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Digital transformation of healthcare during the COVID-19 pandemic: Patients' teleconsultation acceptance and trusting beliefs

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ABSTRACT

The COVID-19 pandemic boosted the digital transformation of many services, including healthcare, and access to medical care using teleconsultation has increased rapidly. Thus, a growing number of online platforms have been developed to accommodate patients' needs. This paper examines the factors that predict the intention to use medical teleconsultation by extending the unified theory of acceptance and use of technology (UTAUT2) with the three dimensions of trusting beliefs and self-efficacy. A survey was administered to patients who had used a teleconsultation platform during the pandemic period. As one of the largest studies to date, a sample of 1233 respondents was collected and analyzed using a partial least squares approach, often mobilized in the information systems (IS) domain. Furthermore, a deep analysis using all recommended metrics was performed. The results highlight the significance of trusting beliefs, and self-efficacy in the adoption of digital healthcare services. These findings contribute to both theory and practice in COVID-19 research.

1. Introduction

Digital transformation has occurred due to the so-called Industrial Revolution 4.0 (Iizuka and Ikeda, 2021). Gong and Ribiere (2021) define digital transformation as "*a fundamental change process, enabled by the innovative use of digital technologies accompanied by the strategic leverage of key resources and capabilities, aiming to radically improve an entity (…) and redefine its value proposition for its stakeholders*." Due to technologies such as the Internet of Things, electronic recordings, machine learning, blockchain, and artificial intelligence, and based on the collection and analysis of health data, (Burton-Jones et al., 2020; Gopal et al., 2019; Iizuka and Ikeda, 2021; Massaro, 2021), digital transformation of healthcare is impacting internal medical procedures (Sousa et al., 2019). Kraus et al. (2021) found five clusters in research related to digital transformation of healthcare: patient-centered technology, operational efficiency of healthcare organizations, managerial implications, impact on workforce practice, and socio-economic aspects. As the digital transformation of medical consultation services occurs, teleconsultation is obviously a patient-centered technology (Agarwal et al., 2010). However, even if teleconsultation solutions have been established since 2009 (Khodadad-Saryazdi, 2021) and reimbursed in France since 2018 (Baudier et al., 2020), its adoption is likely to face barriers (Khodadad-Saryazdi, 2021) related to trust (Zhao et al., 2018; Fan et al., 2018), age (Zhu et al., 2018; Meng et al., 2019), privacy concerns, and proof of safety (Iizuka and Ikeda, 2021). Nevertheless, the COVID-19 pandemic has changed the factors of adoption and boosted the digital transformation of healthcare, mainly due to contamination avoidance (Baudier et al., 2021). Indeed, the COVID-19 pandemic has been a great shock that has led to the acceleration of digital transformation in several service industries, such as education, consultancy, and healthcare (Cobianchi et al., 2020a; Raj et al., 2020; Alexopoulos et al., 2020; Secundo et al., 2019).

This study aimed to analyze the factors influencing the adoption of medical teleconsultation platforms by patients during COVID-19 times. Therefore, the research question of this article is: What are the factors affecting patients' adoption of teleconsultation solutions that help create a resilient society in terms of healthcare by changing their behavior during the pandemic? To answer this question, we built a research

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model based on the assumption that trusting beliefs and patients' self-efficacy (SE) can affect the UTAUT2 constructs (Venkatesh et al., 2012), namely performance expectancy and effort expectancy. We also postulated that effort expectancy, social influence, habit, performance expectancy, and facilitating conditions could impact the behavioral intention to use teleconsultation. We employed a quantitative (partial least squares) approach and applied a computer-assisted web interviewing (CAWI) method. Between July and October 2020, we conducted a survey of 66,027 patients on a French teleconsultation platform. A sample of 1233 respondents was used in this study.

This article contributes to the literature on the acceptance of IS in healthcare (Constantinides and Fitzmaurice, 2018; Francis, 2019; Jin and Ahn, 2019) by offering a new perspective on the digital transformation of the healthcare system during the pandemic. Scholars may benefit from a novel theoretical model of new IS acceptance by patients and practitioners can frame better marketing strategies to promote their teleconsultation solutions.

The remainder of this paper is organized as follows: First, the literature is reviewed and hypotheses are developed. Then, the methodology is introduced, and the results are analyzed and discussed. Finally, managerial and theoretical contributions are proposed, and limitations and future research are suggested.

2. Theoretical background

2.1. Disruptive technologies and healthcare

Innovative technologies can be classified as radical, breakthrough, or disruptive. Breakthrough technology implies a major technological discontinuity with performance improvements or new capabilities (Garcia and Calantone, 2002), shaping the development of industries (Ahuja and Morris Lampert, 2001). Breakthroughs can lead to radical innovation (Hein and Juliette Brun, 2019) which is considered new and unique compared to what already exists (Chandy and Tellis, 1998), impacting future technology (Dahlin and Behrens, 2005; Datta and Jessup, 2013) but with the same targeted customers. A disruptive innovation, popularized by Christensen (1997), modifies the way individuals, organizations, and industries operate and interact, changing their habits and destroying existing business models (Schuelke-Leech, 2018), much like e-commerce (Hopster, 2021). Disruptive technologies, focused on niche segments in the early development phase, are distinguished from mainstream technologies by a different performance package with low-end and low-profit portions (Adner, 2002; Ray and Ray, 2011). Firms involved in disruptive technologies must break away from the mold and routines that embody their traditional practices to be able to conform to new customers' beliefs (Henderson, 2006). Worldwide, the healthcare system has experienced a digital transformation based on disruptive technology adapted during the pandemic in a resource-constrained environment. Indeed, a pandemic can considerably modify the health system globally, not only because of the level of contamination and death, but also because of limited resources in terms of vaccines, medical staff, and mobility issues (Moazzami et al., 2020; Katz et al., 2020).

