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Exploring determinants of engagement in the use of IoT for healthcare during the COVID-19 pandemic: A fear-driven perspective

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ABSTRACT

Our research analyzes how the fear related to the Coronavirus disease 2019 (COVID-19) epidemic reinforces the engagement in the use of Internet of Things (IoT) devices for healthcare. While prior research has examined the adoption of IoT for healthcare, there is a notable absence of exploration regarding the influence of COVID-19-related factors, such as fear and desire for self-care, on user engagement with IoT devices and their determining factors. A quantitative study using the partial least squares algorithm was conducted to analyze this gap. The mediating role of the desire for self-care between fear and social influences, on the one hand, and engagement in using this technology, on the other, was confirmed by adopting the Macro Process on SPSS.¹ The study results make it possible to put forward several interesting recommendations that facilitate the long-term adoption of the Internet of Things for health. The mediating role of the desire for self-care in the relationship between fear and user engagement explains that IoT users who are afraid of catching COVID-19 will be more concerned about health monitoring, leading them to adopt this technology of IoT devices.

1. Introduction

In early December 2019, the first cases of pneumonia of unknown origin were identified.

by the World Health Organization (WHO) in Wuhan, China. By January 9, 2020, the genomic sequence of the virus was determined. This virus named COVID-19 is a highly contagious disease² causing respiratory difficulties and fatal failure for some infected people. Due to the rapid spread of COVID-19 around the world, it became a global pandemic, disrupting different sectors like tourism. Several studies have examined how the COVID-19 pandemic impacts our daily lives (Akpan, Soopramanien, & Kwak, 2021; Akpan, Udoh, & Adebisi, 2022).

To address the challenges posed by the COVID-19 pandemic, the integration of IoT technology seems to be important and provides a multifaceted approach from early detection and monitoring to optimizing healthcare resources and implementing effective health measures. IoT technology refers to the networking of items equipped with sensors, software, and network connectivity that allow them to collect and exchange data (Noor, Hina, Hayat, & Shah, 2023). In the context of

telemedicine, the integration of IoT devices aims to facilitate remote healthcare services by improving communication, data collection, and monitoring for medical purposes conducted at a distance.

This revolution has led to the development of applications and services, and empowering devices with intelligence through data (Lu, Papagiannidis, & Alamanos, 2018). The study of Hanafizadeh, Hatami Lankarani, and Nikou (2022) highlights the potential of IoT for various industries, including the healthcare industry. It discusses how IoT can facilitate knowledge sharing and predictive capabilities. The data and information generated by IoT can provide knowledge that can be used to monitor, make informed business decisions, and regulate business processes. IoT technology is having a profound impact on several areas of healthcare, including home care, mobile health (mHealth), e-health, and hospital management (Akkaş, Sokullu, & Çetin, 2020). According to Otoom, Otoum, Alzubaidi, Etoom, and Banihani (2020), IoT technology could potentially help to identify and isolate infected people at an early stage, thereby reducing the spread of the virus. The use of digital solutions that facilitate access to healthcare services were widely used in the COVID-19 period (Bamel, Talwar, Pereira, Corazza, & Dhir, 2023).

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¹ SPSS Statistics is a software developed by IBM for advanced statistical analysis.

² https://www.lemonde.fr/planete/article/2020/01/09/une-pneumonie-d-origine-inconnue-enchine_6025276_3244.html. Accessed November 25, 2022.

This research aims to make a valuable contribution to the literature about IoT technology adoption by examining user engagement and how the fear-ridden COVID-19 context leads people to seek out technologies for careful health monitoring. We decided to prioritize IoT devices because of their ability to enable remote access to healthcare services. This capability serves to minimize the need for face-to-face interaction between patients and health professionals, thereby reducing the spread of infections.

Our study goes beyond simple IoT use and deals with user engagement, leading to a long-term projection of the relationship with the technology. We chose to work primarily on the relationship between COVID-19 fear and engagement in the use of IoT devices for healthcare. We operationalize these variables via the social influence, the satisfaction of the desire for self-care, and the perceived autonomy and control while using IoT devices. Even though the role of IoT for healthcare in fighting COVID-19 has been treated in previous studies, the impact of COVID-19 fear on IoT user engagement remains not explored. Given this gap, the purpose of this paper is to analyze the impact of COVID-19 fear on user engagement. This goal leads to the following question:

How well does fear of COVID-19 enhances engagement in the use of IoT for healthcare?

To answer this question, a non-probability convenience sample of 251 IoT users was collected. The results were, then, processed with the Partial Least Squares Structural Equation Modeling (PLS-SEM) method. This approach is adopted because it does not require a large sample size or normally distributed data and it is suited to the analysis of complex models that contain several mediating and moderating variables (Richter, Cepeda Carrión, Roldán, & Ringle, 2016).

The study results are presented as follows. First, we present the theoretical background. Next, we discuss the hypotheses and present our theoretical model, followed by a section reserved to detail the methodology we have adopted. Moving forward, we present the findings of our study. Subsequently, we engage in a comprehensive discussion of these results, delving into their implications and significance within the broader context. Finally, we conclude our research by summarizing our contributions to the field, acknowledging our limitations, and suggesting avenues for future research.

2. Theoretical background

During the COVID-19 pandemic, individuals find themselves navigating a delicate balance between the fear of catching COVID-19 and a deep desire for self-care. The first part looks at the complex dynamics shaped by the pandemic, exploring the emotional component and changing perspectives on individual well-being. As the world grapples with the challenges posed by the pandemic, the second part explores the defining role played by IoT devices in enhancing healthcare capabilities during the current health crisis.

2.1. The COVID-19 context: Between the fear and the desire for self-care

In the peak period of the epidemic, people remain vulnerable to the circulation of false information online and images diffused on social media. This situation reinforces fear especially during the period of containment when people stay at home and consume these sources excessively. The influence of media on individual behavior has been widely discussed and confirmed by several researchers, one study believes that excessive exposure to media sources leads to an unrealistic, even surreal representation of the situation (Girandola, 2004). This amplifies a sense of fear and leads to various symptoms such as eating or sleeping difficulties.

As reported by the Brain and Mind Center at the University of Sydney, the psychological stress and negative financial impact caused by this pandemic could lead thousands of Australians to attempt suicide. In addition to the average of 3000 suicides already recorded, the center estimates that between 750 and 1500 are likely to occur annually and

over the next five years due to the future impact of this health crisis.³ Another key element is the inability to visit isolated patients, which amplifies the fear of those who are in these separate care units and their families.

Containment measures, as highlighted by Brooks et al. (2020), led to adverse psychological effects such as increased stress and fear. Isolated individuals reported heightened stress due to uncertainty about containment duration, infection fears, frustration, financial losses, and lack of information (Presti, McHugh, Gloster, Karekla, & Hayes, 2020). In China, where the epidemic originated, Wang et al. (2020) found that half of the respondents rated the psychological impact as moderate or severe, with 16.5% experiencing moderate to severe depressive symptoms and one-third facing significant anxiety issues. Healthcare workers are also affected, with Liu et al. (2020) reporting psychological distress symptoms in 15.9% of doctors and nurses, anxiety in 16%, and depressive symptoms in 34.6%.

The negative consequences on the economy are also important. The cessation of business in various sectors such as restaurants and coffee shops amplify the fear among the owners of these projects. In these conditions, fear is spreading more and more and constitutes a challenge for the States to reassure citizens and enable them to overcome this difficult ordeal. To summarize, people may have thoughts about fear of the disease itself, the unknown future, economic disruption, and the risk of unemployment.

2.2. IoT devices for healthcare during COVID-19 pandemic

The COVID-19 pandemic forces individuals to respect social distancing and minimize physical contact. The IoT technology seems useful in this sense and allows the monitoring and treatment of diseases remotely. For patients, IoT devices encourage active participation in monitoring their well-being, thus enhancing the overall user experience.

IoT devices can collect and transmit data in real-time, allowing healthcare providers to monitor patients remotely and make timely interventions. This technology empowers healthcare professionals to analyze patients' data, enhance disease diagnosis, reduce healthcare expenses, and promote patient-centered care practices (Arfi, Nasr, Kondrateva, & Hikkerova, 2021). During the COVID-19 pandemic, several studies have examined the role of IoT technology in the healthcare industry. To better understand the context of our research, we present below a summary table of some studies (Table 1).

3. Research model and hypotheses

Our research model focuses on the theoretical variables that significantly influence users' engagement with IoT for healthcare. On the one hand, it takes into consideration the characteristics of the COVID-19 period, such as the rise of fear and a growing awareness of self-care. On the other hand, our model examines the determinants of user engagement, including social influence, perceived autonomy, and perceived control over IoT use. This global approach will enable us to better understand the complex dynamics underlying user engagement in the context of digital healthcare.

