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Does Age Matter?
The Influence of Age on Citizen Acceptance of a Proximity-Tracing Application in France

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ABSTRACT

Previous literature has suggested that age indirectly influences the intention to adopt an information technology, and notably a m-health application. However, few studies have investigated this link. Voluntarily proximity tracing applications (PTA) are the first mobile applications to be implemented nationwide for population health issues. The paper investigates the effect of age on the antecedents (perceived ease of use and usefulness, trust, and privacy control) of the intention to adopt a PTA. The model is tested on a representative sample of 1000 French citizens. All variables were measured using scales drawn from the extant literature and adapted to suit the context. Age was measured as a continuous variable. The authors found that age directly influences privacy control, but it has no direct effect on trust nor on the perceived ease of use or the perceived usefulness of a PTA. The results show that age is not a direct determinant of the antecedents of behavioral intention except of privacy control.

KEYWORDS

Age, Privacy, Technology Acceptance, Tracing Application, Trust

INTRODUCTION

User acceptance of IT in healthcare has mainly been studied from the point of view of healthcare professionals (Abolfotouh et al., 2019; Aggelidis & Chatzoglou, 2009; Chau & Hu, 2002; Chen & Tseng, 2012; Vitari & Ologeanu-Taddei, 2018). However, the rise of mobile health applications (m-health) has also highlighted the importance of citizen IT acceptance. Voluntarily proximity tracing applications (PTA) are the first mobile applications implemented for health issues in the general population without targeting a specific age group or disease. The acceptability and adoption of these "apps" has been investigated by an increasing number of scholars (eg., Touzani et al., 2021; Walrave et al., 2021; Wyl et al., 2021; Fox et al., 2021; Janssen & van der Voort, 2020) and privacy concerns have been identified as significant barriers (Fox et al., 2021; Janssen & van der Voort, 2020; Wyl et al., 2021). While the world's aging population has driven governments to implement healthy aging strategies (World Health Organization, 2015) including m-health (Kampmeijer et al., 2016; Parker et al., 2013), little is known about the effect of age on m-health adoption and especially on PTA.

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There is also no consensus as to the use of age ranges and categories (Fox et al., 2021). To date, for reasons of convenience and without any theoretical or empirical ground, health organizations and scholars have considered such categories as "older adults". For example, the World Health Organization (2015) considers the age of 60 to be a threshold age as it is related to accelerated losses in hearing, sight and mobility, as well as increased risk of heart disease, stroke, chronic respiratory disorders, cancer and dementia. Fox et al. (2021) defend the definition of "older adults" as those aged over 50 as this age range encompasses individuals from the Baby Boomer generation, is frequently used by research centers such as Statistica and PEW, and prior studies have found that individuals in this age range tend to have limited technology usage. In addition, while Fox et al. (2021) chose to use the conventional categories of 50-54, 50-59, 60-64, 65-69 and 70+ in their study of citizen acceptance of contact tracing mobile applications, neither these ranges nor the "older adults" category are supported by evidenced differences in the psychological or sociological characteristics of those age categories. Similarly, Trkman et al. (2021) chose similar conventional categories (equal categories of 6 years from 18 to 74 years) to assess the impact of age on the intention to use a PTA, with no theoretical justification for this categorisation. As a result, the arbitrary choice of age groups tends to limit the cross-comparison of results (Zhou et al., 2014).

Beyond the weak arguments supporting different categorisations, another issue is that the relationship between categories and technology adoption may evolve as experience with the technologies themselves changes. For example, most members of the current 60+ and 50+ age groups may have already experienced mobile technologies in their professional and private lives while limited technology usage was commonly found for the 50+ groups a decade ago. In other words, the age effect evolves overtime. These changes are likely related to generational differences (Smola & Sutton, 2002). For example, we can expect that when the Generation Z (born after 1985-1990)[1], characterized by more "sophisticated technological skills" (Margaryan et al., 2011) than previous generations, reaches 50, the relationship between this age category and technology adoption will be significantly different to what it is today for the current 50+ category. Thus, the extant literature that has established an influence of age on technology adoption (e.g., Morris & Venkatesh, 2000) needs to be regularly updated.