The IT approach to healthcare helped to improve services, delivery processes, and patient safety (Chao et al., 2007), reduce the risk of human error (Ball et al., 2003), facilitate organizational tasks, and provide more precise medical care (Kraus et al., 2021).

Innovations in healthcare are changing the paradigm, moving from a focus on disease to a focus on patients, their quality of life, and well-being. Emerging technologies such as e-health, telemedicine, and robotics (Chen et al., 2014; Latifi et al., 2021; Iizuka and Ikeda, 2021; Biancone et al., 2021) promote a patient-centered approach (Bice-Urbach et al., 2018; Khodadad-Saryazdi, 2021). The implementation of telemedicine solutions represents a challenge for the healthcare sector (Khodadad-Saryazdi, 2021). Telemedicine can contribute to reducing health costs, waiting time, and the risk of contamination which occurs with face-to-face consultation (Baudier et al., 2020). It also helps to diagnose and support patients with limited abilities. With e-health solutions, patients and medical staff can exchange information such as photos and documents through message services (Ghose et al., 2021) which enables regular contact.

Digital transformation involves new actors, such as service providers and platforms (Kraus et al., 2021). Moreover, the sanitarian crisis forced the healthcare system to rapidly adopt existing e-solutions. Winterhalter et al. (2017) defined these as frugal innovations. In other words, the adoption of such innovation is directly related to constrained contexts, such as a sanitarian crisis.

2.2. Teleconsultation and COVID-19

Teleconsultation solutions can be implemented quickly, changing first the way individuals access healthcare services, and second, the way practitioners provide patients with diagnostics and support. During the last decade, several countries have faced viral outbreaks such as cholera in India in 2003 (Ayyagari et al., 2003), the SARS epidemic in Taiwan in 2003 (Chang et al., 2004), the H1N1 influenza in 2009 (Chiu et al., 2009), the Ebola virus in Africa in 2014 (Elmahdawy et al., 2017; Tracey et al., 2015), the MERS Coronavirus in Seoul in June 2015 (Alshakka et al., 2021), and the COVID-19 pandemic in 2020 (Baudier et al., 2021).

Telemedicine is considered a solution to tackle COVID-19 (Drago et al., 2021) as it contributes to the resilience of healthcare organizations during the pandemic (Tortorella et al., 2021). Since the pandemic outbreak and lockdown restrictions worldwide, medical research on teleconsultation has increased in many areas. Some medical departments who were already using the technology recommended it, for example, to all non-critical patients with chronic urology diseases (Tamayo et al., 2020; Pinar et al., 2020) or diabetes (Banerjee et al., 2020). Indeed, according to Romani et al. (2021), a strategy has been quickly implemented to provide patients with adequate care remotely. For example, blood oxygen levels can be monitored in patients with COVID-19 without physically seeing a health professional.

Moreover, medical cases that declined remote consulting initially, eventually reconsidered, including psychiatry (Colle et al., 2020), rheumatology (Naveen et al., 2021), ophthalmology (Bourdon et al., 2020), and cardiology (Hermans et al., 2020).

Teleconsultation themes in literature focus on performance improvement of the proposed solutions (Pérez-Noboa et al., 2021) and analyze adoption factors by using technology acceptance models (Baudier et al., 2021; Rahi et al., 2020; Dash et al., 2021; Barua and Barua, 2021). The intersection of both medical and technology research paths contributes to the understanding of the challenges and insights of teleconsultation.

This study proposes an investigation of teleconsultation acceptance by patients of general therapeutic practice provided by the dedicated platform as an intermediator between patients and physicians. The following section presents the research model.

3. Research model and hypotheses

The research model and hypotheses were developed to change the way individuals access healthcare during the COVID-19 pandemic. All health stakeholders from public or private institutions and medical staff have had to innovate the way they deliver care and patients have had to accept innovation which may result in radical changes in their behavior. The model is based on existing scales adapted to teleconsultation. First, the constructs of UTAUT2 (Venkatesh et al., 2012) were selected: Effort-expectancy (EE), social-influence (SI), performance-expectancy (PE), facilitating-condition (FC), habit (HT), and behavioral intention to use (BIU). Due to the study subject, hedonic-motivation and price-value were removed from our model. Indeed, patients do not consult for pleasure, and the price of a consultation is similar to face-to-face consultations but is 100% reimbursed in France. The

UTAUT2 was selected as it is the most cited theory and is accurate for the acceptance of innovative solutions, especially in the health context for medical staff (Alazzam et al., 2016; Owusu Kwateng et al., 2019) and patients (Baudier et al., 2020; Talukder et al., 2020).

To measure a patient's trusting beliefs of remote physicians, three dimensions were selected: trusting benevolence, trusting competence, and trusting integrity, developed by McKnight et al. (2002). Finally, the scale of SE created by Bonsaken et al. (2013) was used. Items were scaled using a five-point Likert scale ranging from one (strongly disagree) to five (strongly agree).

Five hypotheses measured the impact of the five dimensions of the UTAUT2 retained on the BIU. Then, the three dimensions of the trusting beliefs were used, and their influence on PE was tested. Finally, the impact of SE on EE was controlled.

3.1. UTAUT2

3.1.1. Effort expectancy

EE describes the perception of users of expected ease of use or complexity of a product or service. EE was developed based on the ease of use of the Technology Acceptance Model (TAM) and TAM 2 (Holden and Karsh, 2010). Technology adoption has a strong prediction power, similar to PE (Venkatesh et al., 2003, 2012). Thus, in the medical technology use context, the EE significantly influences the BIU (Jang et al., 2016; Sari et al., 2018) and indeed, the newer the technology is, the more significant the influence of the EE on the BIU (Hoquea and Sorwar, 2017; Shiferaw and Mehari, 2019). However, Baudier et al. (2020) found that EE has no impact on students' intention to use a telemedicine cabin, and Francis (2019) found no evidence of this impact on the adoption of health self-monitoring devices. Nevertheless, in the context of COVID-19, Napitupulu et al. (2021) demonstrated a significant influence of EE when using telehealth services (Napitupulu et al., 2021).

