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The Impact of Gender, Education, and Age on Installing a Proximity Tracing Application: Survey on a German Population

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Abstract: *During a crisis such as COVID-19 citizens of countries all over the world were asked to use a proximity tracing application voluntarily and install it on their smartphones. Even though the use of the application in times of the pandemic crises was promoted as crucially important, many citizens refused to install it. In this paper, we raised the question of why. Previous literature confirmed the impact of universal UTAUT predictors, namely, social influence, performance expectancy and effort expectancy, on intention to use. However, the impact of the predictors has not yet been confirmed in actual use. We propose a research model to examine the direct influence of the predictors on actual use. Furthermore, we assess if the impact of age, gender and education on PTA's use behavior is significant. We present our preliminary results on data collected in Germany.*

1. INTRODUCTION

Proximity tracing applications (PTAs) are used to predict, monitor and minimise the spread of a contagious disease (Rowe, 2020). Many PTAs were developed and deployed by counties worldwide within a short time for large-scale use among citizens (Farrelly et al., 2022). However, most countries did not attract enough users to reap the planned benefits of PTA's use (Trkman et al., 2021). The question is which factors impact PTA's use?

The answer can be offered by the Theory of Acceptance and Use of Technology (UTAUT). Similar to Trkman et al. (2023) we assessed the impact of some of the theory's universal predictors, namely, performance expectancy, effort expectancy and social norms. Since the intention to use PTA as a dependent variable has been widely studied, we assessed their impact directly on the use. Furthermore, in our study, we assess the role of age, gender, and education in PTA's use behavior.

All the factors of the use were assessed with data from 361 respondents collected in 2022 in Germany. We used smartPLS to conduct the structural equation modelling (SEM) technique.

The structure of this paper is as follows: Section 2 presents the hypotheses and our research model. Section 3 informs about our research methodology, while section 4 shows the results. Finally, we provide a short discussion and conclusion.

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2. HYPOTHESIS DEVELOPMENT

The Unified Theory of Acceptance and Use of Technology (UTAUT) is a theoretical model that theorizes about factors that could have an impact on the intention of using the technology and/or its actual use (Mishra et al., 2023). Indeed, the UTAUT model has been used to investigate the adoption of various information technologies. The model includes three universal predictors of intention to use: performance expectancy, effort expectancy, and social influence (Venkatesh et al., 2003). Effort expectancy is a degree of ease associated with using information technology (Venkatesh et al., 2003). *Performance expectancy* is the degree of an individual's belief that using information technology helps enhance personal health (Trkman et al., 2023). Finally, social influence is the degree of an individual's belief that important others believe that information technology should be used (Venkatesh et al., 2003). The impacts of the UTAUT tree predictors on intention to use have been confirmed in a recent paper by Trkman et al. (2023). However, the assessment of their direct impact on use is missing (H1-H3). In our research, we measured the use of PTA by asking the respondents whether they had installed the PTA on their smartphones at any point in time in the past. Age, education, and gender might be respondent characteristics that might also have a significant impact on the use (H4-6). We propose a research model in Figure 1.

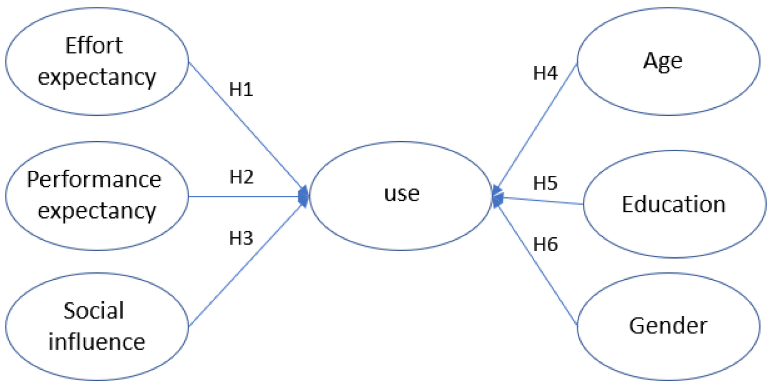

Figure 1. Research model

Source: Author

3. METHODOLOGY

3.1. Measures

The items for all constructs were adapted from previous studies as depicted in Table 1. All of the constructs above were modelled as reflective. The constructs' items were measured with a 7-point Likert scale (Sharma et al., 2022). Only the use construct was measured with a nominal variable (yes, no). We also included control variables: age (interval variable calculated for the year 2022), education level (ISCED 1-2, ISCED 3-4, ISCED 5-6, ISCED 7-8), and gender (male, female),

3.2. Data Collection

The survey was implemented with Qualtrics. The respondents were hired from Prolific's opt-in panel members. The survey was held in the English language. We collected data in June 2022. We gathered data from 361 adults living in Germany.

3.3. Data Analysis

We analysed data with structural equation modelling (SEM). Such modelling enabled us to incorporate unobservable constructs such are the UTAUT's constructs (Hair et al., 2017). The statistical analysis was conducted with the tool SmartPLS3 (Ringle et al., 2012). We used a bootstrap analysis with 5,000 subsamples (Hair et al., 2017).