3.1. Fear of COVID-19

Fear is an anxious emotion. It occurs in the presence of danger often accompanied by emotional distress and behavioral avoidance (Presti et al., 2020). Individuals respond to fear symbolically and arbitrarily relating it to other events. As a result, it affects the way we are oriented to the world around us and thus influences our behavioral patterns.

³ <https://www.20minutes.fr/monde/2773827-20200506-coronavirus-direct-emmanuel-macron-attendu-aujourd'hui-plan-urgence-culture>, Accessed December 8, 2022.

Table 1
Summary of studies about IoT technology during the COVID-19 pandemic.

IoT advantages	Context of the study	Theoretical model	Results of IoT application	Patient care	Prevention	Author, Year
Identify symptoms and provide better treatment for infected patients	This study proposes an IoT-based framework for early identification of COVID-19 cases.	The model is an IoT-based system that collects real-time data on users' symptoms via wearable sensors and uses machine learning algorithms to identify potential cases of COVID-19.	The results of the IoT application are not presented in this study, as it is a conceptual paper that proposes an IoT-based framework for COVID-19 detection and monitoring.		X	(Otoom et al., 2020)
Controlling COVID-19 Spread	The study presents several applications of IoT devices, including wearable sensors for patient monitoring and sensing technologies for early detection of COVID-19 cases.	The model is an IoT-based model that leverages machine learning to identify and predict the severity of COVID-19 based on onset symptoms.	The IoT technology is useful in combating the pandemic and improving traditional healthcare systems to manage the possibility of future outbreaks better		X	(Kumar, Sood, & Rawat, 2023)
	impact of IoT on COVID-19 and its variants in the healthcare sector	The model is the use of IoT devices to reduce transmissions of COVID-19 and its variants	They include real-time and remote monitoring of COVID-19 patients and people in self-quarantine, rapid intervention in emergencies, and limiting the spread of the virus.		X	(Fagroud, Toumi, Talhaoui, Achtaich, & El Filali, 2021)
Real-time information	The study proposes a real-time detection system based on an IoT framework to aid in the early detection of COVID-19.	The model presented is a deep learning optimization system that can work with imbalanced datasets to improve the classification of patients.	The developed models are demonstrated to handle data bias and achieve high classification accuracy for patients with COVID-19.		X	(Mohammedqasim & Ata, 2022)
	The study presents a secure remote health monitoring model that uses the benefits of cloud and IoT technologies for early diagnosing critical conditions of patients.	The model includes elements for data acquiring, securing, and storing, data preprocessing, and data mining for the disease diagnosis process through different data classification methods	The proposed model is efficient in early disease detection and diagnosis using IoT technology and data mining methods.		X	(Akhbarifar, Javadi, Rahmani, & Hosseinzadeh, 2020)
Proper monitoring	The context of the study is the development of an intelligent health monitoring and diagnosis system for COVID-19 patients.	The model presented is based on the IoT and fuzzy logic to autonomously detect arrhythmia and alert doctors in case of critical indications or thresholds.	This study describes the proposed system as a cost-effective and efficient way to provide timely diagnosis and treatment to COVID-19 patients		X	(Rahman et al., 2023)
Vaccine supply chain management	The article presents an intelligent system that utilizes blockchain, IoT, and machine learning to address major issues in the vaccine supply chain.	The model presented is a framework of an intelligent vaccine supply chain management system based on digital technologies	The results include improved visibility, real-time monitoring, and timely decision-making in the vaccine supply chain		X	(Hu, Xu, Liu, & Lim, 2023)
Quick and effective medical intervention	Investigate different IoT applications for healthcare in the face of COVID-19	A process chart that identifies basic IoT applications for the medical field during the COVID-19 Pandemic	They include the capability to reduce the risk of surgery during complicated cases and real-time monitoring of patients		X	(Javaid & Khan, 2021)
	This study highlights the potential of IoT and artificial intelligence techniques in healthcare, specifically in the detection of COVID-19 using medical images and deep learning models.	The model presented is an IoT-based deep learning framework for early assessment of Covid-19	The proposed framework achieved high accuracy in detecting COVID-19 from chest X-ray images.		X	(Ahmed, Ahmad, & Jeon, 2020)
Workload reduction	The context of the study is the COVID-19 pandemic and its impact on the healthcare sector	The model proposed is based on Machine Learning and IoT to diagnose COVID-19 patients. It can reduce the workload for doctors and tackle the issue of patient overcrowding.	The proposed model can improve the accuracy rate of diagnosis and serve as a clinical decision support system		X	(Abdulkareem et al., 2021)
COVID-19 strains screening	The context of the study is the COVID-19 pandemic and the need for remote screening of patients to reduce the possibility of infection	The model presented is an IoT framework that integrates wearable sensors and a smartphone app for real-time communication between various devices. It uses a custom algorithm to evaluate the patient's critical status.	The use of wearable sensors and IoT technology can help quickly identify COVID-19 patients and allow doctors to examine patients without the need for physical contact.		X	(Mukhtar, Rubaiee, Krichen, & Alroobaea, 2021)

Fear is reinforced by arbitrarily applicable relational responses (Dymond & Roche, 2009). Individuals can feel themselves in a situation through their thoughts, without it being real. Thus, these thoughts can evoke feelings that determine behavior (Presti et al., 2020). For example, for someone healthy but worried about his health status, the word “virus” may evoke the same feelings of fear as people who have the virus (Hayes & Hofmann, 2018). Based on the above, we can make the following hypotheses:

Hypothesis 1a. The feeling of fear enhances the desire for self-care.

Hypothesis 1b. Feeling fear of COVID-19 reinforces engagement in using IoT for health.

3.2. Social influence

Humans need to live in a group and share ideas and social values. Several researchers have confirmed that the community influences members' behaviors persistently (Brown, Kozinets, & Sherry Jr, 2003; Muniz Jr & Schau, 2005). The individual may make his decision to comply with the ideas of his community and to satisfy his social group expectations (Anne et al., 2012). Therefore, he may use a technology just to comply with the community values.

Several researchers have confirmed that social influence determines the decision to adopt new technologies (Chong, Chan, & Ooi, 2012; Hsu & Lu, 2004; Venkatesh, Thong, & Xu, 2012). In the context of IoT devices, some studies confirmed the positive impact of social influence on the usage intention of this technology (Lingling & Xuesong, 2014; Samhale & Ladwein, 2019). We therefore advance the following hypotheses:

Hypothesis 2a. Social influence enhances perceived control.

Hypothesis 2b. Social influence positively influences perceived autonomy.

Hypothesis 2c. Social influence reinforces engagement in using IoT for health.

3.3. Perceived control

The impact of perceived control on the adoption of new technologies is widely confirmed (Casalo, Flavian, & Guinaliu, 2010; Hajli & Lin, 2016; Lu, Zhou, & Wang, 2009). It is a major predictor of behavior, emotions, motivation, and performance that determines the success or otherwise of an action (Skinner & Zimmer-Gembeck, 2011). It describes the user's perception of their ability to accomplish and master a situation (Hidoussi, Dubois, Gandit, & El Methni, 2016). For Wang, Zhang, and Liu (2015), the control over the purpose of personal data requested determines the user's acceptance to provide it. In the context of IoT, Beales and Muris (2019), explain that IoT users, who perceive their ability to control the data provided, will be more ready to share their data with IoT providers. According to Samhale and Ladwein (2019), perceived control is a key determinant of intention to use these devices. Regarding IoT for healthcare, Princi and Krämer (2020) explain that giving people control over their data will increase the probability of using IoT devices for healthcare.

Hypothesis 3a. Perceived control promotes perceived autonomy.

Hypothesis 3b. Perceived control reinforces engagement in the use of IoT for health.

3.4. Perceived autonomy

Several researchers have suggested that perceived autonomy is a predictor of acceptance (Liaw & Huang, 2011; Liaw, Huang, & Chen, 2007). Tasks perceived as autonomous trigger higher intrinsic motivation (Sørebø, Halvari, Gulli, & Kristiansen, 2009; Standage, Duda, &

Ntoumanis, 2006). Perceived autonomy promotes perceived usefulness (Roca & Gagné, 2008).

Self-determination theory suggests that individuals seek to satisfy three essential needs: the need to feel able to control the situation, to act autonomously, and to belong to a community (Deci & Ryan, 2000; Sheldon, Elliot, Kim, & Kasser, 2001). According to Nikou and Economides (2017), Autonomy refers to the ability to self-monitor. These factors are crucial variables in our study as they strongly impact engagement in the use of IoT for health. According to Samhale (2022), the perceived autonomy reinforces engagement in the use of IoT for healthcare. We therefore advance the following hypothesis:

Hypothesis 4. Perceived autonomy reinforces engagement in the use of IoT for health.