Therefore, we postulate that:

Hypothesis H1. EE has a direct and significant impact on BIU.

3.1.2. Social influence

In a medical context, people can be socially influenced by others, such as family members, friends, or medical staff. Arfi et al. (2021) found a direct link between social influence (SI) and the intention to use IoT for healthcare devices. However, other studies on the acceptance of telemedicine solutions found that SI does not influence the intention to use such solutions (Francis, 2019; Alexandra et al., 2021; Baudier et al., 2021; Beh et al., 2021). Nevertheless, during the pandemic, a strong government campaign during and after the lockdown reminded people every day of the danger of being outside and having unprotected social interaction. Consequently, it could have influenced people in their decision to prefer teleconsultation over face-to-face consultation with a doctor. Moreover, SI is often a key variable in the medical context (Bawack and Kamdjoug, 2018), especially if the technology is new (Pal et al., 2018) and the opinion of the physician is important for the patients (Napitupulu et al., 2021): Thus, we assume that:

Hypothesis H2. SI has a direct and significant impact on BIU.

3.1.3. Habit

In terms of technology use, habit refers to certain automaticity based on previous experiences (Alazzam et al., 2016). People who are less resilient will depend more on habit to modify their behavior (Venkatesh et al., 2012). Some researchers (e.g., Ahmed et al., 2020; Schmitz et al., 2022) found that habits are a weak predictor in the medical context, as patients are not used to such technology, except for patients receiving special treatment such as for diabetes (Vinnikova et al., 2020; Wong et al., 2021). Nevertheless, teleconsultation can be regarded as a simple video conference where habit can predict the intention to use it (Baudier et al., 2020). Therefore, we postulate the following:

Hypothesis H3. Habit has a direct and significant impact on BIU.

3.1.4. Performance expectancy

Based on Venkatesh et al. (2012), performance expectancy (PE) is one of the strongest determinants of BIU. Indeed, this variable is critical for the adoption of medical technology (Baudier et al., 2020; Hoquea and Sorwar, 2017; Wang et al., 2020; Schmitz et al., *2022*; Francis, 2019; Beh et al., 2021) and demonstrates that PE predicts intention to use self-monitoring wearables. Pal et al. (2018) found a significant impact of PE on intention to use smart home and home telehealth services. Moreover, PE is the strongest predictor of UTAUT2 for telemedicine services, according to Schmitz et al. (2022), confirming its significance during the COVID-19 outbreak (Napitupulu et al., 2021). PE projects the expected positive outcomes due to technology use, which is critical for patient decisions. Indeed, patients will use the technology if they believe in a high level of outcomes (Beh et al., 2021). Therefore, we propose the following hypothesis:

Hypothesis H4. PE has a direct and significant impact on BIU.

3.1.5. Facilitating conditions

Facilitating conditions (FC), including the technological and organizational environment (Venkatesh et al., 2012), is considered crucial for the acceptance of technologies that provide health services (Sun et al., 2013; Venugopala et al., 2016) or telemedicine solutions (Kohnke et al., 2014). However, Alexandra et al. (2021) found no impact of FC on the behavioral intention to use hospital telemedicine. Wang et al. (2021) found a positive and direct influence of FC on the intention to use online hospital services and Arfi et al. (2021) in the context of healthcare IoT acceptance. Thus, we suggest that:

Hypothesis H5. FC has a direct and significant impact on BIU.

3.2. Self-efficacy

Several research outputs confirm that resilient people demonstrate common psychological and dispositional attributes for health resilience, such as SE (Park et al., 2020) and trust (Kimhi et al., 2020). Indeed, a person with a high level of SE is not scared to use new technology but is rather motivated by this challenge. According to Connor and Davidson (2003), SE is a key variable in measuring the ability of a person to be resilient. When describing how individuals evaluate their personal capacity to achieve a specific task (Bandura, 1977), the concept of SE is a key determinant influencing the future use of new technology. Indeed, technology SE is the intimate conviction that a person has the aptitude/skills set to deal successfully with a technology-related mission (McDonald and Siegall, 1992). Telemedicine is perceived as an innovative technology (Wu et al., 2007) and SE can influence the level of its acceptance (Rho et al., 2014) by impacting effort expectancy or ease of use (Gajanayake et al., 2016; Shiferaw and Mehari, 2019; Baudier et al., 2021). Therefore, we assume that:

Hypothesis H6. Self-efficacy is positively associated with effort expectancy.

3.3. Trusting beliefs

Sibley et al. (2020) considered trust in institutions critical for digital healthcare resilience during the COVID-19 lockdown. Trust is a relevant and important variable for reducing reluctancy playing a vital role in the acceptance of innovative technologies (Pavlou, 2003; Luo et al., 2010) and is often the source of fundamental positive consequences which depend on the technology and the studied context (Palmer et al., 2000). According to Lee and Turban (2001), trust depends on three factors: (1) the perceived technical competence of the system, (2) the perceived performance level of the system, and (3) the human operator's understanding of the process governing the system. Many researchers have analyzed trust in a general sense, but few have examined the first experiences with technology as a primary condition in the future acceptance process (Hernandez-Ortega, 2011).

Trusting beliefs, a multi-dimensional construct (McKnight et al., 2002; Mpinganjir, 2018), comprises competence (ability to perform), integrity (principles such as honesty, promise-keeping), and benevolence (caring). Trusting beliefs are critical for the acceptance of innovative solutions within the healthcare sector (Baudier et al., 2019) and can impact patients' performance expectations. Thus, we postulate the following three hypotheses:

Hypothesis H7. Trusting benevolence (TB) is positively associated with PE.

Hypothesis H8. Trusting competence (TC) is positively associated with PE.

