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Understanding users' behavioral intention to use voice assistants on smartphones through the integrated model of user satisfaction and technology acceptance: a survey approach

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Mine Bertan Yılmaz
Faculty of Communication, Kadir Has University, Istanbul, Turkey, and
Kerem Rızvanoğlu
Faculty of Communication, Galatasaray University, Istanbul, Turkey

Abstract

Purpose – This study aims to determine system quality (SQ) and information quality (IQ) characteristics of voice assistants (VA) on smartphones that are affecting users' satisfaction and technology acceptance, and how these affect behavioral intention (BI) to use.

Design/methodology/approach – This study uses the integrated model of user satisfaction and technology acceptance to evaluate users' behavioral intention to use VAs on smartphones. The model represents a causal chain from the key characteristics of SQ and IQ to beliefs and attitudes that ultimately affect use. An online survey was conducted with 75 university students, and the data was analyzed using multivariate analysis: Simple linear regression analysis and multiple regression analysis.

Findings – While SQ and IQ of VAs had stronger effects on perceived ease of use (PEU), information satisfaction and PEU showed significant influences on perceived usefulness (PU). The results supported the influence of PEU, PU, and attitude on BI to use but with lesser effect than what PU and attitude together had on BI.

Research limitations/implications – The sample was drawn from a population of students at a single and small university. Although this study received 160 responses, only 75 were appropriate for analysis.

Originality/value – There is no research, which adopts technology acceptance and user satisfaction approaches to VAs. To measure the causal effects, this study determined system and information characteristics that could explain SQ and IQ of the current VAs on smartphones. This study tested the proposed framework within the scope of the integrated approach.

Keywords User satisfaction, Technology acceptance, Information systems success, Voice assistants

Paper type Research paper

Introduction

Voice assistants (VAs) are one of the emerging technologies; voice-user interfaces have become the center of many companies' ecosystems. Technology companies are developing VAs available on smartphones such as *Google Assistant* and *Apple Siri*, and on smart speakers, such as *Amazon Echo and Alexa* and *Google Home*. While these assistants are able to support users in executing simple tasks such as doing online searches and getting things

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done via voice-enabled natural language interaction, they are also capable of controlling apps, such as messaging and setting alarms.

VAs are defined for this study as "intelligent softwares, which make human-computer interaction possible through natural language use and touch-based interface" (Budiu and Laubheimer, 2018a). This new interaction style has changed the way users interact with search systems (Kiseleva *et al.*, 2016a). In 2020, there were "4.2 billion digital voice assistants being used in devices around the world" (Statista, 2021). This number was 3.25 billion in 2019 (Statista, 2021). This shows a 29% increase in one year. "There are over 110 million virtual assistant users in the United States alone, and the software is especially common in smartphones and smart speakers [. . .] Forecasts suggest that by 2024, the number of digital voice assistants will reach 8.4 billion units – a number higher than the world's population" (Statista, 2021).

With the increasing use of VAs for different needs, "conversational design" is becoming an emerging space for user experience (UX) researchers. Recently, the field has received great attention among HCI professionals. However, VAs still have a long way to become excellent assistants (Budiu and Laubheimer, 2018a, 2018b; Budiu and Whitenton, 2018a; Budiu and Whitenton, 2018b). Budiu and Whitenton (2018b) stated that "there are big gaps between what users need to do, what they actually do, and what is possible to do with today's VAs." Usability problems and social concerns (e.g. privacy and security) associated with VAs may influence the use of VAs (Moorthy and Vu, 2015). Thus, UX researchers should consider both user demands and their concerns associated with the assistants.

Voicebot published the Smartphone Voice Assistant Consumer Adoption Report among US adults in 2020 (Kinsella, 2020). Results showed that VA use on smartphones rose from 51.5% in 2018 to 56.4% in 2020. *Siri* has the largest market share by 45.1%, compared to 29.9% *Google Assistant*, 18.3% for *Amazon Alexa* and 4.7% for *Samsung Bixby*. Owing to the increased use of VAs on smartphones (Heitzman, 2019), this study focuses on the VAs available on smartphones. We conducted a survey to determine how user satisfaction and technology acceptance of VAs affect users' intention to use VAs. There is a vast literature on technology acceptance and user satisfaction in the domain of information systems (IS) research (Ghobakhloo *et al.*, 2010). However, there is limited research, which applies these approaches to VAs in different contexts (Kiseleva *et al.*, 2016a; Kiseleva *et al.*, 2016b; Moorthy and Vu, 2015; Jiang *et al.*, 2015). In the context of VAs, some studies have looked at only user satisfaction or technology acceptance. However, there is no study that combines both of these approaches. Other studies covered more specific topics like the privacy issues related to VAs.

This study aims to determine system quality (SQ) and information quality (IQ) characteristics of VAs that are affecting users' satisfaction and technology acceptance, and how these affect intentions to use. To have a comprehensive understanding regarding VA use from both approaches, the research framework was mainly built and tested on the integrated model of user satisfaction and technology acceptance proposed by Wixom and Todd (2005). In addition, while forming the research framework, some professional research reports were reviewed. The voice-specific characteristics of VAs, which constituted the research framework, were derived from previous studies in the academic and professional research literature. The research questions of this study are as follows:

RQ1. What are the main system and information quality characteristics of VAs on smartphones?

RQ2. How these system and information quality characteristics of VAs on smartphones affect user satisfaction and technology acceptance?

RQ3. How user satisfaction and technology acceptance of VAs affect users' intention to use VAs on smartphones?

Current research on the use of voice assistants

A research conducted by *Highervisibility* showed that people mostly used VAs while they were driving (Heitzman, 2019). VAs offered a different interaction opportunity when the users were not able to look at their phone (e.g. when watching TV, working, cooking, exercising or walking) (Heitzman, 2019). According to the research conducted by Budiu and Laubheimer (2018a), people used VAs mostly in two types of situations: When their hands were busy and when asking the question was faster than typing it and reading through the results.

Budiu and Laubheimer (2018a, 2018b) identified six characteristics of current VAs. These are: voice input, natural language, voice output, intelligent interpretation, integration and agency. They found that current VAs failed on all the six characteristics. They also stated that the assistants only met vare minimum usability requirements for simple interactions since VAs weren't able to understand multiclause sentences and to produce a satisfactory vocal response to queries. Additionally, they found that the assistants did not work well with other available apps on the device. Another study was conducted by Budiu and Laubheimer (2018b) indicated that users avoided to interact with VAs naturally because of social and mental-model challenges.

In the research conducted by Budiu and Whitenton (2018a), the most common use of VAs the participants reported was simple information retrieval and communicating with a person. The study also indicated that people mostly asked VAs to do tasks with only one step (e.g. setting an alarm). Other multistep tasks or more complex jobs which combine several tasks or require open-ended research were rare. People stated that they did not try to use VAs for complex needs. Budiu and Whitenton (2018b) conducted another study to understand the gap between user needs and VAs' ability to fulfill those needs. They determined that VAs had poor usability, especially in more complex tasks. For this reason, people tended to ask for fairly simple requests. On the other hand, the study proposed that the potential usefulness of VAs was much higher. To reveal this potential, Budiu and Whitenton (2018b) proposed that the usability gap and the utility gap had to be closed or at least narrowed. In terms of task types, they found that the local needs (e.g. navigation) and reminders were most likely to be addressable with existing VAs. When they asked participants how they expected to trigger the assistant's help, a spoken command was the most commonly mentioned trigger.

Theoretical background

Regarding the attitude and behavior that leads a person to use information technologies, several theories and models have been proposed. In general, these theories and models try to explain how the effects of external variables, as well as users' perceptions and beliefs, have an impact on their attitudes and behavioral intentions to use a technology or IS (Wixom and Todd, 2005). The theoretical framework of this study is based on some major concepts in IS literature. These concepts are technology acceptance, user satisfaction, IS success and intention to use.

