Modeling adoption, security and privacy of COVID-19 Apps: findings and recommendations from an empirical study using UTAUT

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The global health crisis caused by COVID-19 has drastically changed human society in a relatively short time. However, this crisis is also an opportunity to address existing problems and propose new solutions. This paper proposes a model based on the UTAUT constructs to study the determinants for adoption of COVID-19 apps. We tested the model via confirmatory factor analysis and structural equation modeling using travelers' data to an insular tourist region (N=9555). Results show an increased understanding of the vital role of safety, security, privacy, and trust in usage intention of safety applications. We also show how the impact of COVID-19 is not a strong predictor of adoption, while age, education level, and social capital are essential moderators of behavioral intention. These empirical findings provide valuable theoretical contributions to researchers and practical implications for policymakers by explaining the reasons behind the adoption and usage of COVID-19 apps.

CCS Concepts: • **Human-centered computing → Empirical studies in HCI**; **User studies**; • **Security and privacy → Privacy protections**.

Additional Key Words and Phrases: HCI, COVID-19, empirical study, SEM, CFA, security, privacy

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1 INTRODUCTION

There have been many papers addressing and tackling COVID-19 related impacts, more than 23.000 papers have been published between January and May 2020, [Brainard 2020] hence it has proved difficult to remain up-to-date with all the released studies. However, it is evident to all of us that the global health crisis caused by the COVID-19 [Wang et al. 2020] has drastically changed human society in a relatively short time.

The pandemic's socio-economic impacts [Nicola et al. 2020] are unprecedented, e.g., in the education sector, more than a billion students were affected due to the schools' closure [UNESCO 2020]. This situation created stress, especially for low-income families [Nicola et al. 2020]. COVID-19 pandemic has severely challenged the healthcare sector, especially the medical workers, severely exposed to physical and psychological impacts [Shaukat et al. 2020]. Also, some ethnic groups suffered more than others due to socio-economic, healthcare disparities, and lack of privileges [van Dorn et al. 2020; Yancy 2020]. In summary, COVID-19 has disclosed to the world and exacerbated problems and inequalities based on gender, age, ethnicity, socio-economic situation, and nationality [Blundell et al. 2020]. Supporting communities to promote well-being, cohesion, and safe behaviors, especially for vulnerable groups, are a welcome suggestions. However, governments and health institutions play a crucial role in supporting the well-being and providing economic, social, and health support and promoting trust [Templeton et al. 2020].

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The pandemic challenges our progress and growth-based society and its capitalistic nature, and tourism, as a growth-based phenomenon, suffers from these challenges [Sigala 2020]. However, the health crisis is also an opportunity [Mair 2020] to address the existing problems and explore new solutions to local and global challenges. While much effort was made to develop and deploy several COVID-19 contact-tracing mobile applications [Ahmed et al. 2020; Azad et al. 2020; Li and Guo 2020], these technologies raise several ethical challenges (e.g., privacy, security, surveillance) [Dubov and Shoptawb 2020; Gasser et al. 2020; Tang 2020]. Although technologies for citizen engagement have been considered helpful to manage crises [Chen et al. 2020], there is still a lack in this research area concerning COVID-19.

The general aim of this paper is to examine people's perceptions and attitudes towards COVID-19 applications through a case study on a European island, which deployed a successful safety system to mitigate the impact of the pandemic while preserving mobility after lockdown and isolation. More specifically, the research purposes of this work are: (i) to investigate the effects of the COVID-19 pandemic on technology adoption and especially safety, security, privacy, and trust; (ii) to increase our understanding of differences in the determinants of safety in technology use; and (iii) to improve the explanatory power and predictive accuracy of a parsimonious questionnaire based on known UTAUT constructs for broader application in HCI research.

A vital component of this research's successful execution was the experimental setup's contained and isolated nature (i.e., small European island with extensive tourism economy), which enabled a rapid mobilization of research in tandem with the deployment of COVID-19 security measures. Intending to seize a potentially rare opportunity to peek into the near future in which safety tech apps will be one of the best attempts to deal with this "new normal", we collected data from an international audience recovering from the pandemic's first wave. However, the race to study rapidly emerging topics can sometimes lead researchers to sacrifice rigor for expediency. To avoid making such a sacrifice, we designed and distributed a questionnaire based on the UTAUT constructs [Venkatesh et al. 2003] and collected data from 9555 participants from different nationalities. We applied exploratory and confirmatory factor analysis and structured equation modeling to analyze the data. The results of this study contain several implications for HCI research and COVID-19 tech design. The empirical findings demonstrate the validity of parsimonious assessment in evaluating UTAUT based constructs to understand the adoption and usage of safety apps. Safety concerns and willingness to follow safety measures are strong predictors of intention to use, which also affects security. Privacy is a central concern that needs to inform the design of safety apps. Our results are valid across the moderating roles of demographics such as gender, age, and social capital.

The rest of this article is organized as follows: we start by providing an overview of the current literature pertinent to this study (Section 2). Then we describe the Research Questions, the hypotheses, and Methods adopted for this study (Section 3) and the results (Section 4). The work outcomes are analyzed and discussed and the limitations of the research are presented, also considering the particular context of the research, the COVID-19 pandemic (Section 5). At the end of the paper, we present the conclusion and future works (Section 6).

2 STATE OF THE ART

This section presents the state of the art regarding the main topics of this paper. The first part provides an overview on the transformations of the tourism sector and research caused by COVID-19 (Section 2.1); the second part deals with the technological measures and their ethical challenges involved with the COVID -19 pandemic (Section 2.2); the third part touches on the citizen engagement and social capital researches also in the context of COVID-19 (Section 2.3); and finally, the last part surveys the technology adoption scales and methodology, which we used and extended in our study (Section 2.4).

2.1 Tourism transformations in time of COVID-19

One of the sector most scarred by the COVID-19 pandemic crisis is tourism [Gössling et al. 2020; Nicola et al. 2020]. According to a World Tourism Organization's (UNWTO) report from May 2020[1], the health crisis caused 22% less international arrivals in the tourist destinations during the first quarter of 2020 and placed many tourism jobs at risk. This led to substantial policy measures [2] to reboot Europe's tourism, which is an essential source of income for many countries.

As described in [Sigala 2020], the COVID-19 pandemic challenges our progress and growth-based society, also in its capitalistic nature, and tourism, as a growth-based phenomenon, suffers from these threats. Nevertheless, COVID-19 can also be seen as an occasion for slowing down [Latour 2020] to criticize the current state of affair [Bohman 2019] and explore transformations by re-imagining tourism [Sigala 2020] towards sustainable tourism [Hunter 1997], community-centered initiatives, and "socialised" tourism [Higgins-Desbiolles 2020; Higgins-Desbiolles et al. 2019]. Zenker et al. [Zenker and Kock 2020] suggest some possible directions for the tourism research agenda involving COVID-19: (i) to address the complexity of the current pandemic and trace relationships among different impacted areas and involved variables; (ii) to consider the possible changes in the destinations' images based on the pandemic history of the destination itself, (iii) to examine behavioral changes in the visitors (e.g., changes in travel choices), (iv) in the locals (e.g., in-group and out-group dynamics between locals and visitors), and in (v) the tourism sector (e.g., increase collaborations among different sectors), (vi) to assess and predict the long-term and indirect effect of COVID-19 in tourism, such as observing the change of priorities in the sector.

The transformations in the tourism sector could also benefit from the use of COVID-19 technologies. A call for transformative e-Tourism research has been made [Gretzel et al. 2020] to re-invent the field from an ontological and epistemological perspective. As mentioned in [Gretzel et al. 2020], although technology solutions are powerful catalysts for transformations and have been already used in the tourism research and sector, e-Tourism research should reflect on COVID-19, look at the future, and be re-shaped following the principles of historicity, reflexivity, transparency, plurality, creativity and finally social equity and diversity in e-Tourism solutions. All of them require different points of view and research fields to develop theories and interventions.

