Voice Assistants: (Physical) Device Use Perceptions, Acceptance, and Privacy Concerns

Ali Farooq [1][0000-0003-4864-3155] Debora Jeske[2][0000-0002-4779-9345]
Paul van Schaik [3][0000-0001-5322-6554] and Michael Moran [4][0000-0002-2496-0992]

[1] University of Turku, 20500 Turku, Finland
[2] University College Cork, Cork T23 K208, Republic of Ireland
d.jeske@ucc.ie
[3] Teesside University, Middlesbrough TS1 3BA, United Kingdom
[4] Atlantic Technological University, Galway H91 T8NW, Republic of Ireland

Abstract. Using UTAUT2 model and privacy concerns, the study identifies the factors that predict users' and non-users' behavioral intention to continue or start using physical voice assistant devices in the future as their prominence is increasing significantly in both work and home locations. Users and non-users of voice assistants were recruited via an online survey in both Ireland and Finland. The final sample (N = 119) included 54 users and 65 non-users of voice assistants. Group differences and predictive effects were investigated using independent samples t-tests, analysis of covariance, and multiple regression. Users differed significantly from non-users on a number of UTAUT2 model variables such as effort expectancy, social influence, facilitating conditions, hedonic motivation, private value, and privacy concern. Users' behavioral intention to continue using voice assistants was stronger than non-users' behavioral intention to start using such voice assistants. Multiple regression results show that, for non-users, both effort expectancy and privacy concerns appear to impact their intention to adopt voice assistants – in contrast to participants who are already users. However, social influence, facilitating conditions, price value, effort, and performance expectancy were not significant predictors of behavioral intention. The findings suggest that the continued or future use of voice assistants can be predicted by assessing both users' and non-users' expectations regarding the degree to which they are or expect to become habituated to the use of voice assistants, enjoyment and value derived from these devices. The findings add to the emerging evidence-base about users' and non-users' perceptions, acceptance, and concerns regarding using voice assistants and highlights the importance of context in the adoption, acceptance, and perceptions of both user groups.

Keywords: Voice assistants, UTAUT2, Performance Expectancy, Effort Expectancy, Smart Speaker, Behavioral Intention.

1 Introduction

Many recent articles focus on user acceptance of a number of different voice assistant tools (e.g., Burbach et al., 2019). These are known under names such as smart speaker assistants (Brause and Blank, 2020), smart voice assistant speakers (Lee et al., 2020), smart home devices, smart home hubs (Chhetri and Motti, 2019), intelligent and digital personal assistants (De Barcelos Silva et al., 2020), artificial intelligence-based voice assistant systems (Lee et al., 2021), intelligent personal assistants (Liao et al., 2019), and in-home or home voice assistants (Lucia-Palacios and Pérez-López, 2021; McLean and Osei-Frimpong, 2019; Pal et al., 2020). Indeed, the market for such devices with speaker functions and speaker compatibility has increased as these devices become more well-known and find wider acceptance in various settings and countries. Current popular devices include many well-known devices such as Amazon's Echo, Google Home, Wing (Chhetri and Motti, 2019), Insteon's Hub (2021), or Xiao Ai, a voice assistant that is part of the Mi AI speaker by Xiaomi (Tan, 2021). It is important to note that many computers and smartphones now offer preinstalled and integrated voice assistant functions (e.g., Siri, GoogleAssistant, Cortana, and OpenSource assistants such as Mycroft and Rhasspy Voice Assistant). In this paper, we are particularly interested in exploring user and non-user perceptions of voice assistant devices that are visible as devices in the home or workplace (rather than integrated into devices that existed before voice assistants came about, such as smart phones, computers, or smart watches). Good examples include Amazon Echo, Alexa, and Google Home, as these are physical devices in their own right that are usually placed within the users' and non-users' line of sight, often in private and shared premises such as office spaces. The guiding theoretical framework in this research is the unified theory of acceptance and use of technology (UTAUT) (Venkatesh et al., 2003) and its successor (UTAUT2; Venkatesh et al., 2012) as both models have been used to explore consumers' adoption of new, intelligent assistant devices (e.g., Liao et al., 2019; Sohn and Kwon, 2020).