Theories regarding technology acceptance and user satisfaction

Technology acceptance has been studied for years in IS to explain what factors influence users' adoption. The theories behind the technology acceptance include the theory of reasonable action (Fishbein and Ajzen, 1975) and the theory of planned behavior (Ajzen, 1985). A famous model evaluating users' acceptance of IS is the technology acceptance model (TAM), developed by Davis (1989). TAM determines how users are adapted to use information and communication technologies based on the perceptions caused by system's features. Davis (1989) asserted that the design features of a system would result in a cognitive response from the user, and this response was divided into two personal beliefs: perceived ease of use (PEU) and perceived usefulness (PU). Research has shown that these beliefs determined the attitude of a person toward using an IS. This theory has been further developed by the addition of different constructs. These included, but were not restricted to, TAM2) (Venkatesh and Davis, 2000); unified theory of acceptance and use of technology (UTAUT) (Venkatesh *et al.*, 2003); TAM3 (Venkatesh and Bala, 2008); and UTAUT2 (Venkatesh *et al.*, 2012) .

Although a large number of comparisons and model variants have been tested, and model extensions have been proposed in technology acceptance literature, a few studies have focused on the role of system and information characteristics as determinants of PEU and PU (Wixom and Todd, 2005). Venkatesh *et al.* (2003) stated that there was a need to extend the technology acceptance literature by considering system and information characteristics of IS. In this context, some researchers (DeLone and McLean, 1992; DeLone and McLean, 2003; Davis, 1993; Igbaria *et al.*, 1995; Lim and Benbasat, 2000; Hong *et al.*, 2002) measured technology acceptance by referring to the system and information characteristics of IS. Information systems success model, created by DeLone and McLean (1992), is one of the popular models. The IS model focuses on the role of SQ and IQ on user satisfaction and system use. The model has been later revised with the inclusion of "service quality" as a factor (DeLone and McLean, 2003).

As it was mentioned by Wixom and Todd (2005), to evaluate IS's success, there are two dominant approaches: user satisfaction (DeLone and McLean, 1992; DeLone and McLean, 2003; Bailey and Pearson, 1983; Ives *et al.*, 1983; Melone, 1990; Seddon, 1997) and technology acceptance (Davis, 1989; Venkatesh *et al.*, 2003; Hartwick and Barki, 1994; Szajna, 1996). Wixom and Todd (2005) proposed that both approaches present valuable contributions to the literature. However, each tells only one part of the story. While the user satisfaction enumerates system and information characteristics as explicit determinants, it is seen as a weak predictor of system use (Wixom and Todd, 2005; Melone, 1990; Hartwick and Barki, 1994; Davis *et al.*, 1989; Goodhue, 1988). User satisfaction is generally seen as the users' attitude toward the IS (object). Therefore, Wixom and Todd (2005) classified it as an "object-based attitude." This is an important part of the Wixom and Todd's integrated model because some empirical studies have found inconsistent and inconclusive results regarding the role of attitude on BI. Zhang *et al.* (2008) discussed that this problem could be attributed to the fact that attitude toward behavior and attitude toward object were two dissimilar type of attitudes which had different impacts on intention, but have been combined together in many studies. Thus, in their integrated model, Wixom and Todd (2005) separated object-based attitudes from behavioral attitudes.

Technology acceptance literature provides substantial predictions regarding use. According to Wixom and Todd (2005), TAM does this "by linking behaviors to attitudes and beliefs (ease of use and usefulness) that are consistent in time, target, and context with the behavior of interest (system usage)". For example, in our case, "beliefs and attitudes about a specific behavior" (e.g. use of a VA), "in a particular context" (e.g.

to take information about weather condition), "at a particular point in time" (e.g. in the mornings) "may predict behavioral intention" (Wixom and Todd, 2005; Fishbein and Ajzen, 1975). In short, while technology acceptance literature has focused on users' beliefs and behaviors, user satisfaction literature has focused on system and information characteristics (Ghobakhloo *et al.*, 2010).

Integrated model of user satisfaction and technology acceptance

Wixom and Todd (2005) introduced a model by combining user satisfaction and technology acceptance concepts: the integrated model of user satisfaction and technology acceptance. They suggested that user satisfaction and technology acceptance were not contradictory approaches. Rather, they represent complementary steps that affect usage (Wixom and Todd, 2005; Ghobakhloo *et al.*, 2010). They empirically tested the model by a sample of 465 users from seven different organizations who completed a survey regarding their use of data warehousing software (Wixom and Todd, 2005). The proposed model was supported, providing preliminary evidence that the two perspectives should be integrated (Wixom and Todd, 2005).

Wixom and Todd (2005) stated that the integrated model distinguished the object-based beliefs and attitudes found in the user satisfaction literature from behavioral beliefs and behavioral attitudes in the technology acceptance literature. The model is composed of five main parts (Figure A1). The left side of the model lists the characteristics of SQ and IQ. Wixom and Todd (2005) asserted that object-based beliefs shaped system satisfaction (SS) and information satisfaction (IS). At this point, SS and IS represented object-based attitudes that served as external variables shaping behavioral beliefs. Satisfaction influenced PEU and PU. The authors proposed that "the higher the overall satisfaction with the information, the more likely one would find the application of that information useful". "A similar effect was anticipated in terms of SS" (Wixom and Todd, 2005). They indicated that "SS represented a degree of favorableness with respect to the system and the mechanics of interaction" (Wixom and Todd, 2005). "The more satisfied one was with the system itself, the more likely one was to find the system to be easy to use" (Wixom and Todd, 2005). They also indicated that SS influenced IS. Consistent with the TAM (Davis, 1989), PEU influenced PU. To summarize, this model suggests that technology acceptance and user satisfaction are not competing approaches, but together they may provide a holistic view to measure the intention to use information technologies. The integrated model provides a useful framework to test the usability of VAs because it integrates both technical dimensions related to usability and predictions regarding use.

Methodology

This study aims to determine the system and information characteristics (e.g. flexibility, answering, understanding, etc.) of VAs that affect users' technology acceptance and satisfaction, and how these, in turn, affect intention to use. The study uses the integrated model of user satisfaction and technology acceptance to evaluate VA users' intention to use VAs through quantitative research. The integrated model approach (the integration of user satisfaction and technology acceptance) is used to provide a comprehensive understanding to measure causal effects.

The research framework, which is described in detail below, was derived from a vast literature review. As we pointed out in the previous section, user satisfaction was mainly determined by SQ and IQ. Thus, to measure the user satisfaction of VA users, first, we needed to determine system and information characteristics that could explain the SQ and IQ of the current VAs on smartphones. The voice-specific characteristics of VAs, which constituted the research framework, were derived from previous studies in the academic and professional research literature. Thus, we proposed and tested a new framework to study SQ and IQ characteristics of VAs on smartphones. To analyze the survey data, two multivariate analysis methods were used: simple linear regression analysis and multiple regression analysis.

Survey

An online survey was conducted with 160 university students in Istanbul, Turkey. The survey was conducted through Survey Monkey, and it consisted of 43 questions based on the research model, divided into six groups. Five different constructs (object-based beliefs, object-based attitudes, behavioral beliefs, behavioral attitudes, behavioral intentions) were measured by the survey. All answers were taken in seven-point Likert scales [1], where 1 = strongly disagree, 4 = neutral, 7 = strongly agree.

The first group was demographics. These questions determined respondents' age, operating systems, VA use, use of frequency, activities done by VAs and situations that users needed to use VAs. The second and the third group focused on users' experiences on SQ and IQ. The fourth group focused on users' satisfaction. The fifth and the sixth group surveyed users' attitudes toward VAs and their intentions to use. The seventh group consisted of survey items from PEU and PU.

Research framework

As there was no detailed academic research which defined the exact features of VAs on smartphones, some professional research reports were reviewed in addition to the related works in the IS literature. We found that the research frameworks and construct items that were mainly developed to analyze IS were not quite different from each other. For example, previous research on survey constructs showed that while Wixom and Todd (2005), Bailey and Pearson (1983); and Ives *et al.* (1983) used the word "flexibility" to refer to the way the system adapts to changing demands of the user, Claessen *et al.* (2017) used "flexible wording" and DeLone and McLean (2003) used "adaptability" to refer to the same concept (Table A1).