2.2 COVID-19, technological interventions, and ethical challenges

COVID-19 has also changed our relationship with technology [Doyle and Conboy 2020]. Thanks to the digital tools we were able to monitor the evolution of the pandemic day-by-day (see e.g., https://covid19.who.int/ and https://www.worldometers.info/coronavirus/), to perform predictions based on models [Wynants et al. 2020], to participate in digital meetings, conferences and classes, and to remain in contact with our loved-ones [Doyle and Conboy 2020].

Several tools have been developed and proposed to mitigate the risks associated with the COVID-19 and the spread of the disease, and to perform diagnosis. Kumar et al. [Kumar et al. 2020] discuss different technologies, e.g., Artificial Intelligence (AI), used for several COVID-19 applications by dividing them in the following groups: (i) diagnosis using radiology images, (ii) disease tracking, (iii) health conditions prediction, (iv) computational biology, (v) protein structure prediction, (vi) drug discovery, and (vii) social awareness and control. Whitelaw et al. [Whitelaw et al. 2020] have provided a framework for describing the digital applications in response to COVID-19 (e.g., planning, management, tracking, testing, and quarantine) by explaining their functionalities, the technology used, the countries that adopted these digital tools as well as their respective advantages and disadvantages. Shu Wei Ting et. [Ting et al. 2020] review

[1]See: https://www.unwto.org/news/covid-19-international-tourist-numbers-could-fall-60-80-in-2020
[2]See: https://ec.europa.eu/commission/presscorner/detail/it/FS_20_851

the impact of several technologies, e.g., AI, Big Data, Internet of Things (IoT), in the service of health interventions for COVID-19, e.g., monitoring, prevention, and diagnosis. Finally, Golinelli et al. [Golinelli et al. 2020] provide a literature review that tackles the digital measures embraced by the healthcare system to manage COVID-19. One result of the study [Golinelli et al. 2020] outlined that the diagnostic technologies form the majority, followed by surveillance and prevention technologies.

Many surveys have been performed to classify and discuss contact-tracing apps [Ahmed et al. 2020; Azad et al. 2020; Li and Guo 2020]. Contact-tracing technology has been promptly identified as a powerful tool to control and mitigate the spread of the pandemic and several frameworks exist, such as centralised, decentralised, and hybrid architectures, and various data management concerns populate the literature [Ahmed et al. 2020; Azad et al. 2020; Li and Guo 2020; Vaudenay 2020]. To deal with some of the differences and find common ground, in April 2020 the European eHealth Network developed a common toolbox for member states to follow, called *Mobile applications to support contact tracing in the EU fight against COVID-19 Common EU Toolbox for Member States*[3]. According to this document, the EU apps should be compliant with some recommendations: epidemiological (e.g., inform the persons that have beer at risk of contracting with the virus), technical (e.g., use of proximity technology), interoperability (e.g., epidemiological alignment among member states), cybersecurity (e.g., adoption of encryption), and safeguards (e.g., use of consent-based application). The EU toolbox for contact-tracing addresses further ethical challenges, for instance the importance of accessibility and inclusivity as fundamental rights to be preserved in the development and deployment of such applications.

Many authors have examined the ethical dimension of COVID-19 digital tools [Dubov and Shoptawb 2020; Gasser et al. 2020; Tang 2020]. While Tang [Tang 2020] describes and discusses concrete privacy-aware digital interventions for contact-tracing, Morley et al. [Morley et al. 2020] propose some ethical guidelines for the development and the deployment of tracking and tracing applications. The authors identify some high-level principles (i.e., necessity, proportionality, scientific soundness, and time-boundedness) and enabling conditions (e.g., voluntariness, consent, anonymity, right to be forgotten, accessibility) related to these kinds of applications. Also, Dubov et al., [Dubov and Shoptawb 2020] consider the ethical challenges of contact-tracing; for example, that some of these challenges involve the number of tests necessary for a practical contact-tracing application, aggregated and identifiable data, privacy, voluntariness and consent, transparency, and inclusion. More general is the study of Gasser et al., [Gasser et al. 2020] in which the ethical and legal challenges of COVID-19 digital health tools are discussed (e.g., symptom checkers, quarantine compliance) and not only tracking and contact-tracing applications. Examples of these challenges are the validity and necessity of the research, privacy requirements, the autonomy of the users, possible discrimination risks, and the risk of re-purposing retrieved data for other aims. These issues are closely connected with several ethical principles, such as autonomy, privacy, solidarity, justice, are fundamental to recommendations for COVID-19 digital tools.

2.3 Technologies, citizen engagement, and social capital

Despite the plethora of digital tools proposed for COVID-19, (see., e.g., [Ahmed et al. 2020]), many are still debated due to ethical challenges and criticalities regarding user perceptions and preferences [Simko et al. 2020]. The development and the importance of applications based on *citizen engagement* and *participation* in times of COVID-19 have been proposed as an alternative [Marston et al. 2020; Richards and Scowcroft 2020] since engagement and communication

[3]https://ec.europa.eu/health/sites/health/files/ehealth/docs/covid-19_apps_en.pdf

are critical factors for managing crisis, as also identified by Chen et al. [Chen et al. 2020] during this latest pandemic crisis, in which have studied the effect of the national health authority's social media accounts on citizens' engagement.

Public and citizen engagement is based on communication and building relationships between authorities and citizens, for instance, through dialogue and participation [Chen et al. 2020; Taylor and Kent 2014]. Today digital platforms and near universal access to mobile technologies have the power to support citizen engagement with governance and municipalities (see e.g., [Falco and Kleinhans 2018], regarding pretty much any issue that relates to the citizens' lives. Digital technologies can shorten citizen feedback loops with government and enhance implementation of public policy and improve experience [Bäcker 2018]. For this reason, many self-service apps are being deployed, as major cities leverage mobile technologies [Snow 2017]. Yet, self-service apps can be expensive and hard to deploy for smaller communities dealing with public funding [Bäcker 2018]. Recently the healthcare industry has focused interest into wearables devices [Canhoto and Arp 2017; Cruz and Lousado 2018], in which technology is seen as an enabler for self-prevention programs. However, the adoption, trust and sustained use of these systems is challenging and involves critical and complex design considerations [Canhoto and Arp 2017].

Digital technology for citizen engagement can also facilitate building *social capital* [Mandarano et al. 2010]. Social capital is a term that is commonly used but often poorly defined and conceptualized [Adler and Kwon 2002], yet it can be generally defined as the values of social relationships and networks to which an individual belongs [Holt 2008]. As described in [Mandarano et al. 2010], relationships, trust, and norms are the three elements that comprise social capital and can be increased with participation, collective actions, and decisions. Social capital and health are also connected, such as in the mortality rate and heart disease, especially when associated with one's level of income [Borgonovi and Andrieu 2020; Harpham et al. 2002]. Focussing specifically on COVID-19, the study of Borgonovi et al. [Borgonovi and Andrieu 2020] shows that communities with high social capital could be better prepared for COVID-19 also in terms of change in behaviors and isolation to protect other members. Another research (i.e., [Kokubun 2020]) confirms that social distancing measures alone are not enough to mitigate COVID-19 spreading, instead increasing social capital and sense of community is more effective to prevent the effects of the pandemic.