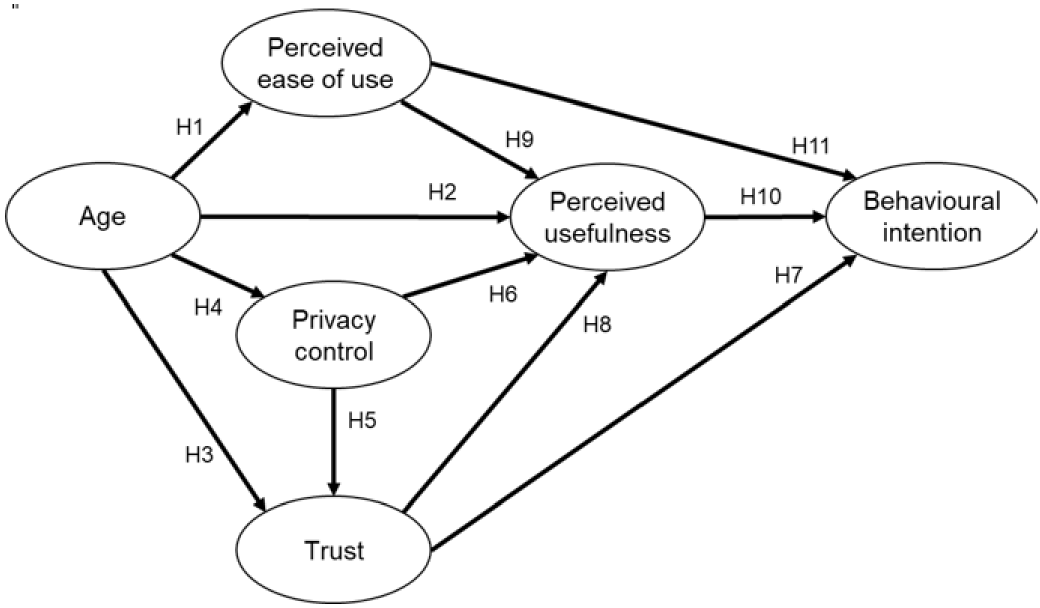
Given these findings, we investigate whether age differences influence citizen acceptance of PTAs and formulate the following research question: "To what extent does age influence the intention to use a Coronavirus tracing app?" We suggest assessing age as a continuous variable in order to avoid the issues related to the age categories presented above.

To answer the research question, the authors develop a research model (Figure 1) and test it empirically. The model is based on the technology acceptance model (TAM) (Davis, 1989). The TAM has been widely used to assess users' IT acceptance, and notably presents the advantage of being parsimonious (Bagozzi, 2007; Diop et al., 2019). According to the TAM, two main antecedents - perceived ease of use (PEOU) and perceived usefulness (PU) - influence the behavioural intention (BI) and actual use of new IT. We argue that age influences PEOU and PU of m-health apps. Recently, researchers have also highlighted the influence of trust (TRUST) and privacy control (PRICT) on user acceptance of online services (McCloskey, 2006) and in particular personal health record (PHR) systems (Li et al., 2014). We advance that age also influences TRUST and PRICT.

CONCEPTUAL MODEL

As presented above, several researchers have advanced that older citizens use IT less, especially mobile applications and are therefore less skilled in their use of IT. McCloskey (2006) and Zhou et al. (2014) have shown that age negatively impacts both PEOU and PU.

Figure 1. Conceptual model



Therefore, we propose the following hypotheses:

H1. Age is negatively related to PEOU of a PTA.
H2. Age is negatively related to PU of a PTA.

Several researchers have argued that older citizens are less capable of or less willing to adopt m-health technologies due to privacy concerns and low trust beliefs (Fischer et al., 2014; Fox & Connolly, 2018; Joinson et al., 2010; Or et al., 2011). In their study of m-health, Fox & Connolly (2018) showed that the privacy concerns and trust beliefs of older individuals' directly influenced adoption intentions to use a mobile app. However, their study could not conclude that there was an age effect as it was only conducted on older adults defined as over 50. Age has been also been found to explain that privacy concerns act as a barrier to usage among older citizens (Fischer et al., 2014).