In addition, while developing our research framework, we took advantage of frameworks proposed by the professional research reports. Budiu and Laubheimer (2018a) determined key distinguishing features of VAs as voice input, natural language, voice output, intelligent interpretation, integration and agency. The Chatbottest Collaborative Guide (2017) proposed a compilation of questions ordered under seven different categories to test specific functionalities on chatbots. These categories were: answering, error management, intelligence, navigation, onboarding, personality and understanding. Therefore, we expanded our research framework with the addition of "understanding," "answering" and "intelligence" as the measurement factors of SQ and IQ. However, we excluded error management, navigation, onboarding and personality factors. This is because qualitative user studies based on observation are more appropriate in measuring these characteristics rather than self-reported data collection. Table A1 shows the survey constructs we used to formulate the survey questions.

Hypotheses development

Based on the related literature, we created 13 hypotheses in six different sets: Object-based beliefs and object-based attitudes; object-based beliefs and behavioral beliefs; object-based attitudes and behavioral beliefs; behavioral beliefs and behavioral attitudes; behavioral beliefs, behavioral intentions; behavioral attitudes and behavioral intentions.

Object-based beliefs – object-based attitudes. User satisfaction has been measured by various object-based beliefs. For example, Wixom and Todd (2005), Bailey and Pearson (1983); Ives *et al.* (1983), Baroudi and Orlikowski (1988); and Doll and Torkzadeh (1988) used a characteristics-based approach to measure user satisfaction. Wixom and Todd (2005) found that IQ and SS had significant influences on IS. They proposed that SQ was a significant determinant of SS. DeLone and McLean (2003) proposed a causal relationship, "in which IQ, SQ, and service quality were related to intention to use, as well as user satisfaction." DeLone and McLean (2003) and Ajzen and Fishbein (2005) found that object-based beliefs were linked to object-based attitudes. Based on the literature review, we proposed the following hypotheses:

H1. VA's SQ influences SS of the VA.

H2. VA's IQ influences IS of the VA.

H3. VA's SS influences IS of the VA.

Object-Based Beliefs - Behavioral Beliefs. Kääriä (2017) found that VAs' SQ influenced PU of the VAs. Besides, Wixom and Todd (2005) found that when they excluded the satisfaction constructs, IQ and SQ were significant determinants of PU and PEU. Thus, we proposed the following hypotheses:

H4. VA's SQ and IQ influence the PU of the VA.

H5. VA's SQ and IQ influence the PEU of the VA.

Object-based attitudes – behavioral beliefs. Object-based attitudes can predict behavioral beliefs (Ajzen and Fishbein, 2005; Fazio and Olson, 2003; Eagly and Chaiken, 1993). Wixom and Todd (2005) stated that the influences of object-based attitudes on behavioral beliefs demonstrated strong and significant relationships between IS and PU, and between SS and PEU. Therefore, we proposed the following hypotheses:

H6. SS has a positive effect on the PEU of the VA.

H7. IS has a positive effect on the PU of the VA.

Behavioral beliefs – behavioral attitudes. Studies (Wixom and Todd, 2005) have shown that behavioral beliefs directly influenced attitudes toward use and usage. Besides, Davis (1989) suggested PEU as a causal antecedent to PU, as opposed to a parallel, direct determinant of system usage. Wixom and Todd (2005) stated that PEU influenced the PU of the system. Davis (1989) indicated that PU and PEU determined the attitude toward the use of information technology. Dobrowolski (2014) also found that PEU was positively affecting consumers' attitudes toward products. Therefore, we proposed that attitude toward using VAs can be shaped by behavioral beliefs:

H8. PEU influences the PU of the VA.

H9. PEU of the VA has a positive effect on user's attitude toward a VA.

H10. PU of the VA has a positive effect on user's attitude toward a VA.

Behavioral beliefs – behavioral intentions. Wixom and Todd (2005) suggested that BI to use was mediated by PEU and PU. Also, research has shown that these constructs had a positive effect on attitude and BI (Al-Gahtani and King, 1999; Childers *et al.*, 2001; Koufaris, 2002; Pavlou, 2003; Ha and Stoel, 2009; Mäntymäki and Salo, 2011; Kim *et al.*, 2009). Thus, we proposed the following hypotheses:

H11. PEU of the VA has a positive effect on BI to use a VA.

H12. PU of the VA has a positive effect on BI to use a VA.

Behavioral attitudes – behavioral intentions. The relationship between attitude and BI has been measured in different contexts for years. In the context of information technologies, research has shown that attitude would reflect in actual system use. Fishbein and Ajzen (1975) indicated that beliefs and attitudes toward a specific behavior were predictive for intention and behavior. Venkatesh *et al.* (2003) proposed that the target behavior of interest was driven by BI and the intention was determined by attitude toward use. While behavioral attitude may be a strong predictor of behavior, object-based attitude may be not. For example, Wixom and Todd (2005) found the correlation between object-based attitude and behavior averaged only 0.13, whereas the correlation between behavioral attitude and the behavior itself averaged 0.54. Thus, we proposed that behavioral attitude can have an impact on BI:

H13. Attitude toward a VA has a positive effect on a user's BI to use a VA.

Sample

The survey was distributed online and responses were collected between December 3 and December 12, 2018. 160 responses were received, and 75 responses were chosen as the final sample, after removing responses that were taken from the participants who have never used a VA before and who have not completed the questionnaire. 33.75% (n = 54) of all respondents stated that they have never used a VA before. Respondents who reported that they had never used a VA before could give us important clues about why they had not used before. However, this study focuses on the experiences of people who used a VA before at least once. In total 57.33% of the remaining respondents were female and 41.33% were male. The sample of the study consisted of university students because the VA user profile on smartphones mainly consists of young people under 30. Since we conducted this research with university students, the largest group of respondents by age was between 17 and 24 by 92%. The most common operating system was iPhone IOS by 70.67%. In total 78.67% of respondents reported that they used VAs in Turkish, followed by 18.67% in English. Most participants reported that they mostly used VAs when their hands were busy. The single most common use participants reported was information retrieval, followed by communicating with a person (e.g. making a call, texting or emailing). A notable use of the assistants was for controlling the phone and having fun. An overview of the sample demographics is displayed in Table A2.

Results

We tested our model by evaluating internal consistency and correlation matrixes. We found that the value of Cronbach's alpha (α) (Nunnally, 1978) for each construct is exceeding 0.7, which is considered to be quite acceptable. Overall Cronbach's alpha (α) is 0.91. It is considered to be a measure of scale reliability. Total variance explained is 91.72%. The descriptive statistics of the analyzed constructs are presented in Table A3. The correlation matrixes which show the correlations among constructs are listed in Tables A4–Table A7.

All correlations among constructs resulted positive. In Tables A4 – A7, *p*-values are provided to show the significance of correlations and variances.

In addition, we provided two more tests that indicate the suitability of our data. Kaiser-Meyer-Olkin (KMO) test measures sampling adequacy for each variable in the model. KMO value of our data is 0.774, which indicates that the sampling is adequate. Bartlett's test of sphericity value of our data is 0.000. This value represents a high significance. Although Bartlett's test is generally seen as a test of compliance with factor analysis, it is essentially based on the principle of testing the correlation matrix of variables against the unit matrix. Therefore, Bartlett test is also a test of the significance of the correlation matrix. Thus, we believe that the value 0.000 shows the significance of our correlation matrix.