Hypothesis H9. Trusting integrity (TI) is positively associated with PE.

3.4. Impact of moderators

A substantial number of moderating variables, such as organizational, technological, and individual factors, can explain the acceptance of new technology (King and He, 2006; Sun and Zhang, 2006). With specific reference to health-related technology research, demographic moderators such as gender and age are widely considered to influence the acceptance of technology (Griebel et al., 2013). For instance, prior research has reported that these two moderators are crucial variables for the acceptance of telemedicine for diabetes management (Rho et al., 2015).

Age is an important moderator where the older generation is usually more reluctant to adopt disruptive technology than the younger population (Baudier et al., 2020). Nevertheless, gender can also be a significant moderator in the adoption of telemedicine (Lee and Rho, 2013). Thus, in line with prior research in the field of health technology, we suggest that all the relationships of the model can be impacted by both gender and age.

Finally, all the relationships of the research model are presented in Fig. 1.

4. Methodology

A survey was conducted using scales drawn from literature. According to Publicis Media, 66.1% of teleconsultation users make appointments on this type of platform.[1] The questionnaire, created in English, was translated into French. The content validity of the French version was controlled by native French academics. The answers were based on respondents' free will and the questionnaire was anonymous. No data related to the identity of the respondents were collected, including data concerning reasons for using the teleconsultation platform, and respondents had to answer all questions (no lack of response possible). The aim of the survey was introduced by the teleconsultation platform with a short introduction, including the completion time and the identity of researchers. The potential respondents approached via the newsletter of the platform using the CAWI method, were used as a minimum once the service. A control of the sample characteristics was performed by comparing it with the patient's profile on the platform. The teleconsultation platform confirmed that our sample was representative of its customer base. A comparison at item level was then run using the 300 initial and late respondents, and results from 0.0003 to 0.2951 confirmed the consistency of the responses.

Several control variables that remained unchanged throughout other experiments were identified, such as the pandemic (virality of the virus) and the use of the teleconsultation platform, @mesdocteurs (experimentation of the service). Indeed, all respondents contacted during the COVID-19 pandemic used the service at least once. Thus, control variables should simplify the reproduction of the research study. Viruses and their variants can attack anyone regardless of age, gender, race, and social status, and for a COVID-19 analysis, it was crucial to obtain vast data sources and reach as many people as possible during the study. The survey was conducted with 66,027 patients. A sample of 1233 respondents was collected between July 27 and October 2, 2020 (Table 1). Each sample corresponds to a real person to reflect the situations, hypotheses, and research questions investigated during the study.

With regard to the frequency of visits, 40.8% did one teleconsultation, 20.4% did two, and 9.2% did three teleconsultations. During the COVID-19 pandemic, 85% used the service for the first time whereas only 15% before the COVID-19 pandemic (early adopter of teleconsultation before October 2019).

According to the French Healthcare Institution,[2] 20% of patients using teleconsultation solutions are 65 years old and above; thus, 18% of our sample is representative of this population (Table 2). Females and users aged 40 years[3] represent most of teleconsultation users. Thus, the sample can be considered representative.

5. Findings

According to Dash and Paul (2021), the two most popular methods of structural equation modeling (SEM) used by researchers to measure the cause-effect relations are the co-variance and partial least squares (PLS-SEM). The PLS approach, based on variance, was selected for this research because this method is recommended for prediction and identification purposes as indicated by Hair et al. (2022). According to Goodhue et al. (2017), structural equation models using PLS-SEM are often used in IS research. Indeed, in recent years, the PLS method has been widely used in ranked journals. Thus, the SmartPLS 3.2.6 software was mobilized using the following procedures: PLS algorithm, bootstrapping (5000 samples), blindfolding ($d = 7$), and multigroup analysis (MGA).

5.1. Outer model

The reliability and convergent validity of the outer model were also controlled (Table 3). We assessed the reliability of the variables by verifying that the Cronbach's alpha (CA) and composite reliability (CR) values reached the recommended threshold of 0.7. Table 3 demonstrates that the average value extracted (AVE) for each variable in the model satisfied the minimum value of 0.5, thus confirming convergent validity.

Discriminant validity was first controlled using the Fornell-Larcker criterion (1981) by verifying, as recommended by Hair et al. (2012), that the square root of the AVE of each construct was above its correlations with other constructs (Table 4).

Second, a cross-loading analysis was used to confirm discriminant validity. Thus, Item FC3 (teleconsultation is compatible with other technologies you use) with a loading factor of 0.531, below the recommended threshold of 0.700, was removed (Appendix 1).

5.2. Inner model

To validate the inner model, the explained variance (R^2), the size effect (f^2), the predictive relevance (Q^2), and the size effect (q^2) of the endogenous variables were analyzed. Some parameters were mobilized

[1] http://www.newsroom-publicismedia.fr/profil-dun-utilisateur-de-la-teleconsultation/.

[2] https://www.ameli.fr/sites/default/files/2020-09-16-cp-teleconsultation-anniversaire.pdf

[3] https://www.usine-digitale.fr/article/quel-est-le-profil-type-d-un-utilisateur-de-la-teleconsultation.