Therefore, we propose the following hypotheses:

H3. Age is negatively related to TRUST in a PTA.
H4. Age is negatively related to PRICT for a PTA.

Privacy concerns data collection, secondary use, ownership, accuracy and access (Conger et al., 2012; Hauff & Nilsson, 2021). The data collection and analysis capabilities of new IT as well as the online environment also create new risks for individual privacy (Belanger et al., 2002; Belanger & Xu, 2015). Privacy concerns can affect an individual's willingness to disclose information and adopt a new technology (Bélanger & Crossler, 2011; Dinev et al., 2015). These concerns are particularly acute in healthcare because of the sensitivity of personal data (Sajid & Abbas, 2016). Privacy concerns have been found to be a barrier for PTA acceptance and intention to use (Zimmermann et al., 2021) and as a barrier to m-health (Fischer et al., 2014; Guo et al., 2013; Sun et al., 2013) and PTA adoption (Fox et al., 2021) among older adults. While the concept of privacy concerns remains quite broad, perceived privacy control is more narrowly focused on an individual's assessment of their perceived level of control over the disclosure and subsequent use of personal information (Li et al., 2014). If individuals feel that they control the disclosure and use of their health information, they may more favorably evaluate the benefits and privacy risks associated with using a mobile health app (Li et al., 2014). High perceived privacy control may indicate that the healthcare mobile app provider is likely to behave in their interests, leading to positive perceptions about the app (Li et al., 2014) including trust beliefs and behavioural intentions (Hassandoust et al., 2021). Moreover, Li et al. (2014) has shown in the context of PHR that privacy control positively influences PU.

Therefore, we propose the following hypotheses:

H5. PRICT is positively related to TRUST in a PTA.
H6. PRICT is positively related to PU of a PTA.

Scholars have also found that TRUST influences both BI (Benbasat & Wang, 2005; Fang et al., 2014; Gefen et al., 2003; Kim & Koo, 2016; Liu & Goodhue, 2012; McCloskey, 2006; Suh & Han, 2003; Sun et al., 2013; Vance et al., 2008) and PU (Benbasat & Wang, 2005; Gefen et al., 2003; McCloskey, 2006; Pavlou, 2003) in various contexts including healthcare (Li et al., 2014). Trust, in relation to privacy has notably been highlighted as a major barrier for the adoption of m-health (Klein, 2009).

Therefore, we propose the following hypotheses:

H7. TRUST in a PTA is positively related to BI.
H8. TRUST in a PTA is positively related to PU.

Finally, the authors add the core TAM hypotheses (Davis, 1989), which have also been validated in a healthcare context for m-health (Zhou et al., 2014).

H9. PEOU in a PTA is positively related to PU.
H10. PU of a PTA is positively related to BI.
H11. PEOU of a PTA is positively related to BI.

Table 1 summarizes all eleven proposed hypotheses leading this study.

METHODS

An online questionnaire was administered by a leading market research provider (Panelabs) to test the model. Each variable was measured using a scale previously validated in the literature and each question was answered using a seven-point Likert scale, with 1 indicating "strongly disagree" and 5 indicating "strongly agree". A pilot test was conducted with ten individuals by asking the participants whether any sentences were difficult to understand. The survey measured the constructs of the model related to the French PTA named Stop Covid.

The Stop Covid Proximity Tracing Application

The Stop Covid application was designed by a consortium of French companies managed by the National Institute for Research in Computer Science and Automation (INRIA). Launched in June 2020, the app was available for Android and iOS compatible telephones, was free to download and used a wireless Bluetooth protocol. When the app identified a nearby user who also had the software installed and activated, user codes were exchanged via Bluetooth. The codes changed regularly to ensure user anonymity. If a person tested positive for the virus, they scanned the QR code provided on their test results, and the information was transmitted to a centralized server. An alert would then be sent to anyone who had been within one meter of the infected person for more than 15 minutes

Table 1. Hypotheses Leading this Study

Hypothesized Relationships	
H1	Age is negatively related to PEOU of a PTA.
H2	Age is negatively related to PU of a PTA.
H3	Age is negatively related to TRUST in a PTA.
H4	Age is negatively related to PRICT considering PTA.
H5	PRICT is positively related to TRUST in a PTA.
H6	PRICT is positively related to PU of a PTA.
H7	TRUST in a PTA is positively related to BI.
H8	TRUST in a PTA is positively related to PU.
H9	PEOU of a PTA is positively related to PU.
H10	PU of a PTA is positively related to BI.
H11	PEOU of a PTA is positively related to BI.

during the previous two weeks. Over the six months following its launch, the Stop Covid app had been downloaded 2.3 million times, representing around 3% of the French population and was widely considered a failure.