4. Desire for self-care

Self-care is a reflexive practice that allows individuals to transform themselves and achieve personal goals (Foucault, 2001). Traditional models of self-care present this concept as a task rather than a way of life (Alkema, Linton, & Davies, 2008; Hotchkiss & Cook-Cottone, 2019; Norcross & Guy, 2007; Richard & Shea, 2011). Efforts have been made to transform mindfulness-based interventions into evidence-based techniques that individuals can use to achieve discrete outcomes, such as improved mental and physical health (Gotink et al., 2015; Pickens, 2013). These mindfulness-based models have demonstrated numerous benefits in self-care (Hotchkiss & Cook-Cottone, 2019). They are associated with improved well-being (Burton, Burgess, Dean, Koutsopoulou, & Hugh-Jones, 2017; Raab, 2014).

Some researchers have considered conscious self-care to be an iterative process that involves, first, awareness and assessment of a person's internal needs and external demands (Cook-Cottone & Guyker, 2018). Second, it is an intentional engagement in specific self-care practices. It serves to address needs and demands that enable improved well-being and self-efficacy. Other authors have indicated that mindfulness-based activities can serve to develop quality of life and improve mental and physical health (McCusker et al., 2016; Riegel, Jaarsma, & Strömberg, 2012).

Individual data collection allows for “reflexivity, power over the self, and Foucauldian self-care”. It is developed through the practice of quantifying the self (Arruabarrena & Quettier, 2013). This favors the use of IoT devices to collect data related to the state of health and satisfy the need for self-care. All the above allow us to advance this hypothesis:

Hypothesis 5. The desire for self-care drives engagement in using IoT for healthcare.

4.1. Engagement in the use of IoT devices for healthcare

Engagement is the psychological result of the interaction between users and devices (Brodie, Hollebeek, Juric, & Ilic, 2011). It also refers to the intensity of the connection between consumers and providers (Vivek, Beatty, & Morgan, 2012). Some researchers have argued the need to introduce cognitive, affective, and behavioral aspects in defining this concept of engagement (Brodie, Ilic, Juric, & Hollebeek, 2013; Dwivedi, 2015; Greve, 2014; Hollebeek, 2011; Hollebeek, Glynn, & Brodie, 2014). Dessart, Veloutsou, and Morgan-Thomas (2015); Dessart, Veloutsou, and Morgan-Thomas (2016) addressed three dimensions of engagement namely the affective dimension which refers to the enthusiasm and pleasure felt when using the object. It motivates the user's decision and allows the relationship to be maintained in the long term (Mercier & Roux, 2017). Then, the behavioral dimension encompasses the user's efforts to succeed in the relationship such as sharing and searching product information. Finally, the cognitive dimension translates into the user's attention and immersion.

With regards to IoT devices, engagement is characterized as an

interaction that incorporates four stages with discernable characteristics: Long-term Engagement, Sustained Engagement, Entry Point of Engagement, and Non-engagement (Xiao, Wu, Buruk, & Hamari, 2021). In this research, we concentrate on the entry point of engagement, which is the initialization of engagement and reflects user attention capture. It will expand to frequent.

use and lead to long-term engagement if users do not abandon the experience (Samhale, 2022; Xiao et al., 2021). Based on the above literature and theoretical hypotheses, the research model is framed as shown in the following figure (Fig. 1).

5. Research methodology

This study aims to analyze determinants of engagement in the use of IoT for health in the context of COVID-19 characterized by fear and uncertainty, which reinforces self-concern and motivates the desire for health monitoring.

5.1. Target population and questionnaire administration

In the context of our study, we chose a quantitative approach while collecting primary data through an online questionnaire. This mode of administration meets the study requirement and available resources. We distributed the questionnaire on Facebook by sharing it with groups interested in health and wellness issues. This questionnaire includes an introduction that explains the IoT technology for healthcare. Followed by a question about the use of IoT devices for healthcare to retain exclusively these device users. Table 2 presents a summary of the online survey steps.

5.2. Instruments for measuring the model variables

To gather the data, a non-probability convenience sample was collected. Our research was conducted in France and the questionnaire was administered in French. Respondents answered in a way to notify their choice according to the Likert scale with 5 modalities ranging from 1 in complete disagreement to 5 in complete agreement for social influence, fear, and user engagement variables. The self-care desire scale was measured on a weekly frequency scale ranging from 1 for complete absence to 5 for daily repetition. We translated the scales from English into French and discussed them with researchers who specialized in marketing and were fluent in English. Our questionnaire was then checked on a test sample (95 responses) to ensure the items' reliability as shown in Table 2.

We tested social influence and perceived control with a scale of 3 items established by Lingling and Xuesong (2014). For fear of COVID-19, we adopted a measurement scale with seven items (Ahorsu et al., 2020). Perceived autonomy was measured using the Nikou and Economides

Table 2
Summary of the online survey steps.

Periods	Stages of the Survey
June–July 2022	Development of the research questionnaire (initial version)
August 2022	Testing the initial version of our study questionnaire (sample of 95 responses)
September 2022	Development of the research questionnaire (final version)
October 2022–January 2023	Collection of 315 responses with the final version of the research questionnaire
February 2023	251 responses were retained (only users of the IoT devices for healthcare)

(2017) scale with 3 items. Then, the desire for self-care was measured using a scale with 6 items (Hotchkiss & Cook-Cottone, 2019). Finally, user engagement was measured by Islam and Rahman (2016) scale with 5 items.

5.3. Statistical tool for empirical analysis

To empirically analyze our theoretical model, we use the Partial Least Square (PLS) algorithm, which is based on analysis of variance and optimization of the explanatory power of manifest variables (Fernandes, 2012). This method is best suited for an exploratory approach (Hair, Ringle, & Sarstedt, 2011). It helps to solve complex models that contain mediating and moderating variables (Richter et al., 2016). Its algorithm also offers a novel methodology for handling incomplete and missing data.

6. Findings

This section aims to analyze the results that validate the hypotheses put forward in the literature review. This analysis includes four steps, the first one examines the demographic profile of respondents. The second step presented the measurement model. The third one analyzed the structural model using SmartPLS and the last one verified mediator effects by the macro process for SPSS recommended by Hayes (2017).

6.1. The model analysis results

Table 3 below presents the study characteristics. It shows that women slightly outnumber men. They are mainly aged between 25 and 54 years (77%).

Using Harman's single factor test on SPSS, we found that the total variance explained is confirmed, with a percentage variance of 49% below the recommended value of 50%. The variable reliability is verified by measuring the internal consistency, Cronbach's alpha, and composite reliability (Fornell & Larcker, 1981).

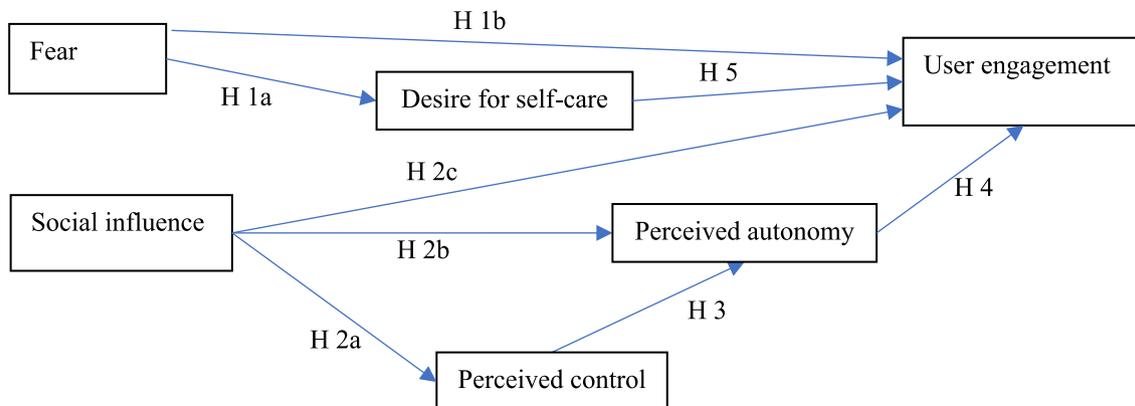


Fig. 1. Framework model.

Table 3
Characteristics of the study sample.

		Nb	(%)
Gender	Men	119	47%
	Women	132	53%
	Total	251	100%
Age	Under 25 years old	32	12%
	25–39 years	95	38%
	40–54 years	97	39%
	55 years and older	27	11%
	Total	251	100%

According to the results presented in Table 4. The values of the composite reliability (CR), which represents the advantage of considering the measurement errors and Cronbach's Alpha are all above the threshold of 0.7, which proves a high level of internal consistency (Fornell & Larcker, 1981). The convergent validity is also verified with all loadings above 0.6 and the average variance extracted (AVE) is confirmed with values above 0.5 (Chin, 1998; Fornell & Larcker, 1981).

