive. (.879)
4. Foolish – Wise. (.859)
5. Unfavorable – Favorable. (.897)

*) Item removed during measurement validation (CFA and reliability tests).