2.4 Technology adoption

Models of technology adoption are among the most used for studying individual intentions to adopt technology. The Technology Acceptance Model (TAM) [Davis et al. 1989] and Unified Theory of Acceptance and Use of Technology (UTAUT) [Venkatesh et al. 2003] have been specifically designed and tested to measure people's attitude towards technology. TAM is an adaptation of the theory of reasoned action (TRA) [Ajzen et al. 1991], a framework that explains human behavior. The TAM applies the TRA to explains the users' behaviour and acceptance in reference to computer systems on the basis of users' intentions/attitudes, subjective norms, perceived usefulness, perceived ease-of-use, and other variables. Although the TAM is a useful theory, it has some flaws. Indeed it does not include some important factors, such as social and organisational dynamics in which the technology is encountered [Legris et al. 2003]. To solve some of these issues [Malhotra and Galletta 1999], UTAUT has been proposed by bringing together several user acceptance models, including the TAM and the the TRA. According to the UTAUT, the following indicators are connected with the use of an information system: (i) performance expectancy, (ii) effort expectancy, (iii) social influence, and (iv) facilitating conditions, these influence behavioural intention and use behaviour. These are the main predictors of behavioural intention, i.e., that a person's performance of a specified behavior is determined by his or her behavioral intention to perform the behavior. The next items describe the meanings of the above constructs from [Venkatesh et al. 2003]:

- Performance expectancy: it is the "[...] the degree to which an individual believes that using the system will help him or her to attain gains in job performance." ([Venkatesh et al. 2003] p. 447);
- Effort expectancy: it is the "[...] degree of ease associated with the use of the system." ([Venkatesh et al. 2003] p. 450);
- Social influence: it is the "[...] the degree to which an individual perceives that important others believe he or she should use the new system." ([Venkatesh et al. 2003] p. 451);
- Facilitating conditions: it is the "[...] the degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system." ([Venkatesh et al. 2003] p. 453).

Technology adoption models (e.g. TAM [Davis et al. 1989] and UTAUT [Venkatesh et al. 2003]) have however been criticized for promoting a deterministic approach without much consideration for users' individual characteristics [Slade et al. 2015]. Regardless these continue to be applied, as reviewed in Venkatesh et al. [Venkatesh et al. 2016], several are the applications, integrations, and the UTAUT paradigm's extensions. For instance, the works of Khalilzadeh et al. [Khalilzadeh et al. 2017a] and Shin [Shin 2009a] investigates security-related factors in the field of e-commerce by integrating UTAUT and TAM and extending them with security constructs, such as perceived security, perceived risk, and trust. By generalising the definitions found in [Khalilzadeh et al. 2017a; Mandrik and Bao 2005; Shin 2009a], (i) perceived security is described as *the degree to which a* user *believes that using a particular* information system *procedure will be secure*, (ii) trust is defined as *the belief that will perform some activity following* users' *expectations*, finally, (iii) perceived risk is *uncertainty* or anxiety related to the (possible negative) final result of an action, behavior, or a situation. The literature shows that many new products are considered inherently risky, then perceived risk has been a common extension of UTAUT [Khalilzadeh et al. 2017b; Slade et al. 2015; Williams et al. 2011]. Also Thakur et al., [Thakur and Srivastava 2014] measured perceived risk as a second-order factor consisting of security risk and privacy risk; their findings supported their hypothesis that risk negatively affects adoption intention. Because trust is a component of expectation, it is possible to infer an effect of trust on performance and effort expectancy [Lee and Song 2013]. Trust is a subjective belief that a party will fulfill their obligations and it plays an important role in specific domains (e.g., electronic financial transactions, healthcare), where users are vulnerable to greater risks of uncertainty and a sense of loss of control [Lu et al. 2011; Zhou 2013].

As shown in [Wilkowska and Ziefle 2011], in the e-health domain, privacy and security are particularly important topics that influence the use and acceptance of technology. In the study conducted by Schnall et al. [Schnall et al. 2015] in the context of mobile health technologies, similar findings revealed that privacy (e.g., access to information), security, and trust concerns do exist among users of such applications.

The UTAUT model, including its extensions, has also been used in the context of COVID-19 technologies. For instance, Békés et. al. [Békés and Aafjes-van Doorn 2020] examine psychotherapists' attitudes regarding online psychotherapy, also considering the new exigencies of the pandemic. Tiwari et al., [Tiwari 2020] focus their study on the adoption of online classes. Finally, the research carried out by Chayomchai et al., [Chayomchai et al. 2020] centered on the use of technology of Thai people during the quarantine. We build on these efforts to extend the UTAUT scale to measure users' attitudes in COVID-19 times.

3 RESEARCH QUESTIONS AND HYPOTHESES

In this research, we utilized the unprecedented opportunity presented by the need to deploy safety measures at scale in a European island with significant tourism industry to better understand the factors affecting the adoption and use of

COVID-19 safety apps. We were particularly interested in investigating the role of safety, security, privacy, and trust in the context of the adoption of a voluntary COVID-19 app that supported air and sea access to an insular region. We also wanted to understand the effect of moderator variables (gender, age, education, and social capital) in the adoption of COVID-19 safety systems.

The [REDACTED] system was part of the COVID-19 safety mechanism designed by the local Health Authorities in order to achieve two main goals: to support travelers coming into the region by guiding them through the health requirements and empower the health authorities with an information system that facilitates the monitoring and managing of the COVID -19 potential effects on the region. After the lockdown, the region opened borders implementing a mandatory COVID-19 PCR screening test. Travelers coming into the Islands should present a valid COVID-19 test 72h before entry or be subject to testing upon entry. Registration of personal and travel details on the regional health system was mandatory either manually or using the [REDACTED] system. After entering the region, travelers would undergo a voluntary 14 day vigilance period to submit an electronic daily health inquiry. The health authorities deployed a web-based [REDACTED] app to stimulate compliance with the safety procedures since screening and monitoring procedures were constitutionally optional.

During their vigilance period, travelers should receive reminders for submitting their health inquiries via SMS. Those using the [REDACTED] app could receive their test results and submit their daily health inquiry electronically. Besides, they could decide to share their location while using the app voluntarily, but the system could not implement any automated contact tracing mechanism. In summary, the [REDACTED] app was an optional digital tool that would improve the COVID-19 safety measures for the health authorities while providing some practical benefits for travelers at their data expense. The researchers involved in this study were asked to assist with the system's design and advise on data protection and privacy issues while producing an independent adoption and usage report of which this research was based. This setup provided a unique opportunity to investigate at scale the effects of safety, privacy, and trust in the adoption of mobile apps and safety monitoring systems.

More specifically, the research purposes of this work are: (i) to investigate the effects of the COVID-19 pandemic on technology adoption and especially safety, security, privacy, and trust; (ii) to increase our understanding of differences in the determinants of safety in technology use; and (iii) to improve the explanatory power and predictive accuracy of parsimony questionary based on known UTAUT constructs for broader application in HCI research.

This study proposes a questionary adapted from the UTAUT model that incorporates variables such as safety, trust, perceived security, perceived usefulness (performance expectancy) and ease of use (effort expectancy). Figure 1 presents the [REDACTED] acceptance/use model proposed here.

For testing the hypothesis the questionnaire comprised 27 questions (items) for responses on a Likert-type scale, ranging from 1-“Strongly disagree”, 2-“Disagree”, 3-“Undecided”, 4-“Agree” and 5-“Strongly agree”. To ensure the content validity of the questionnaire used to assess each construct, all items regarding the measurement of constructs were adapted from previous studies and carefully reworded to fit the context of COVID-19 apps which can ge generalized for safety monitoring systems.

3.1 Items Based on UTAUT Constructs

For the purpose of this study, several hypotheses were developed on the basis of the original UTAUT constructs, we will lay them out in detail below.