Table 1. Measurement items

Ref.	Constr.	Code	Item
(Davis et al., 1989; Venkatesh et al., 2003)	Performance expectancy (PE)	PE1	Using the proximity tracing app would be helpful for monitoring my health.
		PE2	Using the proximity tracing app would make me feel safer in my daily life.
		PE3	Using the proximity tracing app would enhance the level of convenience in accessing medical care.
		PE4	Using the proximity tracing app would make it easier to manage my personal health.
		PE5	Using the proximity tracing app would enhance the quality of my life.
		PE6	I would find the proximity tracing app useful.
(Davis et al., 1989; Venkatesh et al., 2003)	Effort expectancy (EE)	EE1**	Learning to operate the proximity tracing app would be easy for me.
		EE2	I would find it easy to get the proximity tracing app to do what I want it to do.
		EE3	My interaction with the proximity tracing app would be clear and understandable.
		EE4	I would find the proximity tracing app flexible to interact with.
		EE5**	It would be easy for me to become skillful at using the proximity tracing app.
		EE6	I would find the proximity tracing app easy to use.
(Davis et al., 1989; Venkatesh et al., 2003)	Social influence (SI)	SI1	People who influence my behaviour think that I should use the proximity tracing app.
		SI2	People who are important to me think that I should use the proximity tracing app.
(Lin et al., 2021; Venkatesh et al., 2003)	USE	USE1	At this moment in time, I have the proximity tracing app installed on my phone.
	Age (Age)		What is your year of birth?
	Education (Edu.)		Select the level of your accomplished education from the list.
	Gender (Gen.)		Specify your gender from the list. Male/female

Source: adapted from Trkman et al. (2023)

4. RESULTS

4.1. Assessment of the Measurement Model

The item reliability assessment results in Figure 2 confirmed item loadings of 0.7 or higher as significant (Hair et al., 2012). Internal consistency reliability was assessed with composite reliability (CR) and Cronbach's alpha. All of their values are above 0.7 (Hair et al., 2012). The AVE values are also acceptable since they are all above 0.5 (Hair et al., 2012). Discriminant validity was evaluated using the heterotrait–monotrait ratio of correlations (HTMT) (Hair et al., 2017). All HTMT values (Table 3) are below 0.85, which is in line with the requirements (Henseler et al., 2015).

Table 2. Convergent validity and internal consistency reliability.

	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
AGE	1.000	1.000	1.000
EDU	1.000	1.000	1.000
EE	0.928	0.944	0.737
GEN	1.000	1.000	1.000
PE	0.942	0.953	0.773
SI	0.931	0.946	0.745
USE	1.000	1.000	1.000

Source: Author

Table 3. Discriminant validity (HTMT)

	AGE	EDU	EE	GEN	PE	SI	USE
AGE							
EDU	0.267						
EE	0.178	0.039					
GEN	0.114	0.060	0.075				
PE	0.068	0.018	0.260	0.082			
SI	0.035	0.168	0.318	0.052	0.601		
USE	0.037	0.084	0.234	0.065	0.420	0.558	

Source: Author

4.2. Assessment of the Structural Model

We assessed the collinearity issues. The variance inflation factor (VIF) values in Table 4 do not exceed the recommended threshold of 5 (Hair et al., 2017). The values of the coefficient of determination (R^2) that are higher than 0.25, 0.50, and 0.75 are considered to hold weak, moderate and substantial explanatory power, respectively (Hair et al., 2011). The results showed a weak explanatory power for USE (0,322). Next, the effect sizes (f^2) that are higher than 0.02, 0.15 and 0.35 indicate small, medium and large effect sizes (Hair et al., 2019). In Table 5 the f^2 value from social norm is medium (0,167), while from performance expectancy is small (0,028).

Table 4.
Collinearity assessment; VIF values

	USE
AGE	1.128
EDU	1.113
EE	1.156
GEN	1.031
PE	1.522
SI	1.606
USE	

Source: Author

Table 5.
Effect sizes f^2

	USE
AGE	0.002
EDU	0.000
EE	0.005
GEN	0.007
PE	0.028
SI	0.167
USE	

Source: Author

Table 6. Significance testing results for hypothesis

	Original Sample	Sample Mean	Standard Deviation	T statistics	P values
AGE→USE	0.035	0.038	0.045	0.774	**0.439**
EDU→USE	0.002	0.002	0.043	0.046	**0.963**
EE→USE	0.060	0.067	0.042	1.422	**0.156**
GEN→USE	0.070	0.069	0.044	1.604	**0.109**
PE→USE	0.170	0.171	0.052	3.299	**0.001**
SI→USE	0.427	0.426	0.051	8.380	**0.000**

Source: Author

The statistical significance and relevance of the path coefficients in our research model are shown in Table 6. Hypothesis H2 (PE→USE) and H3 (SI→USE) were confirmed, while all the others were rejected.

5. DISCUSSION AND CONCLUSION

In our research model, we explained 32.2% of the total variance in downloading the PTA. Similar PTA adoption studies explain between 51% and 77% (Cobelli et al., 2021; Hassandoust et al., 2021; Sharma et al., 2022; Velicia-Martin et al., 2021). However, they all focused on predicting the intention to use and not use. We confirmed significant direct effects of two universal UTAUT constructs, namely, performance expectancy (H2) and social norms (H3), while the impact on effort expectancy (H1) was not confirmed. Our results regarding effort expectancy and performance expectancy are in line with the study of Trkman et al. (2023). The authors discovered that the impact of performance expectancy on intention to use faded with time as PTA was in use. We contributed to a study assessing the impact of the three UTAUT's constructs directly on the use construct.

Age (H4), education (H5) and gender (H6) showed no impact on downloading the PTA. Interestingly, Trkman et al. (2021) showed the impact of age as a nominal variable on intention to use. They made two groups. The first one is for respondents up to 59 years old, and the second one is for the older ones. However, later research by Trkman et al. (2023) has not confirmed their finding. We contributed with an assessment of the age as an interval variable and reported that there is no impact. In previous research, education and gender were not found to have a significant impact on intention to use (Trkman et al., 2021, 2023). We have confirmed their findings.

This paper shows that neither age, gender nor education makes a significant impact on citizens' decision to use the PTA.

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