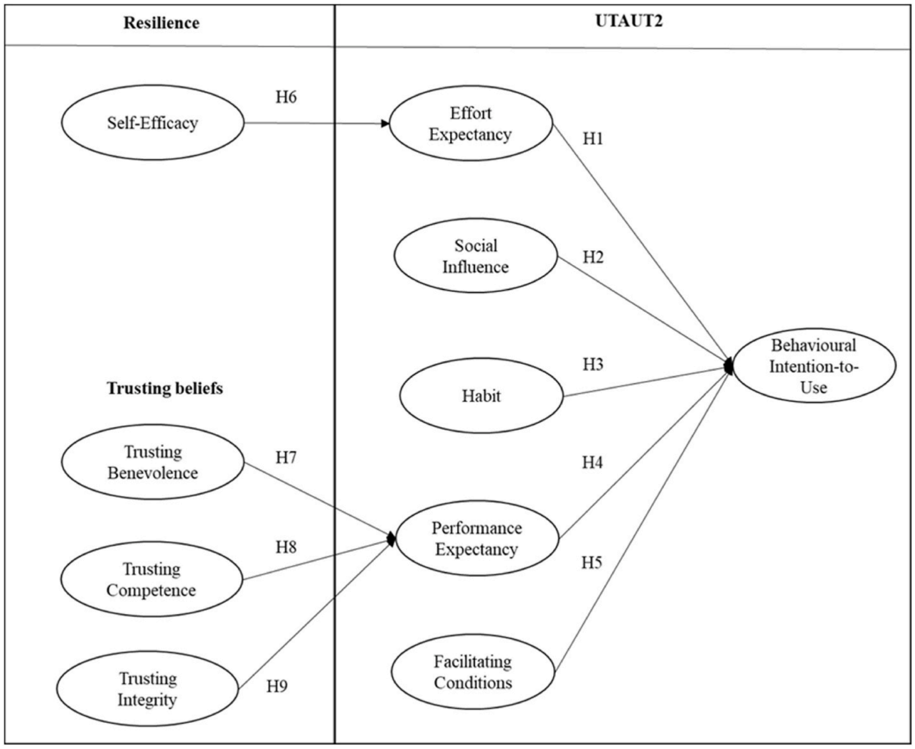

Fig. 1. Model and hypotheses.

Table 1
Data collection.

	Patients	%	Calculation
1. Database	66,027	–	–
2. e-mails opened	10,605	16%	e-mails opened/Database
3. Clicks on the link	1358	13%	Clicks/e-mails opened
4. Respondents	1233	91%	Respondents/Clicks

Table 2
Demographic statistics of respondents.

Demographic variables		Frequency (N = 1233)	Percentage
Gender	Female	769	62.4%
	Male	464	37.6%
Age	18–25 years	27	2.2%
	26–35 years	156	12.6%
	36–45 years	261	21.2%
	46–55 years	312	25.3%
	56–65 years	255	20.7%
	More than 65 years	222	18%
Function	Employee	425	34.5%
	Executive	352	28.5%
	Retired	306	24.8%
	Others	150	12.2%

to study the relationships between constructs such as path-coefficient (β > at 0.200, t-value > at 1.96, and p-value < 0.05) (Table 5).

The R^2 (0.655) shows that the research model explains 65.5% of the variance of BIU defined by three variables: effort expectancy (H1: β = 0.184, t-value = 6.647, p-value = 0.000), habit (H3: β = 0.214, t-value = 9.393, p-value = 0.000), and performance expectancy (H4: β = 0.578, t-value = 18.474, p-value = 0.000), with a huge side effect of performance expectancy (0.486) and a moderate effect for effort expectancy (f^2 = 0.061) and habit (f^2 = 0.089). The relationships between BIU and social influence (H2: β = −0.024, t-value = 1.604, p-value = 0.109), and facilitating-conditions (H5: β = −0.002, t-value = 0.105, p-value = 0.916) are not supported, as the impact is not positive, direct, or significant. Thus, Hypotheses H1, H3, and H4 are validated, and H2 and H5 are rejected.

Table 3
Reliability and convergent validity.

	CA	CR	AVE
EE	0.894	0.934	0.825
FC	0.856	0.932	0.873
HT	0.879	0.916	0.733
BI	0.923	0.951	0.867
PE	0.882	0.918	0.739
SE	0.730	0.846	0.649
SI	0.862	0.905	0.705
TB	0.924	0.951	0.868
TC	0.919	0.961	0.925

The model explains that 45.7% of performance expectancy is determined by two independent constructs, namely trusting benevolence (H7: β = 0.310, t-value = 7.068, p-value = 0.000) and trusting competence (H8: β = 0.398, t-value = 9.075, p-value = 0.000), both having a moderate size effect (TB: f^2 = 0.058; TC: f^2 = 0.095). Therefore, both hypotheses (H7 and H8) are supported. The relationship between.

Finally, the R^2 of effort expectancy, at 24.9%, is explained by SE (H6: β = 0.499, t-value = 18.828, p-value = 0.000) with a large effect size (f^2 = 0.332). The results confirm the direct, positive, and significant effects of SE on effort expectancy. Thus, Hypothesis H6 is validated.

As Henseler et al. (2009) recommended, the confidence intervals were controlled, and zero was not included in all confidence intervals. However, the hypotheses measuring the impact of facilitating condition (H5) and social influence (H2) on behavioral intention to use, close to zero, were rejected (Table 5).

The test for the predictability of the research model (Q^2) was done using the blindfolding procedure of SmartPLS3 (d = 7). With all Q^2 values above 0, a good predictive relevance was confirmed (behavioral intention to use: Q^2 = 0.655; performance expectancy: Q^2 = 0.333; effort expectancy: Q^2 = 0.203). The q^2 values were calculated by

Table 4
Discriminant validity – Fornell-Larcker criterion.

	EE	FC	HT	BI	PE	SE	SI	TB	TC
EE	0.908								
FC	0.533	0.934							
HT	0.548	0.327	0.856						
BI	0.696	0.377	0.715	0.931					
PE	0.697	0.369	0.712	0.847	0.859				
SE	0.499	0.350	0.578	0.538	0.582	0.805			
SI	0.284	0.113	0.435	0.365	0.422	0.43	0.840		
TB	0.594	0.316	0.497	0.586	0.637	0.501	0.272	0.931	
TC	0.596	0.303	0.519	0.605	0.652	0.514	0.298	0.821	0.961

Table 5
Confidence intervals.