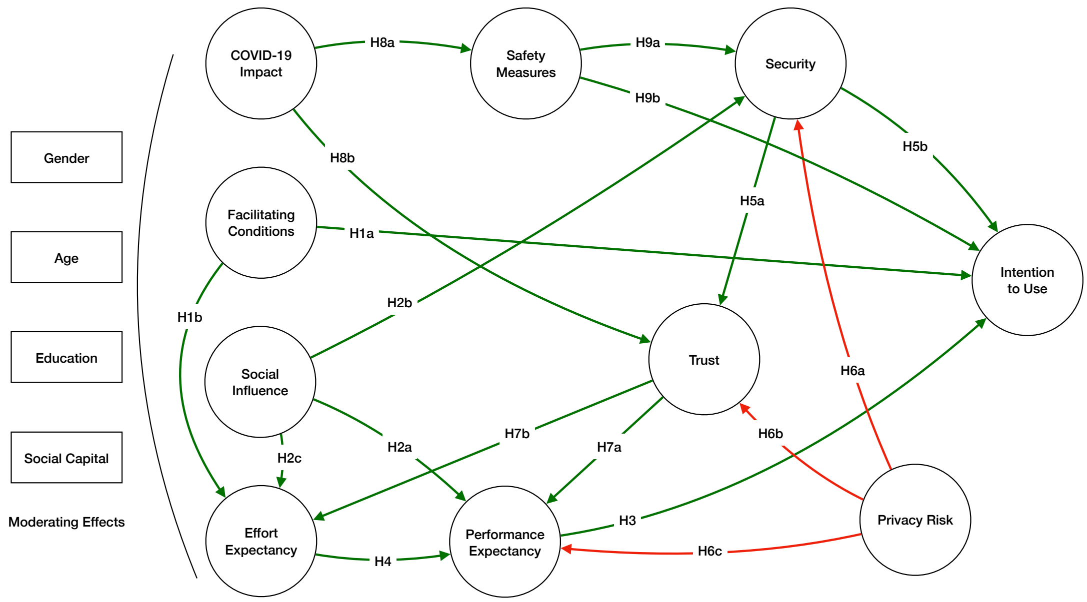

Fig. 1. Proposed Research Model

Facilitating conditions. have direct positive relations with user behavior but no effect on behavioral intentions [Venkatesh et al. 2003]. Like others [Khalilzadeh et al. 2017b] this study uses behavioral intention as a proxy for user behaviour, despite that in the original UTAUT model they are separate constructs. Therefore, we hypothesise that:

> **H1a.** The facilitating conditions (e.g. owning a smartphone) for using COVID-19 safety Apps positively predict users' intentions to use it.
>
> **H1b.** The facilitating conditions (e.g. knowledge to use the app) for using COVID-19 safety Apps has a direct positive impact on effort expectancy.

Social influence. has a direct positive impact on behavioral intention. The underlying assumption is that individuals tend to consult their social network about new technologies and can be influenced by the perceived social pressure of important others. Because perceived security also involves health aspects, it should be highly influential in the proposed model. Therefore, we hypothesise that:

> **H2a.** The social influence (e.g. recommendation from significant others) for using COVID-19 safety Apps positively predicts effort expectancy.
>
> **H2b.** The social influence (e.g. recommendation from significant others) for using COVID-19 safety Apps positively and directly influences perceived security.
>
> **H2c.** The social influence (e.g. recommendation from health authorities) for using COVID-19 safety Apps has a direct positive impact on performance expectancy.

Performance expectancy. is the strongest predictor of behaviour intention [Venkatesh et al. 2003]. Yang [Yang 2010] divided the construct into two separate constructs of utilitarian performance expectancy and hedonic performance expectancy. Although we can argue that enhancing task performance could lead to increased satisfaction, Escobar-Rodríguez and Carvajal-Trujillo [Escobar-Rodríguez and Carvajal-Trujillo 2014] report a weak effect of hedonic motivation. One of the attractive features of the [REDACTED] App is the ability to let travellers enter their own data and avoid queues and paper forms during an already stressful airport transit in pandemics' context. The App offers utilitarian benefits that are likely to be important drivers of adoption. Therefore, we hypothesize that:

> **H3.** Performance expectancy (i.e. usefullness) positively affects behavioral intention to use COVID-19 safety Apps.

Effort expectancy. is one of the most significant predictors of intention to use mobile Apps [Gupta et al. 2018; Kim et al. 2010; Tam et al. 2020]. Others also find effort expectancy to have a significant effect on behavioral intention [Ghalandari 2012; Venkatesh et al. 2008]. The literature describes similar constructs that correlate the direct effect of perceived ease of use on behavioral intention. As the [REDACTED] App provides a new way to secure travel, it is likely that the perceived degree of ease associated with using COVID-19 safety apps will affect behavioral intention. Based on this and UTAUT's hypotheses, it is anticipated that:

> **H4:** Effort expectancy (i.e. ease of use) positively affects performance expectancy (i.e. usefulness) to use COVID-19 safety Apps.

3.2 Items based on UTAUT Extensions for Security and Privacy

Security, trust, and risk became critical additional constructs in studies about technology adoption [Khalilzadeh et al. 2017b; Slade et al. 2015], especially in the case of sharing medical information.

Perceived security. is expected to affect behavioral intention directly. Because COVID-19 safety Apps involve sensitive health information it should be highly influential in the proposed model [Khalilzadeh et al. 2017b]. Moreover, perceived security is an aggregate construct and which changes over time and according to public opinion and social influence[Khalilzadeh et al. 2017b]. Therefore we hypothesize that:

> **H5a.** Perceived security of COVID-19 safety Apps positively and directly predicts perceived trust.

> **H5b.** Perceived security of COVID-19 safety Apps positively and directly behavioral intention to use COVID-19 safety Apps.

Privacy risk. is usually associated with perceived security, the more a user perceives privacy risk the less secure the users feels leading to a negative relationship between risk and security [Khalilzadeh et al. 2017a; Lim 2003]. Based in the findings retrieved from the literature (see Section 2), which state that perceived risk has negative impact perceived security, trust, and performance expectancy the following hypothesis were formulated:

> **H6a.** The privacy risk of using COVID-19 safety Apps has a direct negative impact on perceived security.

> **H6b.** The privacy risk of using COVID-19 safety Apps has a direct negative impact on perceived trust.

> **H6c.** The privacy risk of using COVID-19 safety Apps has a direct negative impact on performance expectancy.

Trust. Perceived security and trust positively affect behavioral intentions [Shin 2009b]. The effect of trust, as a unitary construct, on behavioral intention has gained notable support and was found to be the most significant predictor of behavioral intention [Chandra et al. 2010; Shin 2009b]. As digital technologies become ubiquitous trust supersedes the importance of traditional technology adoption factors such as perceived usefulness. Akin to Chandra et al., [Chandra et al. 2010], this study includes trust as a singular construct, which is likely to be critical due to the novelty of the COVID-19 safety systems and convoluted environment. Hence we hypothesize that:

H7a. Trust positively affects performance expectancy (i.e. usefulness) to use COVID-19 safety Apps.

H7b. Trust positively affects effort expectancy (i.e. ease of use) to use COVID-19 safety web Apps.

3.3 Items related to COVID-19 impact and safety measures

The COVID-19 pandemic had a significant social, economic and personal behavioral impact on citizens all over the world. Most countries in Europe were on complete lockdown during several weeks and months and many closed airports and borders to prevent the spread of the pandemic. After the lockdown COVID-19 measures were enforced in public spaces (e.g., use of masks, temperature screening, hand hygiene, etc.) in order to mitigate the risk of contagion. As introduced in Section 2, technology adoption models are inspired by the TRA, which argues that both the attitude toward an action and subjective norms have an impact on behavioral intention, and in turn affects how people perform an action [Ajzen et al. 1991]. Adapted from TRA and TAM, the UTAUT definition of attitude toward a behavior is *an individual's positive or negative feeling about performing the target behavior* [Venkatesh et al. 2003], while subjective norm refers to a *person's perception that most people who are important to them think they should or should not perform the behaviour in question* [Venkatesh et al. 2003]. Therefore we hypothesise that:

H8a. The extent to which someone is impacted by COVID-19 positively affects the intention to follow safety measures.

H9b. The willingness to follow COVID-19 safety measures positively affects intention to use [REDACTED] Apps.

In addition, a person's attitude toward a behavior is determined by her/his/their salient beliefs and evaluations and several studies report a strong relationship between security, safety and behavioural intentions [Khalilzadeh et al. 2017b; Slade et al. 2015]. Although trust and privacy risk have been found to significantly affect behavioral intention to use digital technologies, and in some of these studies trust has also been found to negatively affect perceptions of risk, the existing studies in this context have not yet specifically examined whether perceived risk plays a mediating role (e.g., [Lu et al. 2011]). As travelers are likely to perceive the COVID-19 safety measures as highly risky, it is likely that trust will play a major secondary role in behavioral intention than privacy risk, and instead, its role will be more important in reducing perceptions of risk. Therefore, given the wide applicability of the UTAUT we can anticipate that:

H9a. The willingness to follow COVID-19 safety measures positively and directly influences perceived security.