The goal of the current quantitative research presented in this paper is to examine users and non-users' behavioral intention to use voice assistants as a function of a number of different perceptions related to the performance of those efforts, the expectations people have regarding the use of such devices, but also aspects such as facilitating conditions and social influence. We focus here on the use of these physical devices in both home and work as voice assistants have become more common in both locations, particularly as many employees now increasingly started working from home due to the Covid-19 pandemic (e.g., Jeske, 2022). An example statistic backs up this trend: according to Juniper Research, up to 55% of American households are expected to own voice assistants such as smart speakers (Dee, 2021).

2 Recent Work on Voice Assistants

The interest in voice assistants has grown significantly over the last five years. This is in part due to the interplay of many stakeholders (Pal et al., 2020), concerns about data leakages and surveillance (Ford and Palmer, 2019; Frick et al., 2021), and malware-

induced misperception attacks (attacks that involve the delivery of manipulated content via voice assistants; Sharevski et al., 2021). Major stakeholders include the manufacturers, users, non-users (as they are essentially bystanders whose interactions with users may also be captured), government and other agencies, third-party application developers and cloud service providers (Chhetri and Motti, 2019; Pal et al., 2020; Pfeifle, 2018). In recognition of these dynamics, more and more studies focus on multiple stakeholders.

Nevertheless, while the research around voice assistants is expanding rapidly, a number of questions remain: is the adoption, acceptance, and use of these (physical vs. virtual) devices influenced by the same characteristics and concerns when they are used in public or private spaces (e.g., see work on virtual voice assistants by Burbach et al., 2019)? Can we consider workspaces truly public venues when they are actually located in our homes (see also virtual voice assistant work by Easwara Moorthy & Vu, 2015)? Does digital competitiveness and societal adoption play a potential role in affecting privacy concerns in different countries? What privacy or additional features may be particularly desirable and attractive for current users (and non-users), such as the option to select a 'home-zone' forget mode when the home office is again used for private activities rather than work? The current study is making an attempt to add to our current knowledge of voice assistants in the hope of contributing to a meta-analysis in the future on how context influences (physical) voice assistant adoption and usage.

In this study, we specifically consider the perceptions of both users and non-users of physical voice assistants in work and home settings. Even individuals who are not users are affected by the popularity of these devices in their homes, office, and public spaces (Pal et al., 2020). Studying both groups is an approach that has been taken by a number of other authors as well. Lau et al. (2018) similarly studied in their qualitative study the perceptions and factors that would predict the adoption of voice assistants by users and non-users in their homes, but not in work settings. Liao et al. (2019) considered the perspective of users and non-users working for a US university regarding intelligent personal assistants in a quantitative study. However, these authors focused on smartphone users where voice assistants are an integrated feature, rather than a visible physical device. No information was provided about the context of use, such as the home and/or the workplace. The current research therefore includes both users and non-users as important stakeholders, in both home and work settings. The following section provides a more detailed overview of recent work on voice assistants and an overview of our hypotheses and research model.

2.1 Performance and effort expectancy

We therefore define performance expectancy as the extent to which users as well as non-users might believe that using a system or electronic tool such as a voice assistant will help them to accomplish certain tasks or achieve a certain level of performance (Venkatesh et al., 2003). In our context, effort expectancy is the extent to which users and non-users they feel that they find voice assistants to be easy to use (Venkatesh et al., 2003). This is a particular concern for many who use devices set up in different languages (which is often the case with voice assistants) or devices that they have had

little or no experience. Past research by Dwivedi et al. (2019) demonstrated that both performance and effort expectancy are positive predictors of behavioral intention to use information systems and technology devices. Liao et al. (2019) similarly found evidence that perceived performance and effort expectancy influenced users' decision to adopt phone-based intelligent personal assistants in a sample of US users and non-users. This leads us to propose the following two hypotheses:

H1: Performance Expectancy is a positive predictor of intention to use voice assistants.
H2: Effort Expectancy is a positive predictor of intention to use voice assistants.