	2.5%	97.5%	
EE - > BIU	0.132	0.239	Supported
FC - > BIU	(-0.045)	0.039	Rejected
HT - > BIU	0.168	0.259	Supported
PE - > BIU	0.515	0.635	Supported
SE - > EE	0.445	0.549	Supported
SI - > BIU	(-0.054)	0.004	Rejected
TB - > PE	0.229	0.395	Supported
TC - > PE	0.312	0.480	Supported

applying the following formula $q^2 = (Q^2_{included}\text{-}Q^2_{excluded})/(1\text{-}Q^2_{included})$. All q^2 values were low except for performance expectancy on BIU ($q^2 = 0.290$).

Finally, the goodness-of-fit was verified by analyzing the standardized root mean square residual (SRMR) and the normed fix index (NFI).

The SRMR is used to avoid model misspecifications. The SRMR, below 0.08 at 0.059 (Henseler et al., 2014), confirmed the goodness-of-fit measure. The NFI (at 0.85) represented an acceptable fit, as it was close to 1. Thus, the SRMR and NFI confirmed the quality of our research model. As recommended by Goodhue et al. (2017), the VIF multicollinearity is controlled, and the results also confirm that the model is free of common method bias as all the inner VIF values were below the recommended threshold of 3.3 (Table 6).

In conclusion, the analysis of the results confirmed that six of the nine hypotheses (H1, H3, H4, H6, H7, and H8) were supported, two (H2 and H5) were not supported, and one (H9: Impact of trusting integrity on performance expectancy) was removed from the model due to a problem with the outer VIF.

Two moderators (age and gender) were identified and an MGA procedure was run to test their impact. The results confirmed that gender does not moderate the relationships between the construct of the model. Regarding age, five groups were studied and one was rejected due to the sample size (27 respondents for the 18–25 year age group). The findings highlight that several relationships of the model are moderated by age (Table 7). For the 26–35 year age group, effort expectancy had no impact on BIU (β = 0.05, t-value = 0.75, p-value = 0.45) when validated by all the other age groups. Nevertheless, the effect of facilitating conditions on BIU was validated by the 26–35 year age group (β = 0.1, t-value = 2.24, p-value = 0.03) and rejected by the others.

6. Discussion

This research aimed to study the digital transformation of healthcare services during the COVID-19 pandemic. Indeed, medical teleconsultation solutions are changing patients' behavior and providing a basis for the creation of a resilient society. This study highlights the determinants that affect the adoption of such disruptive technologies. First, the relationships between the constructs of UTAUT2 were analyzed. The results validate the significance of the primary determinants of BIU, namely PE and EE. Both are essential for the understanding of health-related technology use (Hsu et al., 2013; Wang et al., 2020; Tavares et al., 2018). The more a technology is perceived as responding to customers' needs and is easy to use, the more individuals will adopt it; thus, the findings are aligned with previous research. The influence of habit on BIU was also confirmed. Habit is a crucial concept and has a significant influence on the decision-making process, as raised by several scholars in the healthcare domain (Duarte and Pinho, 2019; Ravangard et al., 2017). Before the pandemic, some individuals were already confident using distance communication at a personal and professional level. However, during the lockdown, videoconference tools were adopted by a wider population to stay in touch with relatives or colleagues in response to their need for social interaction (Kodama, 2020). The findings showed that the patients regarded teleconsultation solutions as automatic and routine procedures. Nevertheless, this study rejects two UTAUT2 determinants, namely SI and FC, thus contradicting previous studies in the healthcare domain. Indeed, the effect of SI on the acceptance of innovative technology is usually important, as both relatives' and physicians' advice could directly influence patients in their decision-making process (Cimperman et al., 2016). In fact, during the lockdown, it was highly recommended not to visit doctors and, if possible, to focus on teleconsultation to avoid contamination. In cases of suspected COVID-19 with no severe symptoms, it was mandatory to consult from a distance to avoid spreading the virus. Finally, the non-impact of FCs on BIU is consistent with other research findings on

Table 6
Inner model.

Construct	Predictor variable	R^2	f^2	Path Coef	SD	t-Value	p-Value	Q^2	q^2	VIF	H
EE		0.249						0.203			
	SE		0.332	0.499	0.027	18.828			0.000	1.000	X
BIU		0.762						0.655			
	EE		0.061	0.184	0.028	6.647	0.000		0.035	2.359	X
	FC		0.000	(-0.002)	0.022	0.105	0.916		0.000	1.409	O
	HT		0.089	0.214	0.023	9.393	0.000		0.052	2.162	X
	PE		0.486	0.578	0.031	18.474	0.000		0.290	2.878	X
	SI		0.002	(-0.025)	0.015	1.604	0.109		0.000	1.281	O
PE		0.457						0.333			
	TB		0.058	0.310	0.044	7.068	0.000		0.003	3.081	X
	TC		0.095	0.398	0.044	9.075	0.000		0.026	3.081	X

Table 7
Moderating impact of age.

	26–35			36–45			46–55			56–65			>65		
	β	t	P	β	t	p	β	t	p	β	t	p	β	t	p
EE→BIU	0.05	0.75	0.45	0.24	4.44	9.03	0.1	2.24	0.03	0.22	4.14	0.00	0.23	2.30	0.00
FC→BIU	0.1	2.24	0.03	(-0.05)	1.33	0.18	0.02	0.67	0.50	(-0.03)	0.85	0.40	(-0.06)	0.80	0.42

telehealth (Dhiman et al., 2019; Owusu Kwateng et al., 2019) and is relevant because teleconsultation technology is not perceived as complex nor requiring external support. Everything is organized through a platform, and patients simply click on a link to be connected using their devices (smartphones, tablets, or computers).