H8b. The extent to which someone is impacted by COVID-19 positively and directly predicts perceived trust.

4 METHODS

In accordance with the recommendation of a two-stage analytical procedure [Anderson and Gerbing 1988]. Confirmatory Factor Analysis (CFA) was used to test the measurement model's validity and reliability. Structural equation modeling (SEM) was used as a preferable technique to regression as it allows simultaneous analysis of all relationships through multiple regression, while also allowing for both observed and latent variables to be analyzed at the same time, and providing overall fit statistics [Mathieu and Taylor 2006; Tabachnick et al. 2007]. Confirmatory factor analysis was conducted in R (v 4.0.2) using Maximum Likelihood Estimation, which was then followed by path analysis of the structural relationships also conducted in R with structural equation modeling libraries (lavaan v. 0.6-7[Rosseel 2012] and semTools v. 0.5-3 [Jorgensen et al. 2020]. Moderation analysis[Hayes 2013] was also undertaken in R.

4.1 Participants and Procedures

The questionnaire was sent via email to 58,954 participants registered in the system and gave prior permission to be contacted via email. The questionnaire was sent at the end of August 2020 to travelers who already finalized their trips or stayed after the 14-day of the monitoring period (July and August). The email was sent in all the five different languages supported by the app and contained a general explanation of the study, the details of the privacy policy and data treatment and a link to a Google Forms survey. The questionnaire was translated into five languages corresponding to the supported idioms of the app according to the following breakdown: 36,930 (62.6%) in Portuguese (PT), 10,178 (17.3%) in English (EN), 6,575 (11.2%) in German (DE), 3,735 (6,3%) in French (FR) and finally 1,536 (2,6%) in Spanish (ES). In total, we collected data from 9,555 participants corresponding to overall participation of 16.2%, the participation was higher in DE (18.6%), PT (17.7%) and lower in FR (12.2%), EN (11.6%), and ES (11.4%).

In terms of the general demographics (N=9,555 - summary in Table 1) the sample consisted of a slightly higher proportion of women (52.0%) than men (47.0%) with 0.5% classifying themselves differently. There was a majority of Portuguese respondents (61.2%), followed by the major traditional tourism markets of [REDACTED] (13.7% German, 5.6% UK, 5.4% French, 3.4% Spanish, 1.3% Italian) and only a few other EU (6.3%), other non-EU (1.3%) and a minority of 1.8% from non-European nationalities. In terms of age groups young (<18 years old - 1.5%) and older people (>65 year old - 5.1%) where a minority when compared with segments of the adult population (18-25 years old - 32.7%, 18-25 years old, 33.5%, 36-49 years old, 27.0%). Finally, the sample was characterised with very high education levels with 70.4% holding a higher degree, 24.1% secondary education and only 2.9% with basic education. The questionnaire also gathered some data on frequency of travel which is harder to characterise because of the different possible combinations between tourists, locals and visitors. Nevertheless, surprisingly 39.0% of respondents said it was their first time in [REDACTED], almost half of respondents came regularly (49.3%) and 11.3% said they were local residents.

4.2 Participants Motivations and Sources of Influence for Travel

Two questions addressed the main motivations and sources of influence for travel. Among the motivations for the trip sun (20.3%), rest (19.8%), nature (18.3%), and family (15.6%) were ranked higher and followed by COVID-19 (14.8%). Culture, work and wellness were ranked much lower in terms of preference (6.4%, 3.4% and 1.4% respectively). In terms of nationality breakdown family ranked higher for Portuguese nationals, while COVID-19 was higher for German and Spanish nationals. In terms of travel frequency, COVID-19 was almost equally higher for local residents and first time visitors which suggests that some people choose to travel to the destination because of COVID-19. This is confirmed by the analysis of sources of influence with safety (31.6%) ranked first, followed by personal (30.7%) family (22.7%)

Table 1. Characteristics of Respondents

Demographic	Group	Frequency	Percentage
Gender	Woman	5019	52.5%
	Man	4493	47.0%
	Other	43	0.5%
Age	<18	142	1.5%
	18-35	3122	32.7%
	36-49	3203	33.5%
	50-65	2581	27.0%
	>65	484	5.1%
	NA	23	0.2%
Nationality	Portuguese (PT)	5847	61.2%
	German (DE)	1310	13.7%
	United Kingdom (UK)	532	5.6%
	France (FR)	516	5.4%
	Spain (ES)	328	3.4%
	Italian (IT)	125	1.3%
	Other EU	603	6.3%
	Other non-EU	125	1.3%
	Other (non European)	169	1.8%
Education	Basic	277	2.9%
	Secondary	2307	24.1%
	Degree	3686	38.6%
	Post-Grad	3035	31.8%
	NA	250	2.6

after much lower influence on media, tour/agencies and social media, 8.5%, 4.2% and 2.1% respectively. In terms of age motivations were not significantly different, although COVID-19 raised consistently from 10.9% from lower age groups (<18) to 19.0% in higher (>65). The same trend was not observed on safety in the sources of influence.

4.3 Measurement Model

The SEM assumptions were checked. Variables showed normal distribution based on a visual inspection of histograms and box plots. The residuals showed a normal distribution with no relationship between them and predictors [Flury et al. 1988]. The model's overall fit was very good, with all of the relevant goodness of fit indices higher than recommended thresholds of 0.9 for AGFI and 0.95 for other indexes [Bagozzi and Yi 1988; Etezadi-Amoli and Farhoomand 1996; Flury et al. 1988; Fornell and Larcker 1981]. The goodness of fit Index (GFI) is 0.95, the adjusted GCI (AGFI) is 0.93, the comparative fit index (CFI) is 0.96, the normative fit index (NFI) is 0.96 and the TLI 0.95. Similarly, there is no misfit evidence, with the Root Mean Square of Error Approximation (RMSEA) showing a very satisfactory level of 0.053, which compares favorably to the benchmarks by [Bagozzi and Yi 1988; Etezadi-Amoli and Farhoomand 1996; Flury et al. 1988; Fornell and Larcker 1981], who suggest that values of 0.06 or more reflect close fit. The standardized RMR was also very good, at 0.063, above the threshold (>0.06) for a good overall fit. X^2 for the model was significant, which is due to the large sample size (N=9555). Given a satisfactory measurement of the model's fit to the data, the initial measurement model was constructed to purify the measurement items, and to check the model fit, and validity and reliability of the measurement scales. Table 3 shows the results of the CFA. All of the loadings were significant at an alpha level of

Table 2. Validity Measures

Measure	Impact	Safety	PerfExp	EffExp	SocInf	FacCond	IntUse	Security	Privacy	Trust
alpha	0.741	0.732	0.855	0.920	0.729	0.918	0.701	0.909	0.910	0.852
CR	0.724	0.728	0.856	0.920	0.759	0.918	0.687	0.907	0.910	0.852
AVE	0.470	0.472	0.749	0.852	0.588	0.848	0.523	0.766	0.835	0.743

Note: constructs abbreviated as follows - COVID-19 Impact (Impact), Safety measures (Safety), Performance Expectancy (PerfExp), Effort Expectancy (EffExp), Social Influence (SocInf), Facilitating Conditions (FacCond), Behaviour Intention to Use (IntUse), Perceived Security (Security), Privacy Risk (Privacy), Perceived Trust (Trust) alpha: Cronbach alpha. CR: Composite reliability, AVE: Average Variance Extracted.