2.2 Social influence and facilitating conditions

The degree to which both users and non-users form the intention to perform a behavior (e.g., Venkatesh et al., 2003), such as using a voice assistant, may vary due to the user's experience, expectations, the supportive conditions as well as encouragement they receive from their social environment. Social conditions reflect circumstances in that users and non-users may be exposed and encouraged by people in their social environments to use certain devices, which – in turn – constitutes social influence in the current study. The degree to which other individuals around a user or non-user believe that such devices ought to be used is also likely to drive the adoption as well as continued use of voice assistant. Evidence on the intention and use of information systems and technology information has linked social influence as well as facilitating conditions significantly and positively to behavioral intentions (Dwivedi et al., 2019). The social benefits have also been studied in relation to voice assistants (McLean and Osei-Frimpong, 2019). This leads us to propose the following hypothesis:

H3: Social Influence is a positive predictor of the intention to use voice assistants.

The increase in interconnectivity in the home and at work has supported the adoption of many tools such as voice assistants. In addition, such devices are becoming increasingly popular gifts from family members and friends to one another (Liao et al., 2019). Facilitating conditions thus capture the resources, knowledge, and technological compatibility of devices. In some cases, they are also likely to be potentially socially supported as well. These circumstances increase the presence of such devices in various locations, while the organizational and technical infrastructure such as wireless access further creates facilitating conditions that will support the use of such devices (Venkatesh et al., 2003). We, therefore, propose that:

H4: Facilitating conditions are a positive predictor of the intention to use voice assistants.

2.3 Hedonic motivation, price value, and the importance of habitual use

Past evidence based on a South Korean sample of 378 survey respondents suggested that purchase intentions of AI-based intelligent products tested using UTAUT2 are

higher when they expected to enjoy these products (Sohn and Kwon, 2020). In the context of UTAUT2 (Venkatesh et al., 2012), hedonic motivation thus captures the extent to which a person finds using a specific technology enjoyable and entertaining. Lee et al. (2020) reported that hedonic motivation predicted satisfaction with voice assistants. Furthermore, the context in which voice assistants may also matter, as McLean and Osei-Frimpong (2019) reported that hedonic benefits would only motivate users in smaller households to use voice assistants, which suggests that the social environment plays a role in terms of how users use such devices. Despite this mixed picture regarding the effect of hedonic motivation on behavioral intention to use various tools, we propose the following hypotheses:

H5: Hedonic motivation is a positive predictor of the intention to use voice assistants.

Price value, together with design and brand value, has been shown to positively influence users' perceived benefits in relation to smart speakers in a South Korean study (Park et al., 2018). Perceived value thus captures the degree to which individuals find that certain devices are reasonably priced and represent good value (see also Venkatesh et al., 2012). Lau et al. (2018) also reported that price, together with convenience, motivate the decision to use and adopt smart speakers among both users and non-users. When users feel that they paid a good price for their device and it will add value to their interactions, they may also be more likely to use voice assistants in the future. Accordingly, we propose that:

H6: Price value is a positive predictor of the intention to use voice assistants.

The routine use of voice assistants may also foster the habitual use of voice assistants over time. Habit in relation to UTAUT2 (Venkatesh et al., 2012) thus refers to the extent to which individuals get first used to a device, use it regularly, and over time automatically resort to using this device over others as a matter of habit. The development of a habit – in the home or at work – of voice assistants may therefore also increase the intention among users and non-users to use voice assistants in the future. Lee et al. (2020) reported that habit formation also predicted the continuous use of voice assistants in their sample. Furthermore, habit operated as a mediator between satisfaction with the voice assistant and the continuous use of the assistants. This suggests a positive association. We, therefore, hypothesize that:

H7: The habitual use is a positive predictor of the intention to use voice assistants.

2.4 The Role of Privacy Concerns

Privacy concern captures the perceptions of users regarding the extent to which virtual and physical voice assistant devices are safe to use, help to support or undermine a user's privacy (Burbach et al., 2019), and the extent to which data shared with such devices are safeguarded appropriately (see also study by Kim et al., 2011). While privacy concerns are absent from the UTAUT2 model, these concerns are particularly

likely when users and non-users are concerned about the security of their data as there is evidence that voice assistants and other smart devices are hacked or compromised (e.g., Park et al., 2018; Sharevski et al., 2021; Yan et al., 2021). For example, Chhetri and Motti (2019) identified various user concerns in user reviews, including aspects such as tracking, storage of conversations, lack of data security, and potential hacking risks. This leads us to propose the following:

H8: Privacy concerns are a negative predictor of the intention to use virtual assistants.