We used the cross-loading technique on SmartPLS to check that the loadings of each variable's items (highlighted with bold in Table 5) explain the respective variable more than the other variables of the model. Table 5 presents the results obtained.

Discriminant validity of the variables requires that the square root of the AVE (highlighted with bold in Table 6) be greater than the variation shared between each variable and other variables in the model (Bagozzi & Yi, 2012). According to the results in Table 6, discriminant validity is verified.

The results obtained show that the variables in our model explain engagement in the use of IoT devices for health. Based on our sample size, we can say that the R² value exceeds the minimum threshold of 0.13, so our research model is significant (Wetzels, Odekerken-Schröder, & Van Oppen, 2009).

To validate our research hypotheses, we adopted the bootstrap analysis on SmartPLS (n = 251, 5000 iterations) (Hair et al., 2011). The analysis results are presented in Table 7.

> H1a: Fear of COVID-19 reinforces the desire for self-care.

The test conducted shows the impact of the fear of COVID-19 on the desire for self-care, so hypothesis 1a is validated. A person who is afraid of catching COVID-19 will pay more attention to his health condition.

Table 4
Results of the model variables analysis.

Variables	Scales	Loadings	Cronbach's Alpha	AVE	Composite Reliability	R Score
Fear of COVID-19	PR 1	0,899	0,935	0,836	0,943	
	PR 2	0,939				
	PR 3	0,927				
	PR 4	0,891				
Perceived Control (CP)	CP 1	0,844	0,799	0,711	0,807	0,208
	CP 2	0,845				
	CP3	0,842				
Perceived Autonomy (AUT)	AUT 1	0,917	0,886	0,813	0,929	0,616
	AUT 2	0,912				
	AUT 3	0,877				
Social Influence (INF_SOC)	INF_SOC 1	0,921	0,909	0,847	0,913	
	INF_SOC 2	0,939				
	INF_SOC 3	0,900				
Desire for self-care (PS)	PS 1	0,678	0,850	0,688	0,909	0,187
	PS 2	0,885				
	PS 3	0,909				
	PS 4	0,826				
User Engagement (ENGAG)	ENGAG 1	0,950	0,944	0,856	0,948	0,656
	ENGAG 2	0,912				
	ENGAG 3	0,923				
	ENGAG 4	0,916				

Table 5
Results of the cross-loading technique.

	AUT	CP	ENGAG	INF SOC	PR	PS
AUT1	0.917	0.601	0.621	0.661	0.532	0.506
AUT2	0.912	0.577	0.704	0.667	0.497	0.501
AUT3	0.877	0.529	0.515	0.575	0.375	0.411
CP1	0.589	0.844	0.502	0.460	0.433	0.367
CP2	0.499	0.845	0.421	0.329	0.313	0.326
CP3	0.497	0.842	0.428	0.356	0.362	0.341
ENGAG1	0.649	0.516	0.950	0.702	0.630	0.560
ENGAG2	0.565	0.472	0.912	0.631	0.554	0.509
ENGAG3	0.607	0.473	0.923	0.663	0.603	0.467
ENGAG4	0.706	0.527	0.916	0.721	0.690	0.506
Inf Soc 1	0.648	0.426	0.712	0.921	0.621	0.516
Inf Soc 2	0.664	0.454	0.704	0.939	0.650	0.502
Inf Soc 3	0.638	0.385	0.612	0.900	0.521	0.430
PR1	0.540	0.456	0.636	0.638	0.899	0.428
PR2	0.502	0.438	0.631	0.604	0.939	0.420
PR3	0.499	0.407	0.646	0.625	0.927	0.444
PR4	0.349	0.299	0.529	0.497	0.891	0.279
PS1	0.299	0.176	0.283	0.300	0.149	0.678
PS2	0.421	0.341	0.444	0.464	0.378	0.885
PS3	0.539	0.415	0.571	0.526	0.491	0.909
PS4	0.434	0.364	0.462	0.403	0.325	0.826

Table 6
Square root of AVE and correlations between variables.

	AUT	CP	ENGAG	INF SOC	PR	PS
AUT	0.902					
CP	0.632	0.843				
ENGAG	0.686	0.539	0.925			
INF SOC	0.706	0.459	0.736	0.920		
PR	0.524	0.444	0.672	0.652	0.914	
PS	0.527	0.411	0.553	0.526	0.437	0.829

> H1b: Fear of COVID-19 enhances engagement in the use of IoT devices.

The test conducted shows that fear of COVID-19 promotes engagement in the use of IoT devices for health. A person who fears getting COVID-19 will be engaged in using this technology to track his health condition.

> H2a: Social influence reinforces perceived control.

Table 7
Validation of research hypotheses.

	T Statistic	P value	Verification
INF SOC - > AUT	8029	0.000	Validate
INF SOC - > CP	6988	0.000	Validate
INF SOC - > ENGAG	3536	0.000	Validate
CP - > AUT	5040	0.000	Validate
AUT - > ENGAG	3111	0.002	Validate
PR - > PS	8227	0.000	Validate
PR - > ENGAG	4412	0.000	Validate
PS - > ENGAG	1881	0.060	Validate*

* Validate with a risk of 6%

The test conducted validates the social influence on perceived control. If the person's relatives (family, friends, and referents) show the ability to control the use of IoT devices, this person will be favorable toward this technology and feels able to use it correctly.

➤ H2b: Social influence promotes perceived autonomy.

The test conducted validates the social influence on perceived autonomy. If the person's relatives (family, friends, and referents) show they are autonomous by using the IoT devices for health. The person will also feel autonomous by using this technology.

➤ H2c: Social influence drives engagement in the use of IoT devices for health.

The test conducted confirms the social influence on engagement in the use of IoT devices for health. If the person's relatives (family, friends, and referrers) recommend IoT technology, he will be more engaged in its use.

➤ H3: Perceived control promotes perceived autonomy.

The test conducted validates the influence of perceived control on perceived autonomy. If users feel able to use IoT devices for healthcare correctly, their sense of autonomy will increase.

➤ H4: Perceived autonomy promotes user engagement.

The test conducted validates the influence of perceived autonomy on user engagement. If users feel autonomous in using IoT devices for healthcare, they will strongly engage in the use of this technology.

➤ H5: The desire for self-care encourages user engagement.

The test conducted shows that the impact of the desire for self-care promotes engagement in the use of IoT devices for healthcare. Hypothesis 5 is therefore validated and indicates that if the person wants to take care of their body, they will engage in the use of this technology, which will facilitate the achievement of their goal.

6.2. The mediating effect of desire for self-care

We examined the mediating effect of the desire for self-care in the relationship between fear and engagement in the use of IoT devices for health. To test this effect, we used the macro process on SPSS recommended by Hayes (2017). After running the bootstrap technique, we confirmed the relationship with $p = 0.0000$ as shown in Table 8.

Table 8
The total effect of fear on engagement in the use of IoT for health.

Effect	Se	P	LLCI	ULCI
0,5585	0,0390	0,0000	0,4816	0,6353

Next, we calculated the confidence interval for the relationship between fear of COVID-19 and user engagement with self-care desire as a mediator. Following Hayes (2017) instructions, both bounds of the confidence interval are greater than zero. The results in Table 9 led us to confirm that the desire for self-care mediates this relationship.

6.3. The mediating effect of perceived control

We examined the mediating role of perceived control in the relationship between social influence and perceived autonomy. As shown in Table 10, the p -value is 0.0000, thus the indirect relationship between social influence and perceived autonomy is validated.

We analyzed the mediating role of perceived control in this relationship. We calculated the confidence interval and found that both bounds of the confidence interval are greater than zero (Hayes, 2017), which means that the mediating effect is validated (Table 11).

6.4. The mediating effect of perceived autonomy

Finally, we examined the mediating role of perceived autonomy in the relationship between social influence and user engagement. As the p -value is 0.0000, the indirect relationship between social influence and user engagement is validated (Table 12).

We analyzed the mediating role of perceived autonomy in this relationship. We found that both bounds of the confidence interval are greater than zero (Hayes, 2017). This result provides evidence that the mediating effect is validated (Table 13).

7. Discussion and implications

According to the study results, the fear of COVID-19 promotes the desire for self-care. This feeling of fear disrupts people's daily lives and makes them take care of their bodies, follow hygiene rules, and monitor their health status carefully. This is consistent with a survey of 1357 healthcare workers in 10 hospitals in China, where more than 85% of respondents were afraid of being infected with the virus and 89.7% were following correct practices to minimize the risk of COVID-19 infection (Zhou et al., 2020).

The Social environment strongly influences the perception of autonomy and control. The person's family and friends strongly influence the feeling of autonomy and control while using IoT devices. The recommendations and opinions of others allow the user to monitor his health condition correctly and autonomously without needing help.