Like Wixom and Todd (2005) did in their study, "the test of our structural model includes the estimation of the path coefficients, which indicate the strengths of the relationships between the dependent and independent variables, and R^2 values, which represent the amount of variance explained by the independent variables". These two estimates show how well our hypothesized model supported by the data (Wixom and Todd, 2005). Figure A2 shows the results of the test of the hypothesized model. We did a curve estimation for all the relationships in our model and determined that all estimated relationships were sufficiently linear to be tested using a covariance based structural equation modeling. Also, we made multicollinearity tests for two or more variables predicting another variable. All values for variance inflation factor were less than 2, which was quite ideal.

Multiple regression analysis suggested that completeness (0.26), accuracy (0.25), format (0.26) and currency (0.23) were all significantly related to IQ, and collectively accounted for 96% of the variance in IQ. Completeness and accuracy together accounted for 72% of the variance in IQ. Flexibility (0.10), understanding (0.09), answering (0.13), intelligence (0.12), integration (0.13), accessibility (0.12), timeliness (0.15) and reliability (0.13) were all significant determinants of SQ, and collectively accounted for 97% of the variance in SQ. Integration, intelligence, accessibility, timeliness and reliability together accounted for 86% of the variance in SQ. Only accessibility accounted for 50% of the variance in SQ. We found that SQ was a significant determinant of SS (0.97), accounting for 33% of its variance. This hypothesis was supported, but with lesser effect than what IQ traits had on SS. IQ was also a significant determinant of SS (0.91), accounting for 43% of its variance. While together, SS was positively influenced by SQ (0.40) and IQ (0.69). Together they explained 46% of the variance in SS. As expected, IQ (0.35) and SS (0.56) had significant influences on IS, accounting for 50% of the variance in that measure.

When we excluded the satisfaction constructs and tested the direct effects from SQ and IQ to PU, we found that SQ (path = 0.36) and IQ (path = 0.61) were significant determinants of PU. Together they explained 41% of the variance. Again, when satisfaction constructs were excluded, SQ (path = 0.49) and IQ (path = 0.70) were significant determinants of PEU. Together they explained 56% of the variance. SS (0.58) also had significant influences on PEU, accounting for 35% of the variance in that measure. Then, we tested a relationship where SQ, IQ and SS were included as antecedents to PEU. We found only SQ and IQ were significant, and collectively, these three factors increased explanatory power for PEU from 0.56 to 0.57.

IS (0.58) had significant influences on PU, accounting for 38% of the variance in that measure. As expected, PEU (0.57) and IS (0.30) together had significant influences on PU, accounting for 64% of the variance in that measure. As a result, we indicated SQ and IQ were more significant predictors of PEU than satisfaction. The path coefficients were significantly higher than satisfaction and the R^2 values for PEU went up from 0.35 to 0.56. However, as we expected, PEU and IS together explained 64% of the variance in PU.

SQ (0.65) and PU (0.61) were significant predictors of change in attitude, they explained 54% of the variance. Then we examined whether SQ, IQ, SS, IS and PEU could serve as direct antecedents to the attitude in the same fashion as SQ and PU. When these five factors were added as direct antecedents to the attitude in addition to PU and SQ, only PU and SQ were found significant. Collectively, the five additional factors increased explanatory power for attitude from 0.54 to 0.56.

PU (0.49) and attitude (0.36) were significant predictors of change in intention to use, they explained 34% of the variance. We also examined alternative relations to determine the degree to which each predicts and explains users' behavioral intention to use. First, we added PEU as a direct antecedent to intention, in addition to PU and attitude. We found only attitude was significant and collectively, these three factors increased explanatory power of intention to use from 0.34 to 0.36. Second, we examined whether SQ, IQ, SS, IS and PEU served as direct antecedents to intention in the same fashion as PU and attitude. Multiple regression analysis suggested that they were weak or even negative predictors of intention. Indeed, when these five factors were added as direct antecedents to intention, in addition to PU and attitude, only attitude was significant. Collectively, the five additional factors increased explanatory power for intention from 0.34 to 0.37.

Next, we tested a model where all SQ and IQ were included as direct antecedents to intention. Only completeness and accuracy were significant. Accuracy (0.67) was an important determinant of PEU, accounting for 46% of its variance. Accuracy was also a significant determinant of PU by 0.52 and accounting for 30% of its variance In addition, accuracy (0.63) was an important determinant of attitude, accounting for 30% of its variance, and directly accounting for 22% of the variance in intention to use.

Hypotheses test

H1 stated that there is a positive effect from SQ to SS. This hypothesis was supported. *H2* stated that IS was positively affected by IQ of the VA. This hypothesis was also supported, but with lesser effect than what IQ and SS together had on IS (*H3*). *H4* and *H5* stated that SQ and IQ have a positive effect on PU and PEU of the VA. These hypotheses were supported. We found SQ and IQ as significant predictors of PEU and PU, but with lesser effect than what PEU and IS had on PU. In relation to that, *H6*, *H7* and *H8* were supported, but with lesser effect than what SQ and IQ had on PEU. *H9* and *H10* were supported by the results. However, we found that PU and SQ were more explanatory in the attitude change. PEU, PU and attitude were hypothesized to have positive effects on intention to use. The results supported their influence on intention to use but with lesser effect than what PU and attitude together had on intention to use. A summary of the hypotheses can be seen in Table A8.

Discussion

The findings of this study were not fully consistent with the integrated model proposed by Wixom and Todd (2005). The proposed influences of object-based attitudes on behavioral beliefs did not demonstrate strong and significant relationships between SS and PEU. Rather, we found that SQ and IQ (object-based beliefs) had stronger effects on PEU (behavioral beliefs). Wixom and Todd (2005) found IQ and SQ as direct determinants of PU and PEU too. However, they calculated this effect by excluding satisfaction constructs. The path coefficients were significantly lower than in the proposed research model. In addition to PEU, we found that IS (object-based attitudes) had significant influences on PU (behavioral beliefs). Besides, PU and SQ were one of the antecedents to attitude, rather than PEU. DeLone and McLean (2003) and Ajzen and Fishbein (2005) found that object-based beliefs were linked to object-based attitudes. Our findings were consistent with their findings. We found a positive effect via the SQ and IQ to the SS and IS. Besides, we found object-based beliefs as significant predictors of behavioral beliefs. This finding was consistent with Kääriä's (2017) and Wixom and Todd's (2005) findings.

Consistent with the findings of Wixom and Todd (2005), Ajzen and Fishbein (2005); Fazio and Olson (2003); and Eagly and Chaiken (1993), we found that object-based attitudes were the predictors of behavioral beliefs. Consistent with Davis (1989) and Dobrowolski (2014), our findings showed that PU and PEU determined behavioral attitudes. We also found that object-based beliefs (especially, SQ) could be predictive in attitude change. Similar to the original conceptualization represented in TAM (Davis, 1989), we found that PEU, PU and attitude indicated positive effects on intention to use. Research also showed that behavioral beliefs (PEU and PU) had a positive effect on attitude and behavioral intention (Al-Gahtani and King, 1999; Childers *et al.*, 2001; Koufaris, 2002; Pavlou, 2003; Ha and Stoel, 2009; Mäntymäki and Salo, 2011; Kim *et al.*, 2009). Besides, as Davis (1989) conceptualized and Wixom and Todd (2005) supported, we found that PEU was a causal antecedent to PU, rather than a direct determinant of system use. Consistent with Fishbein and Ajzen (1975) and Venkatesh *et al.* (2003), we found that the intention to use was determined by attitude.

Our findings showed that system and information characteristics strongly explained the variance for SQ and IQ and all relations were significant. We found that flexibility, understanding, answering, intelligence, integration, reliability and timeliness of VAs served as antecedent beliefs to SQ of VAs, with timeliness, reliability, integration and answering having the strongest effects. Timeliness was one of the most important components of VAs' SQ. Besides, users reported that they mostly used VAs when their hands were busy. We assume that if people are trying to do other things when their hands are busy, it usually means that they are in a hurry. Even if they are not in a hurry, it is compelling to do two things at the same time, so people do not want to wait an assistant to help them to complete a task. Thus, this finding shows that the VAs' timely response to information requests is important for users.