Second, the variables of SE (proposed as an antecedent of EE) and the two dimensions of the trusting beliefs concept (an antecedent of performance expectancy) were analyzed to understand the patients' digital resilience during the pandemic. The analysis demonstrated a significant effect of SE on EE. These findings are consistent with previous research on the acceptance of healthcare systems (Hsiao et al., 2011), home care nursing solutions (Kohnke et al., 2014; Ali et al., 2021), telehealth solutions (Tsai, 2014; Liu and Tao, 2021), or wearables technologies (Gao et al., 2015; Huaeng et al., 2021). Van Houwelingen et al. (2018) confirmed the substantial effect of SE on EE for medical videoconferencing. However, SE does not always appear to be related to previous experience (Middlemass et al., 2017). Gajanayake et al. (2016) demonstrated that the impact of SE on EE decreases with age. Nevertheless, the more the patients experiment with technology and are self-confident, the less they perceive technology as complicated. Thus, SE is a key variable in digital healthcare resilience. The two dimensions of the trusting beliefs concept (benevolence and competence) retained influence on performance expectancy. As antecedents of the expected outcomes regarding teleconsultation, these two trusting beliefs are emphasized in the medical context. Indeed, they expressed the patients' perceptions of the quality of the physician when using teleconsultation solutions. The findings confirmed that remote consulting does not affect feelings regarding competence (knowledgeable, efficient) and benevolence (care, interest). To the best of our knowledge, there is no study in which the trusting beliefs dimensions determine performance expectancy. Few studies have tested the influence of trusting beliefs on the intention to use a technology (Lee and Rao, 2003). Baudier et al. (2020) confirmed that among the three components, only competence directly influences the intention to use a telemedicine cabin. However, trust (conceptualized in various forms) is often considered essential for predicting technology use, particularly in sensitive fields such as health-related contexts (Jin et al., 2020).

Third, as moderators, the effects of age and gender were analyzed. Both demographic characteristics are often used to justify differences in individuals' behavior when using the UTAUT2 model (Venkatesh et al., 2012). Nevertheless, no difference was found in the influence of gender on the adoption of teleconsultation. These results are consistent with those of a study on health IT solutions (Bawack and Kamdjoug, 2018).

However, the influence of age on the two relationships of the research model was demonstrated, confirming the moderating effect of age. Indeed, the effect of EE on BIU was only rejected by the 26–35 year age group. This result is consistent with previous research in the health field to adopt telemedicine cabins (Baudier et al., 2020) or m-health services (Quaosar et al., 2018; Zhang et al., 2014). Moreover, facilitating conditions is validated only by this age group, indicating that they consider having the competencies and knowledge to use teleconsultation or at least obtain some support. Our findings confirm the results of previous research. Jewer (2018) found a relationship between EE and FC. Indeed, when the impact of FC on BIU was validated, the effect of EE was rejected. For the older population, even if they consider the technology easy to use, they do not consider themselves skillful (Quaosar et al., 2018).

6.1. Theoretical and managerial implementations

This study contributes to understanding the role of IS in digital transformation, which creates a resilient society when facing a pandemic situation such as COVID-19 (Alexopoulos et al., 2020; Raj et al., 2020). With the advent of the internet, the digitalization of our modern society allows individuals to maintain social and economic interactions using digital platforms (Kraus et al., 2021; Malgonde et al., 2020). The current health crisis has modified people's behavior in many aspects of their daily professional or personal lives: how they study (online courses), how they work (remote work), how they purchase (click and collect, online sales), how they communicate (videoconferencing), and how they can access healthcare (telemedicine). Thus, digital transformation is critical for healthcare and the adoption rate of teleconsultation, supported by the local government, has drastically increased over the past few months.

6.1.1. Theoretical implications

This study analyzes patients' behavior toward medical teleconsultation use during a pandemic, highlighting the key variables for adopting such solutions and enriching research on the UTAUT2 model by covering the resilience aspect in the specific situation caused by COVID-19. This study has value for both the initial model of UTAUT2 and for studies aiming at the extensions of UTAUT2.

First, some researchers noticed the lack of studies confirming variables such as habit in the medical context, and our study validated this impact. Moreover, the effects of PE and EE, as the most significant of the model, were validated for teleconsultation in the medical context. Aligned with previous papers, we rejected the impact of FC and SI, which are more significant for new technology. Future studies can use the results of this study to adapt UTAUT2 according to the context of the research.

An increasing number of studies use additional factors to predict the intention to use technology. Our paper provides an empirical test of important variables and sheds light on the possible behavior model in the medical context, especially during the pandemic.

SE is rarely studied as an antecedent of effort expectancy, and to the best of our knowledge, this study is the first attempt to relate trusting beliefs to performance expectancy. Thus, these results contribute to literature.

6.1.2. Practical implementation

The healthcare sector has had to move from a resilience strategy to an anti-fragility strategy (Cobianchi et al., 2020b) by adapting their processes and adopting digital solutions.

Even if telemedicine experienced some level of resistance in the past, the COVID-19 pandemic has increased patients' adoption of e-healthcare solutions by enhancing the use of teleconsultation platforms. Several stakeholders, such as medical staff, government, medical institutions, and third parties developing digital platforms, are interested in the managerial implementation of this study. Indeed, the patients confirmed that teleconsultation could become a habit. Thus, the medical ecosystem will need to adapt and market its services to fit their expectations and integrate the digital dimension with healthcare. One of the key fears regarding teleconsultation is the lack of physical human contact and trust due to remote consultation. Nevertheless, our findings highlight that patients consider remote-care physicians as competent, acting in their best interests, doing their best to help them, and are interested in their well-being. Finally, the acceptance of teleconsultation demonstrates society's resilience through digital transformation in healthcare. Teleconsultation was an answer to the pandemic; nevertheless, it could also be a solution for "medical deserts" in regions facing a lack of medical staff.