The results of our research explain that the fear of COVID-19 reinforces engagement in the use of IoT devices for health. Indeed, the person concerned about the risk of being infected by COVID-19 will pay more attention to his health indicators. He will be engaged in the use of this technology if he believes that it will allow him to carefully monitor his health status. This finding is consistent with other researchers who have confirmed that the need to track health status drives demand for care and assistance devices (Van Hoof, Kort, Rutten, & Duijnste, 2011; Vines et al., 2013).

The present study also shows the social influence on engagement in the use of IoT devices. This result confirms that the people around the individual lead them to adopt IoT devices for health. The desire to stay connected with family and friends, to share one's measurements, and to get their advice and support encourages the adoption of this technology. This social aspect of the technology allows the user to satisfy the need for self-esteem and community membership.

Family and friends help persons to monitor their health status. This

Table 9
Results of the mediating effect of desire for self-care.

Effect	Boot SE	Boot LLCI	Boot ULCI
Desire for self-care	0,1062	0,0313	0,0509

Table 10

The total effect of social influence on perceived autonomy.

Effect	Se	P	LLCI	ULCI
0,5645	0,0360	0,0000	0,4935	0,6355

Table 11

Results of the mediating effect of perceived control.

	Effect	Boot SE	Boot LLCI	Boot ULCI
Perceived Control	0,1410	0,0408	0,0698	0,2253

Table 12

The total effect of social influence on engagement in the use of IoT for health.

Effect	Se	P	LLCI	ULCI
0,8097	0,0469	0,0000	0,7174	0,9020

Table 13

Results of the mediating effect of perceived autonomy.

	Effect	Boot SE	Boot LLCI	Boot ULCI
Perceived Autonomy	0,2485	0,0647	0,1278	0,3817

finding is consistent with the results of a study about heart failure. It showed that patients without family and those who live alone and socially isolated are very vulnerable to poor health management (Dunbar, Clark, Quinn, Gary, & Kaslow, 2008). The role of the social environment is therefore crucial in raising the individual's awareness about health status, self-care, and treatment of illnesses. It helps the individual to improve behaviors such as adopting a healthy diet and respecting the frequency of taking medication (Dunbar et al., 2008).

The perception of control in the use of IoT devices for health reinforces user engagement. The favorable feeling of control will moderate the fear related to the safety of use. The user will be able to use this technology whenever he wants. He will tend to use it frequently and continuously. In line with Brickell, Chatzisarantis, and Pretty (2006) results, perceived control promotes a sense of autonomy. If the user feels able to monitor the use of IoT devices for healthcare, he will feel increasingly autonomous.

The mediating role of the desire for self-care is relevant. It means that when the user perceives that the technology allows him to a better health monitoring, he will be more engaged. Indeed, this period of COVID-19 marked by fear and anxiety favors the need to monitor health status, feel comforted by those around them, and receive advice to minimize the pandemic infection risks.

In parallel, perceived control plays a mediating role in the relationship between social environment influence and perceived autonomy. This result shows that when the person's entourage recommends the use of IoT devices. It minimizes the risks and allows the person to feel able to control the use of these connected devices. This reinforces, thereafter, his perception of autonomy.

Finally, perceived autonomy plays a mediating role and allows us to better understand the relationship between the influence of the social environment and engagement in the use of IoT devices for health. This important role shows that when the social entourage recommends IoT devices, the user will feel more autonomous and will be strongly engaged in the use of this technology.

7.1. Theoretical implications

The main contribution of this study is to analyze the determinants of IoT user engagement in the context of COVID-19, marked by growing fear and concern for self-care. The analysis of this relationship makes

this study unique and sets it apart from other studies that have dealt with the use of IoT in the COVID-19 period, which has focused mainly on aspects related to the benefits, risks, and use situations of IoT technology (Abdulkareem et al., 2021; Nasajpour, Pouriye, Parizi, Zhao, & Li, 2022; Ootom et al., 2020).

Our research goes beyond the act of purchasing IoT devices influenced by the wellness ideology that dominates our current society (Cederström & Spicer, 2015). It is part of a long-term relational approach. Several theoretical contributions have been put forward through the consideration of health field specificities, the purposes of use, and users' motivations. The desire for self-care mediates the relationship between fear and engagement in the use of IoT devices for healthcare. The user who is afraid of catching COVID-19 will be more concerned about health monitoring, leading him to adopt IoT technology. Furthermore, perceived autonomy mediates the relationship between social influence and perceived control, on the one hand, and user engagement on the other. The recommendation of the social environment and the perceived ability to control the use of IoT devices for healthcare promote the feeling of autonomy, which reinforces user engagement. These relationships were analyzed for the first time in this study and provide valuable theoretical value.

7.2. Managerial implications

The present study allows us to identify several interesting managerial implications in favor of IoT providers, doctors, and users. It highlights the importance of taking into consideration the user's need to get a technology for health monitoring, a tool that allows them to carefully measure physical performances.

IoT devices for healthcare are relatively new on the market and collect very sensitive personal data. They amplify perceived risks that may slow down the use of this technology. Therefore, doctors have an important role to play in this regard. They can both recommend the use of this technology to their patients and give feedback to IoT providers to better develop it.

It is important to note the favorable role of the French government which has encouraged, since the beginning of this pandemic, the adoption of telemedicine and the use of connected devices for health monitoring. This facilitates disease treatment, promotes intervention effectiveness, makes users more autonomous, and minimizes the risk of contamination for both patients and health personnel. Providers of this technology, for their part, must listen to the market, adapt their offerings to users' needs, and communicate transparently useful tips and information to get through this time of crisis. This positive role of communication and transparency in the success of IoT use has been confirmed in previous studies (Samhale, 2022). They also need to make efforts regarding the security of the data collected through the introduction of blockchain technology (Yu et al., 2018).

7.3. Social implications

The present study provides us with several important social implications for IoT devices for healthcare. It confirms the social influence on the use of IoT devices in line with previous studies results (Samhale & Ladwein, 2019). As part of a community, individuals interact according to their opinions, interests, and attitudes. They always try to conform to what the majority of community members think.

According to our study and in line with the findings of Samhale (2022), IoT technology has the potential to address social inequalities in healthcare. These inequalities appear in the systematic health disparities observed within various social groups based on individuals' socioeconomic status or geographical location. In this sense, IoT devices can play a pivotal role in mitigating these disparities by enabling individuals to take control of their health remotely. Especially in the COVID-19 context, Kumar et al. (2023) explain that IoT technology increased access to healthcare services, improved operational efficiency, and lowered costs.

8. Conclusion

Our study aims to better understand the specifics of the COVID-19 epidemic and its impacts on engagement in the use of IoT devices. Using the PLS-SEM approach, we addressed the initialization of user engagement, which reflects the capture of his attention. The present research also explains the mediating role of self-care desire and perceived autonomy in the relationship between COVID-19 fear, perceived control, and social influence, on the one hand, and user engagement, on the other.

The objective of this work is to generate important recommendations for IoT users and providers for healthcare. These responses reinforce and facilitate a successful relationship between user and technology. We recommend prioritizing more useful functionalities that allow users to carefully monitor their health status, facilitate communication with doctors to reassure themselves, and moderate the fear of COVID-19.

This research complements existing studies on the role and benefits of IoT use in the context of COVID-19. It focuses on the long-term relationship between the user and the technology and addresses the determining factors of engagement in the use of IoT devices. It remains a starting point for future research to better understand the behavior and expectations of users of IoT devices.

Although many precautions were taken, this study is not without limitations, which lead to new avenues of research. First, the impact of sociodemographic dimensions was not analyzed in this work. Future research is recommended to empirically validate these factors' influence and further enrich the theoretical contributions.

A second limitation concerns the analysis of the individual perception of the respondents regardless of their health status, and patient's age and gender, which prevents the verification of disease type, and body performance impact on the engagement in the use of IoT devices for healthcare. A possibility to test this theoretical model in another cultural context also seems interesting to verify the influence of culture on the mobilized variables.

Finally, other factors that influence user engagement such as purchasing power, product price, data privacy, security, and reliability of these devices have not been integrated into this theoretical model. These factors strongly influence the use of technologies, but their integration will make the model complicated to measure. This opens the door for future research to analyze them.