Info retrieval was the most common reason of users to use a VA. Also, the accuracy and the reliability of the information obtained from a VA were important dimensions for users. For example, a VA with an always-on microphone can lead to serious privacy and security concerns. The *PwC* (2018) survey on VAs found that privacy was an important concern among users. VAs are a part of smartphones, apps and websites that collect and analyze personal data about users. These concerns may influence the use of VAs. Thus, we propose that it is critical to understand privacy and security concerns of users. The *PwC* (2018) also found that consumers did not trust the technology and use it with confidence. Another research finding that might be related to reliability of the system was proposed by Budiu and Laubheimer (2018a). They found that when the assistant provided an answer, consumers doubted if the answer was right, and they were not sure if the query was correctly understood in its entirety, or the assistant only matched a part of it. Thus, reliability is an important characteristic of VAs, and it should be investigated further in the context of social factors.

Another important antecedent to SQ was integration. Budiu and Laubheimer (2018a) also found "a common complaint with the assistants that they did not integrate well in the virtual ecosystems in which users lived". For example, "*iPhone* users complained about the lack of integration between Siri and a variety of apps they wanted to use – *Spotify* to play Music, *Google Maps* for directions, and so on" Budiu and Laubheimer (2018a). In this research, we found similar results that showed *iPhone* (*Siri*) users were complaining more about the integration success of the VA.

Answering was another important antecedent to SQ. Budiu and Laubheimer (2018a) found that the assistants could not consistently provide satisfactory vocal answers to the queries. When we looked at the relationship between SQ characteristics and SS, we found that accessibility and answering served as the strongest antecedents to SS. Thus, we propose that answering is an important component that affects overall SQ and ultimately SS. Besides, we examined alternative ways to determine which characteristic better explains the SQ. Regression analysis results showed that accessibility alone explained 50% of the variance in SQ and affected SS.

Completeness, accuracy, format and currency served as antecedents to IQ, with completeness and format having quite important roles. These results showed that providing all necessary information with a good presentation format (e.g. vocal format) was important for the IQ success of VAs. Budiu and Laubheimer (2018a) stated that their "users considered a vocal answer superior to on-screen answers in the vast majority of cases". Our findings also suggested that voice vs. screen results were important for users, especially for the SQ. Completeness is an important characteristic for task completion. People generally use VAs to complete a variety of tasks. We found that some of the most common use of VAs include info retrieval, communication, phone control, checking the weather or getting directions. However, if a VA could not answer the questions and complete the request promptly, the interaction cost increases.

Accuracy of information was a direct antecedent to PEU, PU, attitude and intention to use. Incorrect interpretation of voice commands by VAs can lead to incorrect results, and this may reduce consumer satisfaction. The *PwC* (2018) found that consumers expected their VAs to be correct, accurate and consistent (73% agree). Although *Loup Ventures* found that voice word accuracy rates to be over 80% for *Google Assistant* and *Siri* (Munster and Thompson, 2019), the *PwC* (2018) found that VAs on smartphones had the lowest consumer satisfaction rate in terms of understanding, reliability and accuracy (38% very satisfied). However, the accuracy rates are improving year by year. For example, *Siri's* voice search accuracy improved from 52.3% success rate in 2017 to 83.1% in 2019 (Munster and Thompson, 2019). To further compare *Siri* and *Google Assistant* voice search numbers in terms of accuracy, *Google Assistant* answered 87.9% of questions correctly, surpassing *Siri* by over 10% (Munster and Thompson, 2019). The users' perception that VAs present correct information was an important factor for the reliability of system operation as well. We indicated that accuracy could affect PEU, PU, attitude and ultimately, usage. Therefore, we propose that voice capabilities of VAs should continue to be developed to the point where they are accurate and successfully meet their consumers' needs.

Conclusion

This study uses the integrated model of user satisfaction and technology acceptance to measure behavioral intention to use VAs on smartphones. Consistent with the findings of Wixom and Todd (2005), we suggest that users use VAs to get useful information as far as they interact with VAs effectively and efficiently, and users' SS is highly influenced by their satisfaction with the quality of information produced by VAs. A timely, reliable, accurate, accessible, and current vocal response to the queries creates the most satisfactory user experience. The quality of system and information, and satisfaction that VA produces influence behavioral beliefs regarding the system, which in turn affect attitude and behavioral intention. To conclude, while SQ and IQ of VAs have stronger effects on PEU, IS and PEU show significant influences on PU. There is an influence of PEU, usefulness and attitude on behavioral intention but with lesser effect than what PU and attitude together have on behavioral intention.

Implications and future research

Overall, the results of this study are consistent with the hypotheses. However, in the context of voice assistants on smartphones, we could not find enough potential to integrate user satisfaction and technology acceptance concepts into a single model. In fact, rather than object-based attitudes (e.g. SS) we found a strong relationship between object-based beliefs (SQ) and behavioral beliefs (PEU). In addition, SQ (object-based beliefs) was one of the two antecedents of attitude (behavioral attitude), rather than PEU (behavioral beliefs). Thus, continued research should further investigate the validity of the integrated model in other IS.

The study provides a new research framework to understand and assess the relative influence of system and information characteristics of VAs. We believe that the research presents a useful contribution to UX researchers of VAs. Researchers can examine the effects of system and information characteristics of VAs on usage, and determine what changes in system design may have an impact on system usage by using our framework. For example, if users are having difficulties with the "answering" quality of a VA, then researchers may focus on the "answering" of system design, and try to figure out which feaures of VAs are effecting the user experience. It would also be a useful contribution to the literature to explore whether the system and information characteristics recommended for VAs on smartphones can be adapted to other types of VAs (e.g. home speakers such as Amazon Alexa). Also, future studies may investigate additional system and information characteristics that may explain the usage of VAs that differ on their features.

Note

1. Seven-point scales are considered to be more reliable and valid (Nunnally, 1978).

References

Ajzen, I. (1985), "From intentions to actions: a theory of planned behavior", in Kuhl, J. and Beckmann, J. (Eds), *Action Control: From Cognition to Behavior*, Springer-Verlag, Berlin, Heidelberg, New York, NY, Tokyo, pp. 11-39.

Ajzen, I. and Fishbein, M. (2005), "The influence of attitudes on behavior", in Albarracín, D., Johnson, B.T. and Zanna, M.P. (Eds), *Handbook of Attitudes and Attitude Change: Basic Principles*, Erlbaum, Mahwah, NJ, pp. 173-221.

Al-Gahtani, S.S. and King, M. (1999), "Attitudes, satisfaction and usage: factors contributing to each in the acceptance of information technology", *Behaviour and Information Technology*, Vol. 18 No. 4, pp. 277-297, doi: 10.1080/014492999119020.

Bailey, J.E. and Pearson, S.W. (1983), "Development of a tool for measuring and analyzing computer user satisfaction", *Management Science*, Vol. 29 No. 5, pp. 530-545, doi: 10.1287/mnsc.29.5.530.

Baroudi, J. and Orlikowski, W. (1988), "A short-form measure of user information satisfaction: a psychometric evaluation and notes on use", *Journal of Management Information Systems*, Vol. 4 No. 4, pp. 44-59, doi: 10.1080/07421222.1988.11517807.

Budiu, R. and Laubheimer, P. (2018a), "Intelligent assistants have poor usability: a user study of Alexa, Google Assistant, and Siri", available at: www.nngroup.com/articles/intelligent-assistant-usability/ (accessed 22 June 2020).

Budiu, R. and Laubheimer, P. (2018b), "Intelligent assistants: creepy, childish, or a tool? User's attitudes toward Alexa, Google Assistant and Siri", available at: www.nngroup.com/articles/intelligent-assistant-usability/ (accessed 22 June 2020).

Budiu, R. and Whitenton, K. (2018a), "The paradox of intelligent assistants: poor usability, high adoption", available at: www.nngroup.com/articles/intelligent-assistants-poor-usability-high-adoption/ (accessed 22 June 2020).