The Survey Instrument

The questionnaire was administrated to a representative sample of 1019 individuals from the French population of over 20 years of age that was quota-controlled according to gender, age, geographic area and occupation to ensure that it was representative. The quotas were established according to demographic data provided by the French Institute of Statistics and Economic Studies (INSEE). Accordingly, the sample covered individuals that had installed or had chosen not to install the PTA.

Table 2. Demographic Characteristics of the Sample (n=1019)

		Percent
Sex	Female	52.6
	Male	47.4
Work	Self-employed workers (e.g., farmers, traderperson)	4.5
	Executives, intellectual and liberal professions	10.9
	Intermediate professions, middle management	15.2
	Employees, workers	29.4
	Retirees	29
	Other	11.0
Age	Average (standard deviation)	49.1 (16.2)
	1st quartile	35
	2nd quartile	50
	3rd quartile	65
	Min - Max	20-85

The PEOU construct was only measured for respondents that had already installed the PTA. Table 2 displays the principal demographic characteristics of the sample.

All variables were measured using scales drawn from prior literature and adapted to suit the context. The age variable was a self-reported quantitative value. The fours items used to measure privacy control were based on Li et al. (2014). Perceived usefulness was also measured using six items taken from Li et al. (2014) pertaining to the benefits expected to accrue from the use of the application. Perceived ease of use was adapted from Lai & Li (2005). Two items used to measure behavioural intention were taken from Venkatesh et al. (2016). The two questions used to measure trust were adapted from Venkatesh et al. (2016). All items used in this study, summarized in Table 3, were adjusted to the context of PTA adoption.

Table 3. Latent variables and items used in the study

Latent variable	Label	Item
Privacy control	PRICT1 PRICT2 PRICT3 PRICT4	If I use StopCovid I believe I have control over who can access my personal health information stored in StopCovid. If I use StopCovid I think I have control over what my personal health information in StopCovid is shared with other parties such as my healthcare providers. If I use StopCovid I believe I have control over how my personal health information is used by the government though StopCovid. If I use StopCovid I believe I can control my personal health information provided to StopCovid.
Trust	TRUST1 TRUST2	I believe that StopCovid would act in my best interest. I believe that StopCovid perform their roles very well
Perceived ease of use	PEOU1 PEOU2 PEOU3	Learning to use StopCovid is easy for me. It is easy to use StopCovid to record/visualize data. Overall, I believe StopCovid is easy to use.
Perceived usefulness	PU1 PU2 PU3 PU4 PU5 PU6	Using StopCovid would improve my access to my health information. Using StopCovid would improve my communication with physicians. Using StopCovid would improve my ability to manage my health. Using StopCovid would improve the quality of my healthcare. I would manage my health more effectively using StopCovid. Using StopCovid would improve the quality of healthcare for all
Behavioural intention	BI1 BI2	I intend to use StopCovid in the next four months. I plan to use StopCovid in the next four months.

Data Analysis

Structured equation modelling was used to test the research model, and in particular the variance based partial least squares approach. SmartPLS 3.0 software (Ringle et al., 2015) was employed to estimate the model and the hypothesized relationships. This was a two-step process. Firstly, the discriminant and convergent validity of the measurement model was assessed. Secondly, the structural model was examined to test the hypothesized relationships. The study applied nonparametric bootstrapping (Chin, 2010; Efron & Tibshirani, 1994) with 5000 replications to compute the standard errors of the estimates (Hair et al., 2016) and a path weighting scheme was used to estimate the structural model. Pairwise deletion was used to manage the missing data for the PEOU variable (Hair et al., 2016).