0.000, and the minimum loading was 0.55, with most factor loadings higher than 0.7, which indicates good convergent validity [Fornell and Larcker 1981]. Each item loaded significantly on its underlying construct (P < .001 in all cases). Therefore, all constructs in the model had adequate reliability and convergent validity. The convergent and discriminant validity of the model were examined measuring the reliability of each measure and each construct, and the average variance was extracted (AVE) for each construct. To examine discriminant validity, we compared the shared variance among constructs with the AVE from the individual constructs. The shared variance between constructs was lower than the AVE from the individual constructs, confirming discriminant validity (Table 2). The measurement model was also checked for composite reliability (CR=0.97), which indicated a high measurement reliability of our measurement model [Bagozzi and Yi 1988; Etezadi-Amoli and Farhoomand 1996; Flury et al. 1988; Fornell and Larcker 1981].

Given the complex relationships among the model factors, what should be considered is their moderating effect on other variables. It can be reasonably inferred that there are unexpected moderating relationships in the model. In summary, the measurement model demonstrated adequate reliability, convergent validity, and discriminant validity.

4.4 Structural Model

Since the overall fit of the measurement model was good and there was no misfit evidence, we used structural equation modeling to analyze the data. Structural modeling evaluates whether the data fits the theoretical measurement model. This study extends the proposed research model to include two new constructs (COVID-19 impact and safety measures) and new interactions between these constructs and security, trust and behavioural intention to use. To test the structural relationships we estimated the hypothesized causal paths (see Figure 2 and Table 4). All hypotheses except (**H6b**) were supported at P<0.000.

The coefficient of determination (R^2) was calculated for the constructs of the measurement model (see Table 3). This coefficient, also known as Squared Multiple Correlations (SMC), varies between 0 and 1, is an indication of a model's explanatory power and predictive accuracy [Flury et al. 1988]. It shows the portion of the variance of the endogenous variable which is explained by the exogenous variables. The R^2 of the behavioral intention was the highest at 0.903, which showed that the proposed model explained a substantial amount of the variance of the dependent variable. The lowest amount of R^2 in the model belonged to COVID-19 safety measures (R^2=0.446), followed by trust (R^2=0.510) and security (R^2=0.521), due to their close proximity to independent variables and the nature of the constructs, which are rooted in a person's belief system. The coefficient for performance and effort expectancy were also high at R^2=0.757 and R^2=0.628, respectively, which is consistent with previous results [Khalilzadeh et al. 2017b].

Table 3. The measurement model

Construct	Item	Alpha	StError	Z-Value	P-value
Impact COVID-19 (Impact)	Impact_1	0.75			
Alpha = 0.74	Impact_2	0.76	0.015	58.294	0.000
	Impact_3	0.55	0.016	46.660	0.000
Facilitating conditions (FacCon)					
Alpha = 0.92	FacCon_1	0.90			
	FacCon_2	0.94	0.009	117.527	0.000
Privacy Risk (Privacy)					
Alpha = 0.91	Privacy_1	0.92			
	Privacy_2	0.90	0.014	69.501	0.000
Social Influence (SocInf)					
Alpha = 0.60	SocInfl_1	0.65			
	SocInfl_2	0.61	0.024	44.3131	0.000
Safety COVID-19 (Safety)					
Alpha = 0.73	Safety_1	0.74			
R^2 = 0.446	Safety_2	0.62	0.021	50.066	0.000
	Safety_3	0.72	0.021	55.529	0.000
Effort expectancy (EffExp)					
Alpha = 0.92	EffExp_1	0.90			
R^2 = 0.628	EffExp_2	0.93	0.007	136.111	0.000
Performance Expectancy (PerfExp)					
Alpha = 0.85	PerfExp_1	0.89			
R^2 = 0.757	PerfExp_2	0.85	0.010	105.849	0.000
Security					
Alpha = 0.91	Security_1	0.84			
R^2 = 0.521	Security_2	0.84	0.010	108.731	0.000
	Security_3	0.92	0.008	126.270	0.000
Trust					
Alpha = 0.85	Trust_1	0.79			
R^2 = 0.510	Trust_2	0.94	0.014	79.631	0.000
Behavioral Intention (IntUse)					
Alpha = 0.70	IntUse_1	0.65			
R^2 = 0.903	IntUse_2	0.82	0.015	66.639	0.000

4.5 Moderator Effects

To investigate demographic moderator effects, moderation analysis was done using the split sample approach [Ha et al. 2007; Yol et al. 2006]. This approach uses a pre-established level of a moderator, which emerges naturally from the data and cannot be modified by the study. For example, a person's nationality, gender, or age naturally form different moderator levels. We tested the moderator effects of gender (W/M), age (divided into two groups <36 and ≥36), education (basic/secondary and higher education) and also of a proxy of social capital[Adler and Kwon 2002; Holt 2008], which was calculated from a combination of nationality, residence and regularity of travel. We classified local residents as high social capital, regular travelers or first-time nationals visitors as medium and first-time international visitors as low social capital. The moderating effects of these variables were tested by comparing between the different groups, the path coefficients produced for each moderator after testing for measurement invariance using X^2 difference tests, and

Table 4. Summary of hypothesis tests

Hypothesis	B	StError	Z-value	P-value	Beta	Supported
H1a. FacCond → IntUse	0.229	0.01	23.97	0.000	0.251	Yes ***
H1b. FacCond → EffExp	0.494	0.011	43.088	0.000	0.460	Yes ***
H2a. SocInf → EffExp	0.482	0.019	25.374	0.000	0.394	Yes ***
H2b. SocInf → Security	0.677	0.018	38.13	0.000	0.556	Yes ***
H2c. SocInf → PerfExp	0.511	0.021	24.199	0.000	0.438	Yes ***
H3. PerfExp → IntUse	0.545	0.013	42.502	0.000	0.611	Yes ***
H4. EffExp → PerfExp	0.418	0.013	32.102	0.000	0.438	Yes ***
H5a. Security → Trust	0.667	0.012	54.268	0.000	0.703	Yes ***
H5b. Security → IntUse	0.147	0.009	15.922	0.000	0.172	Yes ***
H6a. Privacy → Security	-0.254	0.009	-29.801	0.000	-0.301	Yes ***
H6b. Privacy → Trust	0.012	0.008	1.528	0.127	0.015	No
H6c. Privacy → PerfExp	-0.078	0.007	-11.588	0.000	-0.096	Yes ***
H7a. Trust → PerfExp	0.080	0.01	8.376	0.000	0.079	Yes ***
H7b. Trust → EffExpe	0.109	0.01	10.408	0.000	0.103	Yes ***
H8a. Impact → Safety	0.461	0.01	44.212	0.000	0.668	Yes ***
H8b. Impact → Trust	0.045	0.009	4.781	0.000	0.047	Yes ***
H9a. Safety → Security	0.212	0.015	14.258	0.000	0.148	Yes ***
H9b. Safety → IntUse	0.196	0.011	17.152	0.000	0.159	Yes ***

the fit indexes. Invariance was tested for factor structure, loadings, residuals, and means. The model supported good evidence of measurement invariance at P<0.001 significance. The results of this analysis are presented in Table 5.

5 RESULTS AND DISCUSSION

Results from the study demonstrates that our research model explains 90.3% of the [REDACTED] intention to use, compared to previous empirical results [Baptista and Oliveira 2015; Khalilzadeh et al. 2017b; Min et al. 2008] which explain between 70% and 87% of variance. Our model has a stronger explanatory and predictive power, including new constructs related to the safety and personal impact of COVID-19, hence shaping a more complex network of interrelated causal relationships, which are not present in the original UTAUT and UTAUT2 models. This idea, borrowed from [Khalilzadeh et al. 2017b] which extends the UTAUT and UTAUT2 models with the inclusion of other influential constructs, increases the explicablility of the model while keeping parsimony. In line with some authors (e.g. [Netemeyer et al. 2003; Watson and Clark 1997]) we reduced the number of items in some constructs while preserving reliability, thus condensing the scale even further than previous research [Khalilzadeh et al. 2017b]. According to the recommendations in Worthington and Whittaker [Worthington and Whittaker 2006] we were able to retain factors with only two items retaining validity, reliability, and correlation.