Budiu, R. and Whitenton, K. (2018b), "What could an intelligent assistant do for you? A diary study of user needs", available at: www.nngroup.com/articles/intelligent-assistant-user-needs/ (accessed 22 June 2020).

Chatbottest Collaborative Guide (2017), "Index", available at: https://github.com/chatbottest-com/guide/wiki (accessed 22 June 2020).

Childers, T.L., Carr, C.L., Peck, J. and Carson, S. (2001), "Hedonic and utilitarian motivations for online retail shopping behavior", *Journal of Retailing*, Vol. 77 No. 4, pp. 511-535, doi: 10.1016/S0022-4359(01)00056-2.

Claessen, V., Schmidt, A. and Heck, T. (2017), "Virtual assistants: a study on the usability and user perception of customer service systems for E-Commerce", in Gäde, M., Trkulja, V. and Petras, V. (Eds), *Proceedings of the 15th International Symposium of Information Science Everything 2017: Changes, Everything Stays the Same? Understanding Information Space*, Verlag Werner Hülsbusch, Berlin, Glückstadt, pp. 116-130.

Davis, F.D. (1989), "Perceived usefulness, perceived ease of use, and user acceptance of information technology", *MIS Quarterly*, Vol. 13 No. 3, pp. 319-339, doi: 10.2307/249008.

Davis, F.D. (1993), "User acceptance of information technology: systems characteristics, user perceptions and behavioral impact", *International Journal of Man-Machine Studies*, Vol. 38 No. 3, pp. 475-487, doi: 10.1006/imms.1993.1022.

Davis, F.D., Bagozzi, R.P. and Warshaw, P.R. (1989), "User acceptance of computer technology: a comparison of two theoretical models", *Management Science*, Vol. 35 No. 8, pp. 982-1003.

DeLone, W.H. and McLean, E.R. (1992), "Information systems success: the quest for the dependent variable", *Information Systems Research*, Vol. 3 No. 1, pp. 60-95, doi: 10.1287/isre.3.1.60.

DeLone, W.H. and McLean, E.R. (2003), "The DeLone and McLean model of information systems success: a ten year update", *Journal of Management Information Systems*, Vol. 19 No. 4, pp. 60-95, doi: 10.1080/07421222.2003.11045748.

Dobrowolski, P. (2014), "The effects of virtual experience on attitudes toward real brands", *Cyberpsychology, Behavior, and Social Networking*, Vol. 17 No. 2, pp. 125-128, doi: 10.1089/cyber.2012.0613.

Doll, W.J. and Torkzadeh, G. (1988), "The measure of end-user computing satisfaction", *MIS Quarterly*, Vol. 12 No. 2, pp. 259-274.

Eagly, A.H. and Chaiken, S. (1993), *The Psychology of Attitudes*, Thomson Wadsworth, Belmont, CA.

Fazio, R.H. and Olson, M.A. (2003), "Attitudes: foundation, function and consequences", in Hogg, M.A. and Cooper, J. (Eds), *The Sage Handbook of Social Psychology*, Sage, London, pp. 123-145.

Fishbein, M. and Ajzen, I. (1975), *Belief, Attitude, Intention, and Behavior: An Introduction to Theory and Research*, Addison-Wesley, Reading, MA.

Ghobakhloo, M., Zulkifli, N.B. and Aziz, F.A. (2010), "The interactive model of user information technology acceptance and satisfaction in small and medium-sized enterprises", *European Journal of Economics, Finance and Administrative Sciences*, Vol. 19, pp. 7-27.

Goodhue, D.L. (1988), "Is attitudes: toward theoretical and definitional clarity", *ACM SIGMIS Database: The DATABASE for Advances in Information Systems*, Vol. 19 Nos 3/4, pp. 6-15.

Ha, S. and Stoel, L. (2009), "Consumer e-shopping acceptance: antecedents in a technology acceptance model", *Journal of Business Research*, Vol. 62 No. 5, pp. 565-571, doi: 10.1016/j.jbusres.2008.06.016.

Hartwick, J. and Barki, H. (1994), "Explaining the role of user participation in information system use", *Management Science*, Vol. 40 No. 4, pp. 440-465, doi: 10.1287/mnsc.40.4.440.

Heitzman, A. (2019), "How popular is voice research?", available at: www.highervisibility.com/blog/how-popular-is-voice-search/ (accessed 22 June 2020).

Hong, W., Thong, J., Wong, W.-M. and Tam, K.-Y. (2002), "Determinants of user acceptance of digital libraries: an empirical examination of individual differences and systems characteristics", *Journal of Management Information Systems*, Vol. 18 No. 3, pp. 97-124.

Igbaria, M., Guimaraes, T. and Davis, G.B. (1995), "Testing the determinants of microcomputer usage via a structural equation model", *Journal of Management Information Systems*, Vol. 11 No. 4, pp. 87-115.

Ives, B., Olson, M.H. and Baroudi, J.J. (1983), "The measurement of user information satisfaction", *Communications of the ACM*, Vol. 26 No. 10, pp. 785-793, doi: 10.1145/358413.358430.

Jiang, J., Awadallah, A.H., Jones, R., Ozertem, U., Zitouni, I., Kulkarni, R.G. and Khan, O.Z. (2015), "Automatic online evaluation of intelligent assistants", *WWW 2015: Conference Proceedings International World Wide Web Conference*, *Florence*, pp. 506-561, doi: 10.1145/2736277.2741669.

Kääriä, A. (2017), "Technology acceptance of voice assistants: anthropomorphism as a factor", Unpublished Master's Thesis, University of Jyväskylä, Department of Computer Science and Information Systems, available at: www.semanticscholar.org/paper/Technology-acceptance-of-voice-assistants-%3A-as-Kääriä/072ef2fc80cfe07e48517ce361482f40b9512d5a

Kim, H.B., Kim, T.T. and Shin, S.W. (2009), "Modeling roles of subjective norms and e-trust in customers' acceptance of airline B2C e-commerce websites", *Tourism Management*, Vol. 30 No. 2, pp. 266-277, doi: 10.1016/j.tourman.2008.07.001.

Kinsella, B. (2020), "Voice assistant use on smartphones rise, Siri maintains top spot for total users in the US", available at: https://voicebot.ai/2020/11/05/voice-assistant-use-on-smartphones-rise-siri-maintains-top-spot-for-total-users-in-the-u-s/ (accessed 19 March 2021).

Kiseleva, J., Williams, K., Awadallah, H.M., Crook, A.C., Zitouni, I. and Anastasakos, T. (2016a), "Predicting user satisfaction with intelligent assistants", *ACM SIGIR 2016: Proceedings of the 39th International ACM SIGIR Conference on Research and Development in Information Retrieval*, *Pisa*, doi: 10.1145/2911451.2911521.

Kiseleva, J., Williams, K., Awadallah, H.M., Crook, A.C., Zitouni, I. and Anastasakos, T. (2016b), "Understanding user satisfaction with intelligent assistants", *CHIIR 2016: Proceedings of the 2016 ACM on Conference on Human Information and Retrieval*, doi: 10.1145/2854946.2854961.

Koufaris, M. (2002), "Applying the technology acceptance model and flow theory to online consumer behavior", *Information Systems Research*, Vol. 13 No. 2, pp. 205-223, doi: 10.1287/isre.13.2.205.83.

Lim, K.H. and Benbasat, I. (2000), "The effect of multimedia on perceived equivocality and perceived usefulness of information systems", *MIS Quarterly*, Vol. 24 No. 3, pp. 449-471, doi: 10.2307/3250969.

MäNtymäKi, M., and and Salo, J. (2011), "Teenagers in social virtual worlds: continuous use and purchasing behavior in Habbo hotel", *Computers in Human Behavior*, Vol. 27 No. 6, pp. 2088-2097, doi: 10.1016/j.chb.2011.06.003.