7. Conclusion

Teleconsultation has played a crucial role in COVID-19 transmission reduction and effective treatment for anyone with mild or suspected COVID-19 symptoms. This study investigated two aspects:First, we blended resilience through digital means and COVID-19 to investigate how the dimensions of trusting beliefs could measure digital resilience and influence performance expectancy and how SE influences effort expectancy. Second, we contributed to the development of the adoption of IS in healthcare from a digital resilience-based perspective of the UTAUT2 model by demonstrating how the dimensions of UTAUT2 influences BIU teleconsultation platforms. This study is one of the largest studies to date (with a sample of 1, 233 valid responses collected and analyzed) using a partial least squares approach. Our study's contributions to literature are as follows: First, we validated the significance of the primary factors of BIU (PE and EE) which explain the acceptance of teleconsultation during the COVID-19 pandemic and consolidated the digital-resilient-based UTAUT2 model. Conversely, the SI and FC determinants reject the assumptions of the original theory and clearly contrast previous applications of the model in the healthcare domain.

Second, we demonstrated the significance of SE and trusting beliefs in performance and effort expectancies in particular. Excellent adoption and management of SE could enhance digital resilience in healthcare services through teleconsultation systems. In summary, our findings offer both theoretical contributions and practical implications for COVID-19 research and can be adopted by other studies. Our future work will include expanding our new methodology to involve multinational studies and investigating the impacts and extent of influence of SE and the effectiveness of the digital-resilience-based UTAUT2 model.

7.1. *Limitations and future research*

This study had some limitations. First, the respondents were all patients who used healthcare digital platforms before or during the pandemic, and therefore this study did not include the perceptions of other patients. Future studies should focus on non-users to better understand the factors that predict their behavior and identify potential barriers. Second, data were collected in France, where the government strongly pushed teleconsultation by offering 100% reimbursement. Other countries should also be considered. Third, the SE and trusting belief variables were included; nevertheless, other constructs could be included in the model.

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Appendix 1

	EE	FC	HT	ITU	PE	SE	SI	TB	TI	TC
EE1	**0.870**	0.428	0.533	0.695	0.701	0.471	0.303	0.618	0.589	0.605
EE2	**0.951**	0.476	0.488	0.619	0.608	0.440	0.234	0.524	0.515	0.537
EE3	**0.952**	0.490	0.488	0.623	0.623	0.447	0.248	0.533	0.515	0.552
EE4	**0.887**	0.554	0.466	0.569	0.563	0.438	0.216	0.454	0.443	0.473
FC1	0.523	**0.901**	0.312	0.370	0.368	0.335	0.108	0.309	0.267	0.300
FC2	0.457	**0.896**	0.300	0.333	0.320	0.318	0.103	0.281	0.256	0.273
FC3	0.233	**0.531**	0.270	0.213	0.259	0.277	0.288	0.224	0.208	0.212
HT1	0.512	0.358	**0.890**	0.689	0.665	0.521	0.368	0.474	0.443	0.501
HT2	0.288	0.205	**0.745**	0.402	0.442	0.406	0.438	0.256	0.245	0.287
HT3	0.440	0.287	**0.885**	0.598	0.597	0.490	0.383	0.416	0.376	0.436
HT4	0.556	0.367	**0.895**	0.694	0.686	0.544	0.344	0.500	0.459	0.506
ITU1	0.660	0.354	0.610	**0.909**	0.796	0.495	0.335	0.572	0.546	0.587
ITU2	0.627	0.373	0.700	**0.948**	0.785	0.500	0.350	0.522	0.500	0.554
ITU3	0.633	0.371	0.687	**0.935**	0.786	0.507	0.333	0.543	0.499	0.559
PE1	0.664	0.363	0.621	0.828	**0.889**	0.502	0.340	0.617	0.570	0.633
PE2	0.611	0.336	0.585	0.741	**0.889**	0.492	0.326	0.570	0.520	0.584
PE3	0.521	0.352	0.636	0.649	**0.812**	0.503	0.382	0.450	0.443	0.484
PE4	0.545	0.325	0.615	0.677	**0.845**	0.511	0.418	0.535	0.502	0.538
SE1	0.328	0.218	0.409	0.412	0.424	**0.727**	0.375	0.378	0.358	0.377
SE2	0.385	0.280	0.553	0.475	0.530	**0.832**	0.398	0.408	0.375	0.441
SE3	0.461	0.411	0.441	0.420	0.458	**0.852**	0.295	0.425	0.385	0.427
SI1	0.198	0.121	0.324	0.281	0.336	0.326	**0.865**	0.201	0.232	0.234
SI2	0.192	0.136	0.330	0.270	0.321	0.322	**0.874**	0.179	0.202	0.215
SI3	0.192	0.118	0.376	0.259	0.309	0.363	**0.820**	0.177	0.205	0.211
SI4	0.308	0.209	0.408	0.379	0.418	0.417	**0.797**	0.317	0.333	0.329
TB1	0.557	0.337	0.473	0.561	0.611	0.496	0.253	**0.937**	0.803	0.776
TB2	0.574	0.323	0.459	0.569	0.605	0.456	0.227	**0.944**	0.810	0.787
TB3	0.504	0.297	0.458	0.506	0.562	0.449	0.285	**0.913**	0.787	0.751
TC1	0.572	0.316	0.493	0.591	0.624	0.485	0.295	0.788	**0.789**	0.952
TC2	0.586	0.317	0.507	0.602	0.637	0.500	0.302	0.812	**0.800**	0.949
TC3	0.547	0.312	0.491	0.562	0.618	0.487	0.271	0.767	**0.775**	0.948
TC4	0.555	0.314	0.482	0.555	0.610	0.483	0.290	0.775	**0.788**	0.946
TI1	0.534	0.285	0.437	0.530	0.569	0.443	0.299	0.837	0.967	**0.801**
TI2	0.565	0.301	0.461	0.554	0.592	0.457	0.292	0.839	0.976	**0.823**
TI3	0.555	0.307	0.441	0.531	0.576	0.447	0.289	0.831	0.976	**0.800**

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