3 Method

3.1 Data Collection and Sample

Data collection took place in two countries: Ireland and Finland. These countries were selected because they both ranked among the top 20 in the world in 2020 and 2021 in terms of their digital competitiveness (IMD, 2021). Both countries also share a lot of similarities in terms of the size of their populations and economies, while both countries are also known as international tech hubs (Gallagher, 2022). Students are digital natives who tend to use various electronic gadgets (including voice assistants; Farooq et al., 2019). We, therefore, expected that familiarity with and the use of physical voice assistants would be likely in the general and student populations.

A cross-sectional research design was used, with data collection in two educational institutions in Ireland and one in Finland. Ethics was obtained from both Irish institutions for this study. Data collection started in July 2020 and concluded in May 2021. All participants were asked to give consent. The two surveys ran separately (one in Ireland and one in Finland) and 145 individuals moved past the consent page. The final dataset includes 119 participants who completed at least 80% of the survey. This included 75 participants from Ireland (63%) and 44 participants (37%) from Finland. Research participants in both countries had the option to register after the study for a raffle (via a separate form not connected to the original survey).

3.2 Participant description

The sample size of 119 participants included 63% males, 37% females with an average of 25.15 years (SD = 7.75, range 18 to 69). At the time of the study, 47% of respondents were students of bachelor, 10% of masters and PhD, and 3% were pursuing non-degree qualifications (another 30% of respondents opted out to provide information about their educational level). Among the respondents, 45% (n = 54) had used a voice assistant previously at home (n = 51), the workplace (n = 12), or both places (n = 9). In terms of participants' work experience, we should note that a significant proportion of the sample was working while studying. In terms of the Irish sample, an estimated 70-80% of students contacted for this survey were working while studying, while 30-40% of students in the Finnish sample – based on Turku statistics – are working while studying.

3.3 Measures

For this study, we used established scales from the previous studies, which we adapted in relation to voice assistants. All UTAUT-related constructs were measured on a 5-points Likert scale (1 = strongly disagree, to 5 = strongly agree). Some of the original response options were reduced cognitive load. In addition, we added a few additional questions to learn more about our participants' past experiences and demographics. The data from current users and non-users were combined (N=119).

Prior experience using a voice assistant. Participants were asked "Please tell us if you have experience with Amazon Echo, Apple's HomePod or Alexa and other voice assistants/smart speakers". In addition, we asked if they used them at home, at work, or both which was the case for 54 participants (45.4%).

Performance expectancy. This variable was measured using three questions from the perceived usefulness scale adapted from Davis (1989) and Venkatesh et al. (2003). We asked both users and non-users (M = 3.22., SD = 1.02, α = .88). An example statement for a current user of voice assistants is: "Being able to use voice assistants enables me to accomplish tasks more quickly at home/at work". A non-user was presented with a slightly amended statement: "Being able to use voice assistants will enable me to accomplish tasks more quickly at home/at work".

Effort expectancy. We used four items from the perceived ease of use scale presented in Davis (1989), which were also featured in Venkatesh et al. (2012). The items were slightly adapted in relation to voice assistants. All four were used in the final composite (M = 3.22, SD = 1.02, α =.88). Current users would receive an item such as this: "Learning to use voice assistants/smart speaker is easy for me" while non-users were presented with this item: "Learning to use voice assistants/smart speaker would be easy for me". Higher scores indicate more positive ease of use perceptions.

Social influence. This measure featured three items Anderson and Agarwal (2010). We focused on assessing participants' perceptions of descriptive social norms, in particular, as to what other people do (M = 2.36., SD = 1.10, α =.90). Both users and non-users were presented with identical items, for example, the statement "I believe people who are important to me use voice assistants/smart speakers."

Facilitating conditions. This was measured using four items adapted from Venkatesh et al. (2012), again adapted in relation to voice assistants (M = 4.21, SD =0.58, α =.57). Both users and non-users were asked to respond to items such as: "I have the resources necessary to use voice assistants/smart speakers."

Hedonic motivation. This was also measured using three items by Venkatesh et al. (2012), also called "perceived enjoyment" in TAM research (M = 3.85, SD = 0.92, α =.92). For example, all participants were asked to respond to items such as "Using voice assistants/smart speakers is enjoyable."