Melone, N. (1990), "A theoretical assessment of the user-satisfaction construct in information systems research", *Management Science*, Vol. 36 No. 1, pp. 76-91, doi: 10.1287/mnsc.36.1.76.

Moorthy, A.E. and Vu, K.P.L. (2015), "Privacy concerns for use of voice activated personal assistant in the public space", *International Journal of Human-Computer Interaction*, Vol. 31 No. 4, pp. 307-335, doi: 10.1080/10447318.2014.986642.

Munster, G. and Thompson, W. (2019), “Annual digital assistant IQ test”, available at: https://loupventures.com/annual-digital-assistant-iq-test/ (accessed 22 June 2020).

Nunnally, J.C. (1978), *Psychometric Theory*, McGraw-Hill, New York, NY.

Pavlou, P. (2003), “Consumer acceptance of electronic commerce: integrating trust and risk with the technology acceptance model”, *International Journal of Electronic Commerce*, Vol. 7 No. 3, pp. 69-103, doi: 10.1080/10864415.2003.11044275.

PwC Report (2018), “Prepare for the voice revolution”, available at: www.pwc.com/us/en/services/consulting/library/consumer-intelligence-series/voice-assistants.html (accessed 22 June 2020).

Seddon, P. (1997), “A respecification and extension of the DeLone and McLean model of is success”, *Information Systems Research*, Vol. 8 No. 3, pp. 240-253, doi: 10.1287/isre.8.3.240.

Statista (2021), “Number of digital voice assistants in use worldwide from 2019 to 2024 (in billions)”, available at: www.statista.com/statistics/973815/worldwide-digital-voice-assistant-in-use/ (accessed 19 March 2021).

Szajna, B. (1996), “Empirical evaluation of the revised technology acceptance model”, *Management Science*, Vol. 42 No. 1, pp. 85-92, doi: 10.1287/mnsc.42.1.85.

Venkatesh, V. and Bala, H. (2008), “Technology acceptance model 3 and a research agenda on interventions”, *Decision Sciences*, Vol. 39 No. 2, pp. 273-312, doi: 10.1111/j.1540-5915.2008.00192.x.

Venkatesh, V. and Davis, F.D. (2000), “A theoretical extension of the technology acceptance model: four longitudinal field studies”, *Management Science*, Vol. 42 No. 2, pp. 186-204, doi: 10.1287/mnsc.46.2.186.11926.

Venkatesh, V., Thong, J.Y.L. and Xu, X. (2012), “Consumer acceptance and use of information technology: extending the unified theory”, *MIS Quarterly*, Vol. 36 No. 1, pp. 157-178, doi: 10.2307/41410412.

Venkatesh, V., Morris, M.G., Davis, G. and Davis, F. (2003), “User acceptance of information technology: toward a unified view”, *MIS Quarterly*, Vol. 27 No. 3, pp. 425-478, doi: 10.2307/30036540.

Wixom, B.H. and Todd, P.A. (2005), “A theoretical integration of user satisfaction and technology acceptance”, *Information Systems Research*, Vol. 16 No. 1, pp. 85-102, doi: 10.1287/isre.1050.0042.

Zhang, P., Aikman, S.N. and Sun, H. (2008), “Two types of attitudes in ICT acceptance and use”, *International Journal of Human-Computer Interaction*, Vol. 24 No. 7, pp. 628-648, doi: 10.1080/10447310802335482.

Appendix 1

1. Object-based beliefs: Represent system quality and information quality	Wixom and Todd (2005)
System quality: Measures the information processing system itself	Wixom and Todd (2005), DeLone and McLean (2003)
1.1.1. Flexibility: Refers to the way the system adapts to changing demands of the user	Wixom and Todd (2005), Bailey and Pearson (1983); Ives *et al.* (1983); analyzed as "adaptability" by DeLone and McLean (2003); analyzed as "flexible wording" by Claessen *et al.* (2017)
1.1.2. Understanding: Refers to the ability of the system to take commands that are spoken instead of issued through typing or clicking/tapping graphical items and natural language understanding	The *PwC* Research (2018); analyzed as "voice input and natural language understanding" by Budiu and Laubheimer (2018a); analyzed as "ease of understanding" by DeLone and McLean (2003); analyzed as "understanding" by the Chatbottest Collaborative Guide (2017)
1.1.3. Answering: Refers to the ability of the system to read the information out loud, instead of displaying information on a screen and to use a set of vocabulary, syntax, and grammatical rules	The Chatbottest Collaborative Guide (2017); analyzed as "voice output" by Budiu and Laubheimer (2018a); analyzed as "language" by Bailey and Pearson (1983), Ives *et al.* (1983)
1.1.4. Intelligence: Refers to the ability of the system to utilize additional information besides the user's literal input, to estimate what the user wants	Budiu and Laubheimer (2018a), the Chatbottest Collaborative Guide (2017)
1.1.5. Integration: Refers to the way the system allows data to be integrated from various sources	Wixom and Todd (2005); Budiu and Laubheimer (2018a); Bailey and Pearson (1983), Ives *et al.* (1983)
1.1.6. Accesibility: Refers to the ease with which information can be accessed or extracted from the system	Wixom and Todd (2005), Bailey and Pearson (1983); Ives *et al.* (1983)
1.1.7. Timeliness: Refers to the degree to which the system offers timely responses to requests for information or action	Wixom and Todd (2005), Bailey and Pearson (1983); Ives *et al.* (1983), Doll and Torkzadeh (1988)
1.1.8. Reliability: Refers to dependability of system operation	Wixom and Todd (2005), Bailey and Pearson (1983); Ives *et al.* (1983), DeLone and McLean (2003); Baroudi and Orlikowski (1988), Doll and Torkzadeh (1988); the *PwC* Research (2018)
Information quality: Measures of information system output, namely, the quality of the information that the system produces	Wixom and Todd (2005), DeLone and McLean (2003)
1.2.1. Completeness: Represents the degree to which the system provides all necessary information	Wixom and Todd (2005), DeLone and McLean (2003); Bailey and Pearson (1983), Ives *et al.* (1983); Baroudi and Orlikowski (1988), Doll and Torkzadeh (1988)
1.2.2. Accuracy: Represents the user's perception that the information is correct	Wixom and Todd (2005), Bailey and Pearson (1983); Ives *et al.* (1983), Baroudi and Orlikowski (1988); Doll and Torkzadeh (1988); the *PwC* Research (2018); Munster and Thompson (2019)
1.2.3. Format: Represents the user's perception of how well the information is presented	Wixom and Todd (2005), Bailey and Pearson (1983)
1.2.4. Currency: Represents the user's perception of the degree to which the information is up to date	Wixom and Todd (2005), Bailey and Pearson (1983); Ives *et al.* (1983), Doll and Torkzadeh (1988)
2. Object-based attitudes: Represent system satisfaction and information satisfaction	Wixom and Todd (2005)

(*continued*)

Table A1.
Survey constructs

2.1. System satisfaction: Represents a degree of favorableness with respect to the system and the mechanics of interaction	Wixom and Todd (2005), DeLone and McLean (2003)
2.2. Information satisfaction: Represents a degree of favorableness with respect to the information and the mechanics of interaction	Wixom and Todd (2005), DeLone and McLean (2003)
3. Behavioral beliefs: Represent PEU and PU of an information system	Wixom and Todd (2005), Davis (1989)
3.1. Perceived ease of use: Refers to the degree to which a person believes that using a particular system would be free of effort	Wixom and Todd (2005), Davis (1989)
3.2. Perceived usefulness: Refers to the degree to which a person believes that using a particular system would enhance his or her job performance	Wixom and Todd (2005), Davis (1989)
4. Behavioral attitudes: Represent users' attitude toward an information technology	Wixom and Todd (2005)
5. Behavioral intentions: Represent users' intention to use an information technology	Wixom and Todd (2005)

Table A1.