RESULTS

Measurement Model

Reliability and validity analyses were first conducted to evaluate the quality of the measures used. The Cronbach alpha and composite reliability statistics that were computed to evaluate the internal consistency reliability for each construct are presented in Table 4. All values are above the recommended acceptable level of 0.70 (Hair et al., 2016).

Table 4. Results of the measurement model for the reflective constructs

Latent variable	Label	Indicator reliability	AVE	Composite reliability	Cronbach's alpha	HTMT criterion
Rule of thumb		Loading > 0.7	> 0.5	0.7 - 0.95	0.7 - 0.95	HTMT interval does not include 1
Privacy control	PRICT1 PRICT2 PRICT3 PRICT4	0.80 0.91 0.90 0.89	0.77	0.93	0.90	Yes
Trust	TRUST1 TRUST2	0.93 0.93	0.87	0.93	0.85	Yes
Perceived ease of use	PEOU1 PEOU2 PEOU3	0.90 0.91 0.94	0.84	0.94	0.90	Yes
Perceived usefulness	PU1 PU2 PU3 PU4 PU5 PU6	0.89 0.91 0.94 0.93 0.92 0.89	0.84	0.97	0.96	Yes
Behavioural intention	BI1 BI2	0.99 0.99	0.98	0.99	0.98	Yes

The outer loadings of each individual item and the average variance extracted (AVE) were inspected to assess the convergent validity of each construct. As all individual item loadings on their respective constructs are above 0.7 and the AVE of each construct exceeds the 0.5 threshold (Fornell & Larcker, 1981), the convergent validity of the measurement model is confirmed.

Two measures were used to evaluate the discriminant validity of each construct. Firstly, the loading of each indicator on its associated construct was greater than its loadings on all other constructs. Secondly, the confidence intervals of the heterotrait-monotrait (HTMT) ratio of correlations for each construct does not include 1. These findings support the discriminant validity of the constructs.

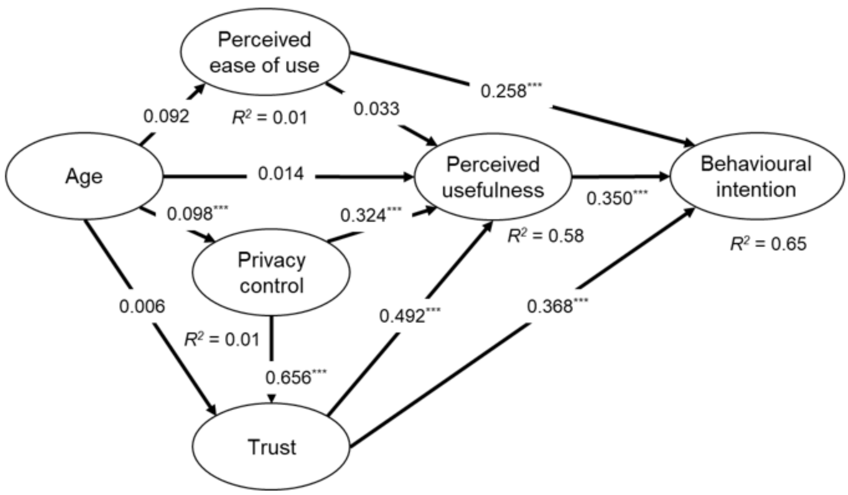
A full collinearity test was conducted confirming that the model was free of common method bias (Kock & Lynn, 2012).

Once we confirmed that construct measures were reliable and valid and that the model was free of common method bias, we then assessed the relationships between constructs in the structural model.

Structural Model

Prior to interpreting path coefficients, we checked for collinearity between predictor constructs. All variance inflation factor (VIF) statistics are below 5 indicating acceptable levels of collinearity (Hair et al., 2011). We then examined the size and strength of the paths in the structural model and its overall explanatory power. The coefficients of all significant structural paths were close to or above 0.20, with the exception of AGE-PRICT indicating that the model had sufficient predictive power (Chin, 2010). The direct effects in the structural model are shown in Figure 2.