Price value (price motivation). We used the three items by Venkatesh et al (2012). The original items asked about internet costs and were amended in relation to voice assistant (M = 3.43, SD = 0.98, α =.88). In order to give non-users an idea of the cost estimates of such devices for 2020, we included a price range (60-100 Euro).

Habit (habitual use of voice assistants). We also wanted to assess the extent to which participants would expect that their use of voice assistants is (in the case of users)

or could be (in the case of non-users) become a habit, using three items from Venkatesh et al. (2012). An example demonstrates this. Users were asked "The use of voice assistants/smart speakers has become a habit for me" while non-users were asked "The use of voice assistants/smart speakers could become a habit for me", followed by the 5-point Likert response scale as with the other scales (M = 3.01, SD = 1.17, α =.85).

Behavioral intention (to use voice assistants in the future). This was assessed with three items from Venkatesh et al. (2012), again adapted in reference to voice assistants (M = 2.93, SD = 1.21, α =.91). Both users and non-users were asked, for example, "I intend to use voice assistants in the future." The same response scale options were applied as above. The composite of the three items represented our outcome variable in this study.

Privacy concern. We included privacy concerns using four items which were slightly adapted in reference to voice assistants from Kim et al. (2011; M = 2.57, SD = 1.04, α =.87) with five answering options (1=strongly disagree, to 5=strongly agree). An example item was "In general, using voice assistants/smart speakers is risk-free". Higher scores indicate lower privacy concern.

Control variables (demographics). We also asked respondents about their gender, age, educational level, the educational discipline they were studying (as we recruited cross-sectionally).

4 Results

4.1 Group Comparisons and Correlations

As expected, users (n = 54) and non-users (n = 65) differed in some respects when we explored the two groups using independent samples t-tests. Please note that due to a sampling error, performance expectancy was only recorded in the Irish data (for 73 participants) but not in the Finnish data. As a result, the analysis of group differences for Performance Expectancy was excluded as the ratio was 8 to 65 users vs. non-users.

Users reported lower effort expectancy than non-users (M_u = 2.22, SD = 1.13; M_n = 4.28, SD = 0.63; t(117) = -12.51, p < .001), more social influence (M_u = 2.85, SD = 1.09; M_n = 1.95, SD = 0.92; t(117) = 4.86, p < .001), and greater hedonic motivation (M_u = 4.09, SD = 0.66; M_n = 3.65, SD = 1.05; t(117) = 2.71, p = .008). Other significant differences emerged: users scored higher on price value (M_u = 3.79, SD = 0.87; M_n = 3.13, SD = 0.97; t(117) = -3.88, p < .001), privacy concern (M_u = 2.82, SD = 0.95; M_n = 2.36, SD = 1.07; t(117) = 2.48, p = .015) and intention to continue using voice assistants in the future than non-users (M_u = 3.56, SD = 1.01; M_n = 2.41, SD = 1.22; t(117) = 5.87, p < .001). No significant differences (p < .05) were observed in relation to habit development (p =.065) and facilitating conditions between users and non-users (p = .123). Most of the scale composites for the combined sample correlated weakly to moderately, as expected; there was little evidence of multi-collinearity (Table 1).

Table 1. Correlations for the combined sample (N = 117)

Constructs	PE	EE	HU	SI	FC	HM	PV	PC	BI
PE	1								
EE	.12	1							
HU	.67**	.27**	1						
SI	.43**	-.28**	.17	1					
FC	.23*	-.09	.13	.23*	1				
HM	.71**	-.04	.40**	.24**	.36**	1			
PV	.36**	-.25**	.33**	.27**	.27**	.42**	1		
PC	.37**	-.07	.26**	.28**	.03	.23**	.34**	1	
BI	.71**	-.29	.57**	.44**	.19*	.61*	.53**	.39**	1

Note. ** p < .01, * p < .05. PE = Performance Expectancy (n=73), EE = Effort Expectancy, HU = Habit Development/Habitual Use, SI = Social Influence, FC = Facilitating Conditions, HM = Hedonic Motivation, PV = Price Value, PC = Privacy Concern, and BI = Behavioral Intention.