CRedit authorship contribution statement

Khalid Samhale: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Writing – original draft, Writing – review & editing. **Richard Ladwein:** Methodology, Project administration, Software, Supervision, Validation. **Soukaina Samhale:** Resources, Software, Visualization, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix A. Measurements

Fear of COVID-19 (Ahorsu et al., 2020)

- PR 1 - « I am most afraid of COVID-19 »
 PR 2 - « It makes me uncomfortable to think about COVID-19 »
 PR 3 - « I am afraid of losing my life because of COVID-19. »

PR 4 - « When watching news about COVID-19 on social media, I become nervous or anxious »

Social influence (Lingling & Xuesong, 2014)

IS 1 - « People who are important to me would recommend using IoT devices for health care »

IS 2 - « People who are important to me would find using IoT devices for health beneficial »

IS 3 - « People who are important to me would find using IoT devices for health a good idea »

Perceived control (Lingling & Xuesong, 2014)

CP 1 - «Using IoT devices for health care is entirely within my control »

CP 2 - « I have the resources, knowledge, and ability to use the IoT devices »

CP 3 - « I can skillfully use IoT devices for health care »

Perceived autonomy (Nikou & Economides, 2017)

AUT 1 - « I feel a sense of choice and freedom while using IoT devices »

AUT 2 - « IoT devices for health care provide me with interesting options and choices »

AUT 3 - « There is much opportunity for me to decide for myself how to use IoT devices for health care »

Desire for self-care (Hotchkiss & Cook-Cottone, 2019)

PS 1 - « I had a calm awareness of my thoughts »

PS 2 - « I had a calm awareness of feelings »

PS 3 - « I had a calm awareness of my body »

PS 4 - « I ate a variety of nutritious foods »

User engagement (Islam & Rahman, 2016)

ENGAG 1 - « Anything related to IoT grabs my attention»

ENGAG 2 - « I like to learn more about IoT for healthcare »

ENGAG 3 - « I pay a lot of attention to anything about IoT for healthcare»

ENGAG 4 - « I spend a lot of my discretionary time on IoT for healthcare»

References

- Abdulkareem, K. H., Mohammed, M. A., Salim, A., Arif, M., Geman, O., Gupta, D., & Khanna, A. (2021). Realizing an effective COVID-19 diagnosis system based on machine learning and IoT in smart hospital environment. *IEEE Internet of Things Journal*, 8(21). <https://doi.org/10.1109/JIOT.2021.3050775>
- Ahmed, I., Ahmad, A., & Jeon, G. (2020). An IoT-based deep learning framework for early assessment of COVID-19. *IEEE Internet of Things Journal*, 8(21), 15855–15862. <https://doi.org/10.1109/JIOT.2020.3034074>
- Ahorsu, D. K., Lin, C. Y., Imani, V., Saffari, M., Griffiths, M. D., & Pakpour, A. H. (2020). The fear of COVID-19 scale: Development and initial validation. *International Journal of Mental Health and Addiction*, 1-9. <https://doi.org/10.1007/s11469-020-00270-8>
- Akhbarifar, S., Javadi, H. H. S., Rahmani, A. M., & Hosseinzadeh, M. (2020). A secure remote health monitoring model for early disease diagnosis in cloud-based IoT environment. *Personal and Ubiquitous Computing*, 1-17. <https://doi.org/10.1007/s00779-020-01475-3>
- Akkaş, M. A., Sokullu, R., & Çetin, H. E. (2020). Healthcare and patient monitoring using IoT. *Internet of Things*, 11, Article 100173. <https://doi.org/10.1016/j.iot.2020.100173>
- Akpan, I. J., Soopramanien, D., & Kwak, D. H. (2021). Cutting-edge technologies for small business and innovation in the era of COVID-19 global health pandemic. *Journal of Small Business & Entrepreneurship*, 33(6), 607–617. <https://doi.org/10.1080/08276331.2020.1799294>
- Akpan, I. J., Udoh, E. A., & Adebisi, B. (2022). Small business awareness and adoption of state-of-the-art technologies in emerging and developing markets, and lessons from the COVID-19 pandemic. *Journal of Small Business & Entrepreneurship*, 34(2), 123. <https://doi.org/10.1080/08276331.2020.1820185>
- Alkema, K., Linton, J. M., & Davies, R. (2008). A study of the relationship between self-care, compassion satisfaction, compassion fatigue, and burnout among hospice professionals. *Journal of Social Work in End-of-Life & Palliative Care*, 4(2), 101–119. <https://doi.org/10.1080/15524250802353934>
- Anne, T. S., Christelle, M., Michael, D., Florence, L., Esther, G., Tourret, I., & Uhlen, D. (2012). Préférences acculturatives des travailleurs sociaux dans le cadre de l'insertion professionnelle: Effets des attitudes personnelles et de la norme professionnelle descriptive sur leurs pratiques. *Psychologie du Travail et des Organisations*, 18(4), 308–327. [https://doi.org/10.1016/S1420-2530\(16\)30073-5](https://doi.org/10.1016/S1420-2530(16)30073-5)
- Arfi, W. B., Nasr, I. B., Kondrateva, G., & Hikkerova, L. (2021). The role of trust in intention to use the IoT in eHealth: Application of the modified UTAUT in a consumer context. *Technological Forecasting and Social Change*, 167, Article 120688. <https://doi.org/10.1016/j.techfore.2021.120688>