Figure 2. Results of the structural model. Standardized coefficients (* < 0.01)**



The R^2 statistic was computed for the endogenous constructs to examine the model's predictive power. Following Hair et al. (2011), the R^2 values for PU (0.58), BI (0.65) and TRUST (0.43) were moderate. The values for PRIVACY (0.008) and PEOU (0.009) were weak. Eight of the eleven standardized path coefficients were statistically significant at the 1% significance level. The path coefficient between PRICT and TRUST was the strongest at 0.656, the second highest of 0.492 was between TRUST and PU and the third highest path coefficient of 0.368 was between TRUST and BI.

The relationship between AGE and PRICT was significant ($\beta = 0.098$) albeit with a weak path coefficient, upholding hypothesis H4. However, the paths between AGE and the PEOU, PU and TRUST variables were not significant (H1, H2, H3). The relationship between PRICT and TRUST was significant ($\beta = 0.656$), supporting hypothesis H5. PRICT also significantly influenced PU ($\beta = 0.324$), validating H6.

TRUST was found to significantly influence BI ($\beta = 0.368$) and PU ($\beta = 0.492$), upholding hypotheses H7 and H8.

The path between PEOU and PU as hypothesized by the TAM model was not significant at the 5% level, indicating that the perceived ease of use of the PTA did not influence usefulness perceptions as expected (H9). However, the hypothesized paths between PU and BI ($\beta = 0.350$) (H10) and PEOU and BI ($\beta = 0.258$) (H11) were significant.

Post Hoc Exploratory Analyses

Given the non-significant direct relationships between AGE and the PU, PEOU and TRUST variables, and between PEOU and PU, we followed the recommendations of Hollenbeck et al. (2017) and undertook a post hoc exploratory analysis of mediation effects in PLS-SEM. Mediation occurs when a third mediator variable governs the nature of the relationship between two other related constructs. We were particularly interested in the possibility that PRICT mediates the relationship between AGE and both PU and TRUST, and the indirect effects of TRUST and PRICT on BI. The results are presented in Table 5.

Table 5. Results of the post hoc mediation analysis

Path	Coefficient	p-value
AGE → PRICT → TRUST	0.064	0.001
PRICT →-> TRUST → PU	0.323	0.000
PRICT→TRUST → BI	0.242	0.000
AGE → PRICT → TRUST → PU → BI	0.011	0.005
PRICT → TRUST → PU → BI	0.113	0.000
AGE → PRICT → PU	0.032	0.002
AGE → PRICT → TRUST→BI	0.024	0.003
AGE → PRICT → PU → BI	0.011	0.004
TRUST→ PU → BI	0.173	0.000
AGE → PRICT → TRUST → PU	0.032	0.002
PRICT → PU → BI	0.114	0.000

The results confirm the expectation that PRICT fully mediates the relationship between AGE and TRUST and between AGE and PU. PU also partially mediates the relationship between TRUST, PRICT and BI.

DISCUSSION

The results show that age does not influence the PEOU or directly influence the PU of a PTA. This finding contrasts with previous literature which argued that older citizens use IT less frequently and have fewer IT skills (Fox & Connolly, 2018; Trkman et al., 2021) leading them to exhibit lower ease of use and usefulness than younger adults (McCloskey, 2006). This result may be explained by the rapid adoption and popularity of mobile apps (Mehta et al., 2020) compared to other IT and the relative ease of use and clear goal of PTAs. Nevertheless, new studies should confirm this result in different settings, especially for other m-health apps and therefore contribute to the poorly explored area of age differences related to m-health adoption. In addition, further studies should investigate a possible difference between people's perceptions related to health mobile apps and other IT (e.g., software implemented in corporate work settings).

The authors also found that age does not impact TRUST in a PTA. This result also contrasts with previous studies which showed that age has an effect on trust in health IT (Fischer et al., 2014; Or et al., 2011). The discrepancy between this result and prior literature may have several explanations. First, authors have measured age as an ordinal variable instead of a continuous variable, which may have an impact on the results. Second, prior studies focused on different kinds of technologies, such as home assistive technology (Fischer et al., 2014), which may involve different concerns than other IT. In addition, the specificity of the PTA setting in the context of the pandemic as well as of the implementation managed by the government (instead of a corporate sponsor) may overcome some concerns. The results also show that TRUST is a strong predictor of BI.