4.2 Main analysis and hypothesis testing

We first examined the predictive effects of the UTAUT variables on behavioral intention for users and non-users (as separate samples) using the forced-entry method in multiple regression. Country was only a significant control variable in the case of non-users. In the case of users (n = 54), the seven predictors collectively explained 60% of the variance in behavioral intention (R^2_{adj} = .60, F(7,46) = 12.15, p <.001). The results for nonusers (n = 65) indicated that all variables explained 64% of the variance in behavioral intention ($R^2\Delta$= .64, F(7,56) = 17.40, p < .001). Only two predictors were significant: hedonic motivation (H5, β = .26, p =.022 in the case of users; β = .43, p <.001 for non-users) and habit development (H7, β = .63, p <.001 in the case of users; β = .50, p <.001 for non-users). In an exploratory analysis, we also controlled for privacy concern in the first step (rather than having it as a regular predictor at the end, following the other UTAUT variables). In this case, privacy concerns (H8) had both a marginally significant effect in the case of users (p = .084) and a significant effect for non-users (p = .004). Furthermore, given this constellation, effort expectancy (H2) appeared to play more of role for non-users alone (β = -.19, p = .052), but not users (β = -.06, p = .538). The negative coefficient suggests that non-users expect that the use of voice assistants will require more effort for them, in line with H2.

Please note that in the earlier analyses, we excluded performance expectancy (H1) due to the missing cases. In a final analysis with the 73 cases for which we had performance expectancy information, we examined the extent to which this variable predicts behavioral intention when we control for the three UTAUT predictors (effort expectancy, habit development, and hedonic motivation) while simultaneously excluding country and privacy concerns as control variables. In that case, all variables were significant (p < .001). Performance expectancy, however, only had a marginal significant and positive effect on behavioral intention (H1, β = .18, p = .098), possibly due to suppression effects through shared variance with other UTAUT variables (see correlations in Table 1).

5 Discussion

The goal of the current study was to provide more insights to the emerging research base around user and non-user concerns about voice assistants, intentions to purchase and use voice assistants, and factors that increase users' and non-users' intention to the adoption of such devices in the home and at work. What is more, the research aimed to provide further evidence regarding the extent to which UTAUT2 model variables and privacy concern are significant predictors of users' and non-users' behavioral intention to continue or start using voice assistants in the future.

The group differences suggested that users differed significantly from non-users in relation to a number of UTAUT2 model variables when we examined these individually (group comparisons). However, the picture is not as clear-cut and should be interpreted with caution as most of these differences disappeared when we analyzed the effect of all variables together in multiple regression analyses. Our regression results indicated that only hedonic motivation (H5) and habit development (H7) significantly predicted behavioral intention among users and non-users alike. This is also in line with research that showed that enjoyment predicts purchase intentions regarding voice assistants (Sohn and Kwon, 2020) and the work by Lee et al. (2020), which showed that habit could positively increase the intention to continue using voice assistants. The case for the effect of effort expectancy (H2) is much weaker as it only emerged as a marginally significant effect for non-users, while performance expectancy (H1) had a very small and only marginally significant effect on behavioral intention in a much smaller sample once other UTAUT variables such as hedonic motivation, habit development and effort expectancy were entered in the first step before performance expectancy.

However, a number of predictors did not have the expected effects on behavioral intention. This included social influence (H3) and facilitating conditions (H4), in contrast to Dwivedi et al. (2019) and the findings regarding social benefits in McLean and Osei-Frimpong (2019). In contrast to our prediction, privacy concern (H8) did not have a direct effect on behavioral intention to use voice assistants in our study as proposed when it was examined as a predictor together with other UTAUT variables (H8). However, privacy concern did seem to play a role when it was entered as a control variable in the first step before all other UTAUT variables. This might be due to suppression effects.

More research in this area may be helpful to understand the role of conflicting beliefs and the way users as well as non-users evaluate the pros and cons of adopting tools when they report strong, moderate, or weak privacy concerns. For example, the interactivity of voice assistants has been shown to reduce the perceived intrusiveness via brand trust, which in turn has a positive influence on performance expectancy (see Lucia-Palacios and Pérez-López, 2021). These findings might also explain why we see no direct effects of privacy concern, but an indication that privacy is possible to interact with performance expectancy in relation to behavioral intention.