- Arruabarrena, B., & Quettier, P. (2013). Des rituels de l'automatisme numérique à la fabrique autopoïétique de soi. *Les Cahiers du numérique*, 9(3), 41–62. <https://doi.org/10.3166/LCN.9.3-4.41-62>
- Bagozzi, R., & Yi, Y. (2012). Specification, evaluation, and interpretation of structural equation models. *Journal of the Academy of Marketing Science*, 40, 8–34. <https://doi.org/10.1007/s11747-011-0278-x>
- Bamel, U., Talwar, S., Pereira, V., Corazza, L., & Dhir, A. (2023). Disruptive digital innovations in healthcare: Knowing the past and anticipating the future. *Technovation*, 125, Article 102785. <https://doi.org/10.1016/j.technovation.2023.102785>
- Beales, H., & Muris, T. J. (2019). Privacy and consumer control. *George Mason Law & Economics Research Paper*, 19–27.
- Brickell, T. A., Chatzisarantis, N. L., & Pretty, G. M. (2006). Autonomy and control. *Journal of Health Psychology*, 11(1), 51–63. <https://doi.org/10.1177/1359105306058847>
- Brodie, R. J., Hollebeek, L. D., Juric, B., & Ilic, A. (2011). Customer engagement: Conceptual domain, fundamental propositions and implications for research in service marketing. *Journal of Service Research*, 14, 352–371. <https://doi.org/10.1177/1094670511411703>
- Brodie, R. J., Ilic, A., Juric, B., & Hollebeek, L. D. (2013). Customer engagement in a virtual brand community: An exploratory analysis. *Journal of Business Research*, 66, 105–114. <https://doi.org/10.1016/j.jbusres.2011.07.029>
- Brooks, S. K., Webster, R. K., Smith, L. E., Woodland, L., Wessely, S., Greenberg, N., & Rubin, G. J. (2020). The psychological impact of quarantine and how to reduce it: Rapid review of the evidence. *The Lancet*, 395, 912–920. [https://doi.org/10.1016/S0140-6736\(20\)30460-8](https://doi.org/10.1016/S0140-6736(20)30460-8)
- Brown, S., Kozinets, R. V., & Sherry, J. F., Jr. (2003). Teaching old brands new tricks: Retro branding and the revival of brand meaning. *Journal of Marketing*, 67(3), 19–33. <https://doi.org/10.1509/jmk.67.3.19.18657>
- Burton, A., Burgess, C., Dean, S., Koutsopoulou, G. Z., & Hugh-Jones, S. (2017). How effective are mindfulness-based interventions for reducing stress among healthcare professionals? A systematic review and meta-analysis: Mindfulness interventions for stress reduction. *Stress and Health*, 33(1), 3–13. <https://doi.org/10.1002/smi.2673>
- Casalo, L., Flavian, C., & Guinaliu, M. (2010). Determinants of the intention to participate in firm-hosted online travel communities and effects on consumer behavioral intentions. *Tourism Management*, 31(6), 898–911. <https://doi.org/10.1016/j.tourman.2010.04.007>
- Cederström, C., & Spicer, A. (2015). Le syndrome du bien-être. L'Échappée. 165.
- Chin, W. (1998). Issues and opinion on structural equation modeling. *MIS Quarterly*, 22(1), 7–25. Récupéré sur <http://www.jstor.org/stable/249674>
- Chong, A. Y., Chan, F. T., & Ooi, K. B. (2012). Predicting consumer decisions to adopt mobile commerce: Cross country empirical examination between China and Malaysia. *Decision Support Systems*, 53(1), 34–43. <https://doi.org/10.1016/j.dss.2011.12.001>
- Cook-Cottone, C. P., & Guyker, W. M. (2018). The development and validation of the mindful self-care scale (MSCS): An assessment of practices that support positive embodiment. *Mindfulness*, 9(1), 161–175. <https://doi.org/10.1007/s12671-017-0759-1>
- Deci, E. L., & Ryan, R. M. (2000). The “what” and “why” of goal pursuits: Human needs and the self-determination of behavior. *Psychological Inquiry*, 11(4), 227–268. <https://doi.org/10.1207/S15327965PLI1104.01>
- Dessart, L., Veloutsou, C., & Morgan-Thomas, A. (2015). Consumer engagement in online brand communities: A social media perspective. *Journal of Product & Brand Management*, 24(1), 28–42. <https://doi.org/10.1108/JPBMM-06-2014-0635>
- Dessart, L., Veloutsou, C., & Morgan-Thomas, A. (2016). Capturing consumer engagement: Duality, dimensionality and measurement. *Journal of Marketing Management*, 32(5–6), 399–426. <https://doi.org/10.1080/0267257X.2015.1130738>
- Dunbar, S. B., Clark, P. C., Quinn, C., Gary, R. A., & Kaslow, N. J. (2008). Family influences on heart failure self-care and outcomes. *The Journal of Cardiovascular Nursing*, 23(3), 258. <https://doi.org/10.1097/01.JCN.0000305093.20012.b8>
- Dwivedi, A. (2015). A higher-order model of consumer brand engagement and its impact on loyalty intentions. *Journal of Retailing and Consumer Services*, 24, 100–109. <https://doi.org/10.1016/j.jretconser.2015.02.007>
- Dymond, S., & Roche, B. (2009). A contemporary behavior analysis of anxiety and avoidance. *The Behavior Analyst*, 32(1), 7–27. <https://doi.org/10.1007/BF03392173>
- Fagroud, F. Z., Toumi, H., Talhaoui, M. A., Achtaich, K., & El Filali, S. (2021). Impact of IoT devices in E-health: A review on IoT in the context of COVID-19 and its variants. *Procedia Computer Science*, 191, 343–348. <https://doi.org/10.1016/j.procs.2021.07.046>
- Fernandes, V. (2012). En quoi l'approche PLS est-elle une méthode a (re)-découvrir pour les chercheurs en management? *M@n@gement*, 15(1), 102–123.
- Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, 18(1), 39–50. <https://doi.org/10.2307/3151312>
- Foucault, M. (2001). *Dits et écrits II, 1976–1988*. Paris: Gallimard.
- Girandola, F. (2004). Violence dans les médias: quels effets sur les comportements? *Questions de communication*, 5, 55–68. <https://doi.org/10.4000/questionsdecommunication.7096>
- Gotink, R. A., Chu, P., Busschbach, J. J., Benson, H., Fricchione, G. L., & Hunink, M. M. (2015). Standardised mindfulness-based interventions in healthcare: An overview of systematic reviews and meta-analyses of RCTs. *PLoS One*, 10(4). <https://doi.org/10.1371/journal.pone.0124344>
- Greve, G. (2014). The moderating effect of customer engagement on the brand image-brand loyalty relationship. *Procedia-Social and Behavioral Sciences*, 148, 203–210. <https://doi.org/10.1016/j.sbspro.2014.07.035>
- Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed a silver bullet. *Journal of Marketing Theory and Practice*, 19, 139–151. <https://doi.org/10.2753/MTP1069-6679190202>
- Hajli, N., & Lin, X. (2016). Exploring the security of information sharing on social networking sites: The role of perceived control of information. *Journal of Business Ethics*, 133(1), 111–123. <https://doi.org/10.1007/s10551-014-2346-x>
- Hanafizadeh, P., Hatami Lankarani, F., & Nikou, S. (2022). Perspectives on management theory's application in the internet of things research. *Information Systems and e-Business Management*, 20(4), 749–787. <https://doi.org/10.1007/s10257-022-00569-0>
- Hayes, A. F. (2017). *Introduction to mediation, moderation, and conditional process analysis, second edition: A regression-based approach*. New York: Guilford Publications.
- Hayes, S. C., & Hofmann, S. G. (2018). Survival circuits and therapy: From automaticity to the conscious experience of fear and anxiety. *Current Opinion in Behavioral Sciences*, 24, 21–25. <https://doi.org/10.1016/j.cobeha.2018.02.006>
- Hidoussi, K. D., Dubois, M., Gandit, M., & El Methni, J. (2016). L'effet du contrôle comportemental, l'auto-efficacité et la charge subjective de travail sur l'intention d'usage d'un progiciel de gestion intégré. *Psychologie du Travail et des Organisations*, 22(1), 22–38. <https://doi.org/10.1016/j.pto.2015.12.004>
- Hollebeek, L. (2011). Exploring customer brand engagement: Definition and themes. *Journal of Strategic Marketing*, 19(7), 555–573. <https://doi.org/10.1080/0965254X.2011.599493>
- Hollebeek, L. D., Glynn, M. S., & Brodie, R. J. (2014). Consumer brand engagement in social media: Conceptualization, scale development and validation. *Journal of Interactive Marketing*, 28(2), 149–165. <https://doi.org/10.1016/j.intmar.2013.12.002>
- Hotchkiss, J. T., & Cook-Cottone, C. P. (2019). Validation of the mindful self-care scale (MSCS) and development of the brief-MSCS among hospice and healthcare professionals: A confirmatory factor analysis approach to validation. *Palliative & Supportive Care*, 17(6), 628–636. <https://doi.org/10.1017/S14789519000269>
- Hsu, C. L., & Lu, H. P. (2004). Why do people play on-line games? An extended TAM with social influences and flow experience. *Information & Management*, 41(7), 853–868. <https://doi.org/10.1016/j.im.2003.08.014>
- Hu, H., Xu, J., Liu, M., & Lim, M. K. (2023). Vaccine supply chain management: An intelligent system utilizing blockchain, IoT and machine learning. *Journal of Business Research*, 156, Article 113480. <https://doi.org/10.1016/j.jbusres.2022.113480>
- Islam, J. U., & Rahman, Z. (2016). Linking customer engagement to trust and word-of-mouth on Facebook brand communities: An empirical study. *Journal of Internet Commerce*, 15(1), 40–58. <https://doi.org/10.1080/15332861.2015.1124008>
- Javaid, M., & Khan, I. H. (2021). Internet of things (IoT) enabled healthcare helps to take the challenges of COVID-19 pandemic. *Journal of oral biology and craniofacial research*, 11(2), 209–214. <https://doi.org/10.1016/j.jobcr.2021.01.015>
- Kumar, D., Sood, S. K., & Rawat, K. S. (2023). IoT-enabled technologies for controlling COVID-19 spread: A scientometric analysis using CiteSpace. *Internet of Things*, 23, Article 100863. <https://doi.org/10.1016/j.iot.2023.100863>
- Liaw, S. S., & Huang, H.-M. (2011). Exploring learners' acceptance toward mobile learning. In *Dans T. Teo, technology acceptance in education: Research and issues* (pp. 145–157). Sense Publishers.
- Liaw, S. S., Huang, H. M., & Chen, G. D. (2007). An activity-theoretical approach to investigate learners' factors toward e-learning systems. *Computers in Human Behavior*, 23(4), 1906–1920. <https://doi.org/10.1016/j.chb.2006.02.002>
- Lingling, G., & Xuesong, B. (2014). A unified perspective on the factors influencing consumer acceptance of internet of things technology. *Asia Pacific Journal of Marketing and Logistics*, 26(2), 211–231. <https://doi.org/10.1108/APJML-06-2013-0061>
- Liu, Z., Han, B., Jiang, R., Huang, Y., Ma, C., Wen, J., et al. (2020). *Mental health status of doctors and nurses during COVID-19 epidemic in China*. Available at SSRN 3551329. <https://doi.org/10.2139/ssrn.3551329>
- Lu, Y., Papagiannidis, S., & Alamanos, E. (2018). Internet of things: A systematic review of the business literature from the user and organisational perspectives. *Technological Forecasting and Social Change*, 136, 285–297. <https://doi.org/10.1016/j.techfore.2018.01.022>
- Lu, Y., Zhou, T., & Wang, B. (2009). Exploring Chinese users' acceptance of instant messaging using the theory of planned behavior, the technology acceptance model, and the flow theory. *Computers in Human Behavior*, 25(1), 29–39. <https://doi.org/10.1016/j.chb.2008.06.002>
- McCusker, J., Cole, M., Yaffe, M., Strumpf, E., Sewitch, M., Sussman, T., ... Belzile, E. (2016). A randomized trial of a depres-Sion self-care toolkit with or without lay telephone coaching for primarycare patients with chronic physical conditions. *General Hospital Psychiatry*, 40, 75–83. <https://doi.org/10.1016/j.genhosppsych.2015.03.007>
- Mercier, J., & Roux, E. (2017). *L'attachement à la marque: mesure unidimensionnelle ou tridimensionnelle?* Marseille: Centre d'études et de recherche en gestion d'Aix.
- Mohammedqasim, H., & Ata, O. (2022). Real-time data of COVID-19 detection with IoT sensor tracking using artificial neural network. *Computers and Electrical Engineering*, 100, Article 107971. <https://doi.org/10.1016/j.compeleceng.2022.107971>
- Mukhtar, H., Rubaiee, S., Krichen, M., & Alrobaiee, R. (2021). An IoT framework for screening of COVID-19 using real-time data from wearable sensors. *International Journal of Environmental Research and Public Health*, 18(8), 4022. <https://doi.org/10.3390/ijerph18084022>
- Muniz, A. M., Jr., & Schau, H. J. (2005). Religiosity in the abandoned apple Newton brand community. *Journal of Consumer Research*, 31(4), 737–747. <https://doi.org/10.1086/426607>
- Nasajpour, M., Pouriyeh, S., Parizi, R. M., Zhao, L., & Li, L. (2022). Internet of things use case applications for COVID-19. *Edge-of-Things in Personalized Healthcare Support Systems*, 377–412. <https://doi.org/10.1016/B978-0-323-90585-5.00016-3>