The inclusion of the COVID-19 impact construct enabled us to understand if there was a significant but weak impact on trust (**H8.b**), especially when considering the moderation effects. Our results show that for some groups (men, young people and participants with some social capital on the premises), the COVID-19 impact on the users personal context is not significantly related to their trust in the technology. The same weak link between influence of trust on effort expectancy, is illuminated on the group that has social capital on the premises, according to **H7.b**. On the contrary the role of COVID-19 safety measures on security (**H9.a**) and behavioural intention (**H9.b**) retains significance regardless of moderator variables. The affecting of COVID-19 safety on security (**H9.a**) decreases with old people and

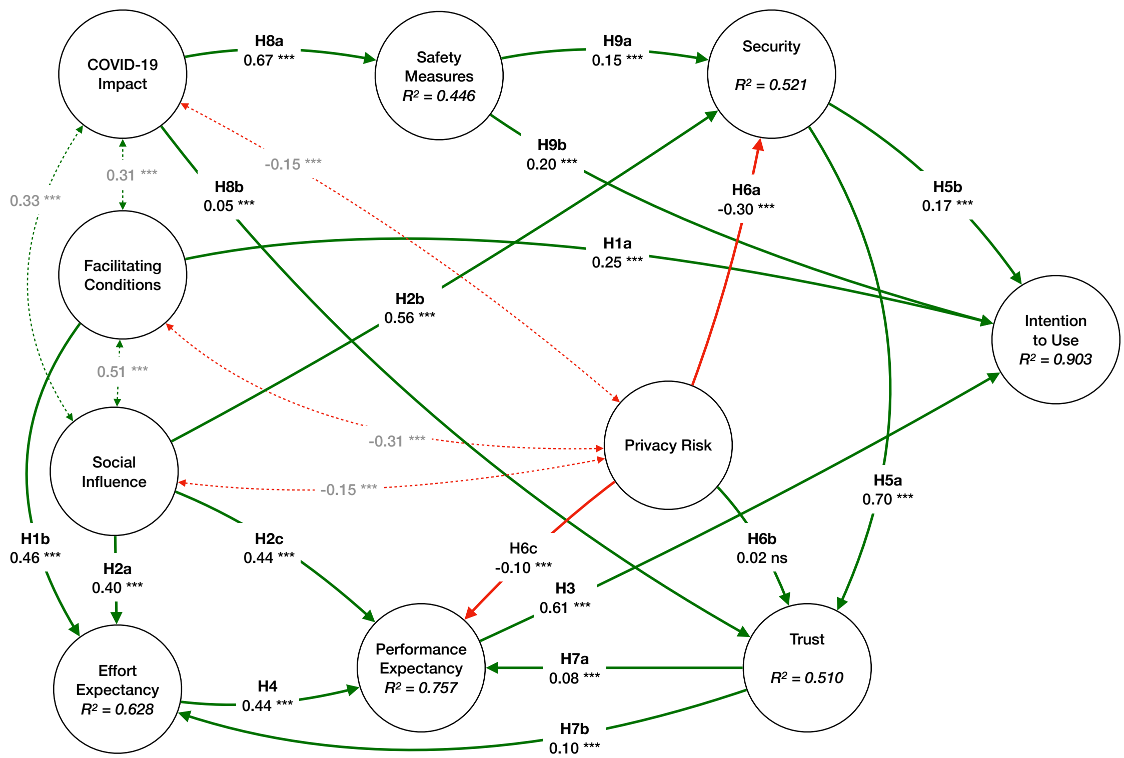

Fig. 2. Results of the Research Model

varies between groups that retain different social capital at the destination of arrival. Conversely, the role of COVID-19 safety on intention to use (**H9.b**) decreases on young people and people with higher social capital. Also, the study results show several significant relationships between COVID-19 impact and several other constructs which we did not hypothesize. These relationships show stronger ties than our initial hypothesis on COVID-19 impact and trust (see Figure 2). Overall, the present results demonstrate that COVID-19 impact would be affected by facilitating conditions and social influence and it would influence privacy risk. Further research could highlight these effects. Interesting is also a negative influence of COVID-19 impact on privacy which we did not hypothesize.

Contrary to other empirical studies on mobile payments [Khalilzadeh et al. 2017b] our results show a higher role of social influence on security and performance expectancy. On the contrary, show a lower impact of privacy risk on performance expectancy and trust. While for mobile payments 67% of the variance of the security construct is explained by risk perception (**H6.a**) and social influence (**H2.b**) in our study the variance explained is lower (52%) but social influence contributes more than privacy (**H6.a**) and safety (**H9.a**) respectively. Like [Khalilzadeh et al. 2017b] our results confirm that users have serious concerns about their privacy and the performance of [REDACTED] systems. However, the impact of privacy is substantially reduced which could be related to users compliance and acceptance of safety measures in general.

Table 5. Results of Moderator Effects

Hyp.	Gender		Age		Education		Social Capital		
	Woman	Man	<36	≥36	BasSec	Degree	Low	Med	High
H1a	0.25 ***	0.23 ***	0.26 ***	0.25 ***	0.27 ***	0.25 ***	0.24 ***	0.24 ***	0.40 ↑↑***
H1b.	0.43 ***	0.49 ***	0.45 ***	0.47 ***	0.51 ↑***	0.45 ***	0.49 ***	0.43 ***	0.52 ↑***
H2a.	0.42 ***	0.37 ***	0.38 ***	0.41 ***	0.36 ***	0.40 ***	0.36 ***	0.41 ***	0.40 ***
H2b.	0.60 ***	0.50 ↓***	0.51 ***	0.60 ***	0.62 ↑***	0.53 ***	0.52 ***	0.57 ***	0.57 ***
H2c.	0.44 ***	0.48 ***	0.41 ***	0.47 ***	0.43 ***	0.45 ***	0.39 ↓***	0.43 ***	0.60 ↑↑***
H3.	0.61 ***	0.62 ***	0.61 ***	0.61 ***	0.59 ***	0.61 ***	0.63 ***	0.63 ***	0.42 ↓***
H4.	0.43 ***	0.43 ***	0.46 ***	0.41 ***	0.48 ***	0.42 ***	0.48 ***	0.45 ***	0.24 ↓***
H5a.	0.68 ***	0.74 ***	0.71 ***	0.70 ***	0.71 ***	0.70 ***	0.67 ***	0.72 ***	0.71 ***
H5b.	0.16 ***	0.19 ↑***	0.18 ***	0.16 ***	0.18 ***	0.17 ***	0.20 ↑***	0.13 ↓***	0.24 ↑↑***
H6a.	-0.29 ***	-0.32 ***	-0.34 ↑***	-0.27 ↓***	-0.22 ↓***	-0.33 ***	-0.29 ***	-0.32 ***	-0.26 ↓***
H6b.	0.02 ns	0.01 ↓ns	0 ↓ns	0.03 ↑↑ns	0.01 ↓ns	0.02 ns	-0.02 ↓ns	0.04 ↑↑*	0.02 ↑↑ns
H6c.	-0.11 ↑***	-0.07 ↓***	-0.09 ***	-0.11 ↑***	-0.08 ↓***	-0.10 ***	-0.10 ***	-0.10 ***	-0.08 ↓**
H7a.	0.09 ↑***	0.05 ↓**	0.07 ***	0.08 ***	0.05 ↓**	0.09 ↑***	0.09 ↑***	0.07 ↓***	0.07 *
H7b.	0.10 ***	0.10 ***	0.12 ↑***	0.08 ↓***	0.09 ↓***	0.10 ***	0.10 ***	0.13 ↑↑***	0.01 ↓ns
H8a.	0.66 ***	0.67 ***	0.63 ***	0.70 ***	0.65 ***	0.68 ***	0.63 ***	0.65 ***	0.78 ↑***
H8b.	0.06 ↑↑***	0.02 ↓ns	0.03 ↓ns	0.06 ↑↑***	0.05 *	0.05 ***	0.04 ↓*	0.05 ↑***	0.04 ↓ns
H9a.	0.14 ***	0.15 ***	0.18 ↑***	0.11 ↓***	0.14 ***	0.15 ***	0.18 ↑***	0.12 ↓***	0.17 ↑***
H9b.	0.15 ***	0.18 ↑***	0.14 ↓***	0.17 ***	0.16 ***	0.17 ***	0.17 ***	0.16 ***	0.08 ↓**

ns - not significant, *, ** and *** - significant at $p<0.05$, $p<0.01$ and $p<0.000$. ↑ and ↓ highlight significant changes in Z-value.