The only direct age effect we found is related to PRICT. Contrary to expectations, this link was positive. This result contrasts with prior studies that have argued for a negative relationship (Fischer et al., 2014; Guo et al., 2013; Sun et al., 2013). The finding may be explained by the increased awareness and concern of younger users about privacy and security issues (Gauzente, 2004; Reisenwitz et al., 2007; Wong & Regan, 2009). Further studies should investigate these aspects in other m-health settings.

In addition, the authors found that PRICT is positively related to TRUST and to PU. These results are consistent with the existing literature (Hassandoust et al., 2021; Li et al., 2014) which emphasizes the role of PRICT as an antecedent of both TRUST and PU. Age was also found to indirectly influence TRUST and PU through the mediation of PRICT. Overall, these results highlight the central role of PRICT in the model more so than the age antecedent.

While the link between PEOU and BI was confirmed, consistent with prior literature (Davis, 1989) including m-health (Tao et al., 2016), the link between PEOU and PU was not validated. While previous literature suggested a link between both variables, this link seems to be stronger in non m-health settings (Tao et al., 2016). The authors explain the result by the importance of TRUST and PRICT as antecedents of PU, which may matter more than PEOU.

Our study makes three main contributions to the extant literature. Firstly, it is one of the first studies to investigate the effect of age on the behavioral intention to adopt a PTA. While age has been previously shown to influence technology adoption intentions, previous studies have used an ordinal measure of age without a convincing rationale. We used a continuous measure of age, which provides a more robust model. Second, we modelled the antecedents of the intention to adopt a citizen health app whereas the prior literature has mainly investigated the antecedents of intention for healthcare workers (Abolfotouh et al., 2019; Boonstra & Broekhuis, 2010; Pan & Gao, 2021; Vitari & Ologeanu-Taddei, 2018). Third, we demonstrated the influence of PRICT on the intention to adopt a PTA. While prior literature has emphasized the role of privacy concerns and privacy risks (Bélanger & Crossler, 2011; Dinev et al., 2015; Li et al., 2011) including privacy concerns related to PTA adoption (Fox et al., 2021; Janssen & van der Voort, 2020; von Wyl et al., 2021), PRICT has been relatively under-investigated. Further studies could explore the antecedents of this construct and propose a conceptual model focused on this concept.

Our findings contribute to practice by underscoring the need for managers and health policy officials to focus their efforts on building trust towards public health apps and enhancing a user's privacy control.

Limitations and Further Studies

The present study is limited in several ways. First, the study follows a cross-sectional approach which only allows the collection of data about the phenomena under study at one moment in time, notably at the beginning of app implementation by the French Government. Future research could use a longitudinal approach to assess the relationships between the variables at different moments of app implementation. Secondly, the research design only involved the collection of quantitative data. Future studies could employ a mixed-methods approach that uses both qualitative and quantitative research methods. Thirdly, unobserved heterogeneity was not assessed in this study (Becker et al., 2013) and future research should consider this issue during the data collection and analysis process.

Our research found that age was only a direct predictor of PRICT, and not of other variables such as PEOU, PU and TRUST. These findings can be used as stepping-stones to further explore the influence of PRICT as well as trust on m-health usage intentions. The model was tested in the specific context of PTA deployment in France. Future studies could investigate the direct and indirect effects of age on m-health usage intention in other contexts (e.g., countries) and for different applications (e.g., for home monitoring, proximity tracing, teleconsultation).

CONCLUSION

In this study, we proposed and tested a conceptual model to analyze the effect of age on different variables (perceived usefulness, ease of use, trust and privacy control) as well as the links between those variables. The model was tested to assess people's perceptions in the specific setting of proximity tracing apps in France. We found that age only directly and positively influences privacy control and that both trust and privacy control are strong predictors of perceived usefulness and, by its mediation of behavioural intention. Age also indirectly influences behavioral intention through privacy control and trust. These results highlight the importance of privacy control and trust as antecedents of intentions to adopt a PTA, beyond demographic variables such as age. For governments and m-health managers, this means that they should focus their effort on how to build trust and privacy control for individuals to encourage app adoption.

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ENDNOTE

1 Also known as Digital Natives or Millennial Generation.

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