- Nikou, S. A., & Economides, A. A. (2017). Mobile-based assessment: Integrating acceptance and motivational factors into a combined model of self-determination theory and technology acceptance. *Computers in Human Behavior*, 68, 83–95. <https://doi.org/10.1016/j.chb.2016.11.020>
- Noor, Z., Hina, S., Hayat, F., & Shah, G. A. (2023). An intelligent context-aware threat detection and response model for smart cyber-physical systems. *Internet of Things*, 100843. <https://doi.org/10.1016/j.iot.2023.100843>
- Norcross, J., & Guy, J. (2007). *Leaving it at the office: A guide to psychotherapist self-care*. New York: The Guildford Press.
- Otoom, M., Otoum, N., Alzubaidi, M. A., Etoom, Y., & Banihani, R. (2020). An IoT-based framework for early identification and monitoring of COVID-19 cases. *Biomedical Signal Processing and Control*, 62, Article 102149. <https://doi.org/10.1016/j.bspc.2020.102149>
- Pickens, J. (2013). *Self-Care, Nursing Theory, and Evidence-Based Practice*, by S. G. Taylor and K. Renpenning. 26 pp. 292–293). New York: Springer, 3. *NursingScience Quarterly*.
- Presti, G., McHugh, L., Gloster, A., Karekla, M., & Hayes, S. (2020). The dynamics of fear at the time of COVID-19: A contextual behavioral science perspective. *Clinical Neuropsychiatry*, 17(2), 65–71. <https://doi.org/10.36131/CN20200206>
- Princi, E., & Krämer, N. C. (2020). Out of control-privacy calculus and the effect of perceived control and moral considerations on the usage of IoT healthcare devices. *Frontiers in Psychology*, 11. <https://doi.org/10.3389/fpsyg.2020.582054>
- Raab, K. (2014). Mindfulness, self-compassion, and empathy among health care professionals: A review of the literature. *Journal of Health Care Chaplaincy*, 20(3), 95. <https://doi.org/10.1080/08854726.2014.913876>
- Rahman, M. Z., Akbar, M. A., Leiva, V., Tahir, A., Riaz, M. T., & Martin-Barreiro, C. (2023). An intelligent health monitoring and diagnosis system based on the internet of things and fuzzy logic for cardiac arrhythmia COVID-19 patients. *Computers in Biology and Medicine*, 154, Article 106583. <https://doi.org/10.1016/j.combiomed.2023.106583>
- Richard, A., & Shea, K. (2011). Delineation of self-care and associated concepts. *Journal of Nursing Scholarship*, 43(3), 255–264. <https://doi.org/10.1111/j.1547-5069.2011.01404.x>
- Richter, N., Cepeda Carrión, G., Roldán, J. L., & Ringle, C. M. (2016). European management research using partial least squares structural equation modeling (PLS-SEM). *European Management Journal*, 34(6), 589–597. <https://doi.org/10.1016/j.emj.2014.12.001>
- Riegel, B., Jaarsma, T., & Strömberg, A. (2012). A middle-range theory of self-care of chronic illness. *Advances in Nursing Science*, 35(3), 194–204. <https://doi.org/10.1097/ANS.0b013e318261b1ba>
- Roca, J. C., & Gagné, M. (2008). Understanding e-learning continuance intention in the workplace: A self-determination theory perspective. *Computers in Human Behavior*, 24(4), 1585–1604. <https://doi.org/10.1016/j.chb.2007.06.001>
- Samhale, K. (2022). The impact of trust in the internet of things for health on user engagement. *Digital. Business*, 2(1). <https://doi.org/10.1016/j.digbus.2022.100021>
- Samhale, K., & Ladwein, R. (2019). L'impact de l'influence sociale sur l'intention d'usage des objets connectés pour le sport. *Revue française des sciences de l'information et de la communication*, 16. <https://doi.org/10.4000/rfsic.5966>
- Sheldon, K. M., Elliot, A. J., Kim, Y., & Kasser, T. (2001). What is satisfying about satisfying events? Testing 10 candidate psychological needs. *Journal of Personality and Social Psychology*, 80(2), 325. <https://doi.org/10.1037/0022-3514.80.2.325>
- Skinner, E. A., & Zimmer-Gembeck, M. J. (2011). Perceived control and the development of coping. In *The Oxford handbook of stress, health, and coping* (pp. 35–59).
- Sørebo, Ø., Halvari, H., Gulli, V. F., & Kristiansen, R. (2009). The role of self-determination theory in explaining teachers' motivation to continue to use elearning technology. *Computers & Education*, 53(4), 1177–1187. <https://doi.org/10.1016/j.compedu.2009.06.001>
- Standage, M., Duda, J. L., & Ntoumanis, N. (2006). Students' motivational processes and their relationship to teacher ratings in school physical education: A self-determination theory approach. *Research Quarterly for Exercise and Sport*, 77, 100–110. <https://doi.org/10.1080/02701367.2006.10599336>
- Van Hoof, J., Kort, H., Rutten, P., & Duijnste, M. (2011). Ageing-in-place with the use of ambient intelligence technology: Perspectives of older users. *International Journal of Medical Informatics*, 80(5), 310–331. <https://doi.org/10.1016/j.ijmedinf.2011.02.010>
- Venkatesh, V., Thong, J. Y., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly*, 157–178. <https://doi.org/10.2307/41410412>
- Vines, J., Lindsay, S., Pritchard, G., Lie, M., Greathead, D., Olivier, P., & Brittain, K. (2013). Making family care work: Dependence, privacy and remote home monitoring telecare systems. *UbiComp*, 597–606. <https://doi.org/10.1145/2493432.2493469>
- Vivek, S. D., Beatty, S. E., & Morgan, R. (2012). Customer engagement: Exploring customer relationships beyond purchase. *Journal of Marketing Theory and Practice*, 20(2), 122–146. <https://doi.org/10.2753/MTP1069-6679200201>
- Wang, C., Pan, R., Wan, X., Tan, Y., Xu, L., Ho, C. S., & Ho, R. C. (2020). Immediate psychological responses and associated factors during the initial stage of the 2019 coronavirus disease (COVID-19) epidemic among the general population in China. *International Journal of Environmental Research and Public Health*, 17(5), 1729. <https://doi.org/10.3390/ijerph17051729>
- Wang, N., Zhang, B., Liu, B., & Jin, H. (2015). Investigating effects of control and ads awareness on android users' privacy behaviors and perceptions. mobileHCI 2015. In *Proceedings of the 17th international conference on human-computer interaction with mobile devices and services*. New York. <https://doi.org/10.1145/2785830.2785845>
- Wetzels, M., Odekerken-Schröder, G., & Van Oppen, C. (2009). Using PLS path modeling for assessing hierarchical construct models: Guidelines and empirical illustration. *MIS Quarterly*, 33(1), 177–195. <https://doi.org/10.2307/20650284>
- Xiao, R., Wu, Z., Buruk, O. T., & Hamari, J. (2021). Enhance user engagement using gamified internet of things. *Hawaii International Conference on System Sciences*. <https://doi.org/10.24251/HICSS.2021.583>
- Yu, B., Wright, J., Nepal, S., Zhu, L., Liu, J., & Ranjan, R. (2018). IoTChain: Establishing Trust in the Internet of things ecosystem using Blockchain. *IEEE Cloud Computing*, 5(4), 12–23. <https://doi.org/10.1109/MCC.2018.043221010>
- Zhou, M., Tang, F., Wang, Y., Nie, H., Zhang, L., You, G., & Zhang, M. (2020). Knowledge, attitude and practice regarding COVID-19 among health care workers in Henan, China. *Journal of Hospital Infection*. <https://doi.org/10.1016/j.jhin.2020.04.012>