Practical implications

Several resources exist to help users of smart home devices such as voice assistant identify more privacy-enhancing solutions (e.g., Chhetri and Motti, 2019) and the different privacy concerns of various stakeholders involved in the use of voice assistants (Pal et al., 2020). Clear communication, interactivity features (that offer more information and communication), and privacy-enhancing defaults may go a long way to build a trusting relationship between users and device manufacturers (see Lucia-Palacios and Pérez-López, 2021). Such steps may also alleviate the privacy concerns of current users and prospective non-users (Pal et al., 2020) and make performance expectancy a more influential predictor of behavioral intention, as our results suggest.

5.1 Limitations

Some methodological and procedural limitations apply. First, we used self-reports and a student sample (although a significant proportion of our participants were working while studying). However, it is worth noting that the two groups – users and non-users – would have different reference points for their self-reports: users have experience using voice assistants to consult, while non-users are more likely to report on their perceptions rather than experience (although it is not definite that they are not passive users or bystanders, Pal et al., 2020). Second, we explored the behavioral intentions of our participants rather than actual use. The second would be preferable, but was a limitation of the design. Future research may wish to consider more longitudinal work similar to the diary study by Lau et al. (2018).

And third, we would like to acknowledge the limitations of using such a cross-sectional, educational, and international sample and outline some suggestions to consider cross-cultural factors in future research sections. However, other researchers also run certain analyses on combined samples of users and non-users (e.g., Liao et al., 2019) or users who are single users of voice assistants or sharing these devices (Lee et al., 2020). Future data collection efforts may need to increase sampling sizes in order to create the statistical requirements for multi-group analysis. And fourth, past research has shown that brand names can also influence trust, as some brand names may be more trusted than others (Park et al., 2018; Frick et al., 2021), leading users and non-users to be potentially more accepting of data collection via these brand devices (Chavanne, 2018). In our case, we used well-known brand names (HomePod, Alexa, and Echo) as examples of physical voice assistants that are not incorporated into other devices. This suggests that the use of those brand names may also have impacted our results, a potential limitation to be confirmed in future work.

5.2 Future Research

Future research may wish to consider the role of user attitudes in relation to behavioral intention to use voice assistants. Attitudes related to trust, malicious attacks via voice assistants and therefore risk management, resistance, intentionality of device ownership (intentional vs. unintentional, e.g., in the case of preinstalled devices or the cases where voice assistants are given as gifts to users), and data sharing may be important areas for investigation in future studies on voice assistants as well (see also Hong et al., 2019;

Michler et al., 2019; Sharevski et al., 2021; Yan et al., 2021). We would propose that future research may consider whether users and non-users have different privacy perceptions depending on the use of voice assistants in private as well as shared spaces.

A number of privacy theories such as the privacy calculus theory may serve as useful starting points. In addition, it may be worthwhile to explore additional theories – in addition to the well-established UTAUT – in the exploration of how, why, and when non-users decide to adopt certain physical and integrated devices in their everyday usage in the workplace and at home. We would also like to make two further suggestions. One, it would be interesting to see a meta-analysis on voice assistants that explored effects given certain context factors (public, private, multi-purpose environments; voluntary vs. involuntary adoption in shared spaces). Two, it would be interesting to see more theoretical frameworks and work in this area in order to move the research further and beyond both UTAUT and the focus on mostly virtual voice assistants.

In addition, we observed some country differences in relation to effort expectancy and facilitating conditions between participants in Finland vs. Ireland. More research on cultural variables could explain some of these findings. And lastly, the possible effects of voice assistants being used or misused, manipulated or compromised, and their use by various users in one environment (e.g., in the home or at work) are certainly worthy of more exploration (see also Lee et al., 2020; Sharevski et al., 2021).

5.3 Conclusions

In our study, the predictors of the acceptance of voice assistants were predominantly intrinsic (hedonic motivation) and habitual (habitual voice assistant use). However, contextual factors (facilitating conditions, social influence, privacy concern) were not predictors, nor did performance or effort expectancy predict behavioral intention to use voice assistants. Our results, therefore, suggest that predominantly individual factors rather than social factors drive the acceptance of voice assistants in users and non-users. Through experimental manipulation, future research may investigate the conditions under which privacy is a driver as well, such as specific contexts (e.g., private vs. public spaces at work and at home, multi-purpose locations such as home offices, shared and personal spaces in the home). This work may also validate the relative importance of drivers of voice assistant acceptance through experimental research.

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