In terms of privacy, and trust, our results differ significantly from previous studies [Khalilzadeh et al. 2017b; Shin 2009b]. The negative influence of risk on performance expectancy (**H6.c**) is lower (from -0.25 to -0.10) and we could not confirm the hypothesis that privacy negatively impacts trust (**H6.b**). We also observed negative correlations between perceived privacy and other constructs that we did not hypothesize (COVID-19 impact, facilitating conditions and social influence). While some of these effects are reported in other studies on security and privacy [Khalilzadeh et al. 2017a; Mandrik and Bao 2005; Shin 2009a], the effect of COVID-19 impact on privacy should be further researched. Also, the direct impact of social influence on security (**H2.b**) is significant and robust and much higher than previous empirical research.

Apart from COVID-19 impact which is a new construct introduced here, security and privacy have a reduced impact on trust as well. Our results suggest that the impact of COVID-19 potentially affects more privacy than trust (one of the unexpected results). Therefore working on user's privacy concerns is crucial for other similar COVID-19 systems since privacy not only influences perceived security, but affects users' trust toward these apps. Privacy also emerged as a more interrelated construct influencing performance expectancy and security but also showing significant relationships with COVID-19 impact, facilitating conditions and social influence. This clearly indicates that privacy needs to be addressed carefully while designing these apps and its impact is not mitigated by COVID-19 impact or users willing to follow safety measures. Overall the results show that performance expectancy is the strongest predictor of behaviour intention to use (H3), which suggests that usability and ease of use are still crucial in designing COVID-19 systems. Effort expectancy is followed by facilitating conditions, COVID-19 safety measures, and finally, security. Our results suggest that willingness to follow COVID-19 safety measures (**H9.b**) is a stronger predictor of usage behaviour than security (**H5.b**). This influence (see **H9.a** on Table 5) is stronger on young people and varies with different levels of social capital. These results suggest that special attention should be paid to personalise the application for these groups, when designing COVID-19 apps.

Finally from all the moderator effects analysed, clearly our indirect measure of social capital was the one showing more differences across the hypothesis. The predictors of intention to use are significantly stronger for this group than any other (see Table 5) which suggests that designing [REDACTED] app targeting the local context will predict a significantly higher adoption. Another relevant trend in the moderation of our hypothesis, is the education level of the users, with lower education leading to less concerns about privacy (**H2.b**) and security (**H6.a**) but also less importance given to trust on performance (**H7.a**) and effort (**H7.b**) expectancy (also of facilitating conditions).

5.1 Limitations of the study.

Despite its contributions, this study is not without limitations, and these limitations provide fruitful avenues for further research discussed in the next section. To the best of our knowledge this is one of the first studies to take a comprehensive look at acceptance of COVID-19 safety apps by incorporating multidisciplinary constructs. However several limitations affect the scope of our results. Although we had a significant sample of several European nationalities and cultures there is still a bias towards a specific nationality. To understand the effect of this bias we analysed the moderator effects of nationality in our model which showed the same evidence of invariance's measurement when compared to other moderators (gender, age, etc.). However, we did not record ethnicity and cultural differences in our sample. Previous work shows a significant impact of cultural diversity on social influence, usefulness and behaviour intention [Im et al. 2011; Schepers and Wetzels 2007].

Another significant limitation of our study is that it involved people who traveled during the pandemic period. Given the mobility restrictions in place, the drastic reductions in travel, and the pandemic's economic consequences, our sample could be biased. The effect of such characteristics limits the generalizability of this research since the sample employed in this study could express different perceptions towards COVID-19 safety apps when compared to the general public. Although the experimental design helps reduce the impact of common method bias (CMB), which we encountered in this research, in particular for the new COVID-19 constructs. Also, combining the survey with outcome variables measured separately and more objectively (e. g. frequency of usage/reporting) will reveal useful results less prone to measurement and method biases.

Despite the limitations mentioned above, we believe that this paper furthers our understanding of the intention to use mobile apps and those associated with safety concerns like COVID-19, and will provide a useful set of design guidelines and recommendations for the provision of mobile services with safety, security and trust concerns to different user groups.

6 CONCLUSIONS AND FUTURE WORKS

The COVID-19 global pandemic should be a stimulus to re-examine how we approach existing challenges (e.g., social inequalities, sustainable tourism) and study some aspects of human behavior, such as our relationship with technology and its role during emergencies, for instance, in tourist destinations. Against the backdrop of the COVID-19 pandemic, this paper provided the first detailed research study on the adoption of a mobile safety applications, designed to mitigate the pandemic's consequences. While we expect that some of our findings will not generalize beyond COVID-19 safety apps, others provide early insight into the increasingly important role of safety, security, privacy, and trust in mobile app adoption and usage. This research aimed to improve the explanatory and predictive power of technology use and adoption research models in the COVID-19 context. We further investigated the differences in determinants of COVID-19 systems' acceptance in a reasonably diverse European demographic context.

The results from this work make apparent how privacy is a fundamental aspect when dealing with users perceptions of COVID-19 related systems. Indeed privacy influences essential aspects, such as security and performance expectancy. Moreover, privacy concerns still stand, even when the impact of COVID-19 on the personal context of the user increases, showing the importance of privacy even in an emergency context. More general, the impact of COVID-19 on people influences positively the adoption of safety measures (e.g., use of masks, temperature screening, hand hygiene). Moreover, users that are more willing to follow COVID-19 safety measures are also more prone to use the COVID-19 safety App.

Finally, this work's fundamental contribution is an increased understanding of the vital role of security, privacy, and trust in usage intention of safety applications. While security holds a strong direct and indirect effect on the model's fundamental construct, it emerges as equally important to safety concerns. Furthermore, our research shows an increased role of social influence on security, security on trust, and trust on performance expectancy compared to previous research that inspired our model. Conversely, we observe a reduced negative impact of privacy on security and a rejection of the hypothesis of the positive role of privacy on trust, compared to previous research. Together with a more complex influence of privacy on the overall model, these are significant results for future research implications.

The recognition of the moderating role of demographics among the factors is particularly important in this study. The intention to use COVID-19 safety apps is different among demographic groups. Notably, the impact of social influence varies with gender, age, education, and social capital. We also observe a significant change in the role of COVID-19 impact over demographics. Finally, high indicators of users' social capital have a tremendous effect on intention to use the COVID-19 safety systems, which suggests that localized version of these apps are likely to be more successful than general ones.

Anticipating user behavior is notoriously tricky, especially under unprecedented circumstances. An obvious avenue for future research would be to apply our measurement model to a longitudinal approach on a more comprehensive technology such as digital contact-tracing. Such a study will be able to sample a more extensive and more culturally diverse user base. This may be achieved using stratified sampling or a quota sampling method to ensure a specific demographic distribution. Our research model's generalized application would require a global data collection process for more thorough validation. Longitudinal research would also allow the examination of change in the importance of constructs over time, mainly to see if the effect of safety, privacy, and trust on behavioral intention over time becomes significant across the board. The results of this study should promote future research. For example, this model's applicability to other contexts where safety plays an important role, such as healthcare, and where privacy is a major concern (e.g., surveillance and social networking). Future research might consider adding other antecedents of behavioral intention.

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