Variables	Options	Frequency (F)	(%)
Gender	Female	43	57.33
	Male	31	41.33
	Mx	1	1.33
Age	17–24	69	92.00
	25–34	6	8.00
	35–44	0	0.00
	45+	0	0.00
Operating system	iPhone IOS	53	76.67
	Google Android	22	29.33
	Other	0	0.00
VA usage frequency	Never (but at least once)	10	13.33
	Rarely	39	52.00
	Sometimes	13	17.33
	Only when I need	11	14.67
	Regularly	0	0.00
	Frequently	2	2.67
	All the time	0	0.00
Language options	Turkish	59	78.67
	English	14	18.67
	Other	2	2.67
Common situations to use a VA*	When my hands are busy	38	50.67
	I can use it in any case	33	44.00
	When asking the question was faster than typing it and reading through the results	25	33.33
The most common activities done with VAs*	Info retrieval	40	53.33
	Communication	23	30.67
	Phone control	22	29.33
	Fun	21	28.00
	Weather	20	26.67
	Directions	15	20.00
	Play music/podcast	13	17.33
	Timer/alarm	13	17.33
	Notes	11	14.67
	Idea	11	14.67
	Navigation	9	12.00
	News	7	9.33
	IOT control	4	5.33
	Games	2	2.67
	Online shopping	0	0.00

Note: *Numbers sum to more than 100% because users reported more than one activity

Table A2. Sample demographics

Constructs	Item	Mean	SD
System quality (SQ) $\alpha = 0.76$			
Flexibility (Flex.)	VA can be adapted to meet a variety of needs	5.12	1.65
	VA can be flexibly adjusted to new demands or conditions	5.15	1.48
	VA can answer questions about a topic regardless of wording	4.29	1.63
Understanding (Und.)	VA can correctly transcribe voice input	5.03	1.15
	VA can understand complex/multiclause sentences	3.71	1.50
	VA can structure the input in many ways, just as in human conversation	4.47	1.44
Answering (Ans.)	Instead of displaying information on a screen, VA reads it out loud	4.77	1.65
	VA produces a satisfactory vocal response to queries	4.53	1.40
	Instead of a computer-optimized vocabulary, VA answers questions using a natural language	3.39	1.82
Intelligence (Intel.)	VA can give meaningful answers to requests	4.83	1.34
	VA can utilize additional information (such as context or past behaviors) besides the user's literal input, to estimate what the user wants	4.81	1.27
	VA usually goes beyond simple contextual information such as current location, contact data or past frequent locations	4.91	1.43
Integration (Integ.)	VA can effectively integrate data from external sources (web, apps, etc.)	5.25	1.31
	VA works well with other available apps on the smartphone	5.40	1.49
Accessibility (Access.)	VA makes information easy to access	5.52	1.13
Timeliness (Time.)	VA returns answers to my requests quickly	5.20	1.27
Reliability (Rel.)	VA operates reliably	4.33	1.53
Overall system quality (Overall SQ)	In general, I would rate the system quality of VA highly	4.67	1.26
Overall		4.84	0.66
Information quality (IQ) $\alpha = 0.73$			
Completeness (Compl.)	VA provides me with all the information I need	4.47	1.44
Accuracy (Accu.)	The information provided by VA is accurate	4.76	1.13
Format (Form.)	The information provided by VA is clearly presented by voice	5.03	0.96
Currency (Cur.)	VA produces the most current information	5.09	1.18
Overall information quality (Overall IQ)	In general, VA provides me with high-quality information	4.87	1.13
Overall		4.80	0.82
Satisfaction $\alpha = 0{,}81$			
System Satisfaction (SS)	Overall, my interaction with VA is very satisfying	4.91	1.13
Information Satisfaction (IS)	Overall, the information I get from VA is very satisfying	4.65	1.20
Attitude (ATT)			
ATT	My attitude toward using VA is favorable	4.95	1.30
Behavioral intention (BI)			
BI	I intend to use VA as a routine part of my daily life	4.00	1.57
Perceived usefulness (PU) $\alpha = 0.87$			
PU	VA enables me to accomplish tasks more quickly	4.67	1.37
	VA addresses my needs	4.72	1.21
	Using VA makes it easier to find information or get things done	4.88	1.30
	Overall, I find VA useful	4.87	1.17
Overall		4.78	1.07
Perceived ease of use (PEU) $\alpha = 0.81$			
PEU	I found it easy to get VA do what I want it to do	4.75	1.36
	My interaction with the VA is easy for me to understand	5.17	1.39
	It was easy for me to become skillful at using a VA system	4.99	1.50
	Overall, I found the VA system easy to use	5.19	1.30
Overall		5.02	1.11

Table A3. Survey constructs and items

Table A4. System quality characteristics' correlations with other constructs

	Flex.	Und.	Ans.	Intel.	Integ.	Access.	Time.	Rel.	Overall SQ
SQ	0.48	0.49	0.48	0.56	0.60	0.71	0.62	0.54	0.59
IQ	0.11	0.19	0.43	0.36	0.43	0.51	0.41	0.39	0.55
SS	0.07	0.18	0.37	0.37	0.33	0.43	0.27	0.39	0.44
IS	0.01	0.21	0.43	0.21	0.27	0.31	0.25	0.41	0.41
ATT	0.23	0.28	0.33	0.22	0.37	0.40	0.35	0.36	0.49
BI	0.20	0.22	0.25	0.14	0.27	0.31	0.12	0.37	0.26
PU	0.13	0.18	0.42	0.23	0.31	0.26	0.28	0.33	0.55
PEU	0.21	0.27	0.29	0.31	0.32	0.53	0.38	0.42	0.50

Note: *All correlations are significant at the 0.001 level

Table A5. Information quality characteristics' correlations with other constructs

	Completeness	Accuracy	Format	Currency	Overall IQ
SQ	0.40	0.53	0.39	0.48	0.59
IQ	0.77	0.65	0.62	0.62	0.83
SS	0.56	0.49	0.23	0.38	0.59
IS	0.52	0.42	0.22	0.37	0.48
ATT	0.38	0.54	0.26	0.36	0.50
BI	0.38	0.47	0.10	0.01	0.44
PU	0.50	0.55	0.26	0.34	0.47
PEU	0.52	0.68	0.34	0.35	0.61

Note: *All correlations are significant at the 0.001 level

	SQ	IQ	SS	IS	ATT	BI	PU	PEU
SQ	1.00							
IQ	0.68	1.00						
SS	0.57	0.66	1.00					
IS	0.50	0.59	0.68	1.00				
ATT	0.60	0.59	0.56	0.48	1.00			
BI	0.43	0.41	0.46	0.37	0.53	1.00		
PU	0.54	0.62	0.61	0.62	0.68	0.54	1.00	
PEU	0.65	0.72	0.59	0.49	0.57	0.51	0.75	1.00

Note: *All correlations are significant at the 0.001 level

Table A6.
Construct correlations (*R*)

Table A7.
Construct variances (R^2)

	SQ	IQ	SS	IS	ATT	BI	PU	PEU
SQ	1.00							
IQ	0.58	1.00						
SS	0.32	0.44	1.00					
IS	0.25	0.35	0.58	1.00				
ATT	0.36	0.35	0.31	0.23	1.00			
BI	0.18	0.17	0.21	0.14	0.28	1.00		
PU	0.29	0.38	0.37	0.38	0.46	0.29	1.00	
PEU	0.42	0.52	0.35	0.24	0.32	0.26	0.56	1.00

Note: *All correlations are significant at the 0.001 level

H	Test constructs	Supported
H1	SQ→SS	Yes
H2	IQ→IS	Yes
H3	SS→IS	Yes
H4	SQ and IQ→PU	Yes
H5	SQ and IQ→PEU	Yes
H6	SS→PEU	Yes
H7	IS→PU	Yes
H8	PEU→PU	Yes
H9	PEU→ATT	Yes
H10	PU→ATT	Yes
H11	PEU→BI	Yes
H12	PU→BI	Yes
H13	ATT→BI	Yes

Table A8. Summary of hypotheses (H) tests

Appendix 2

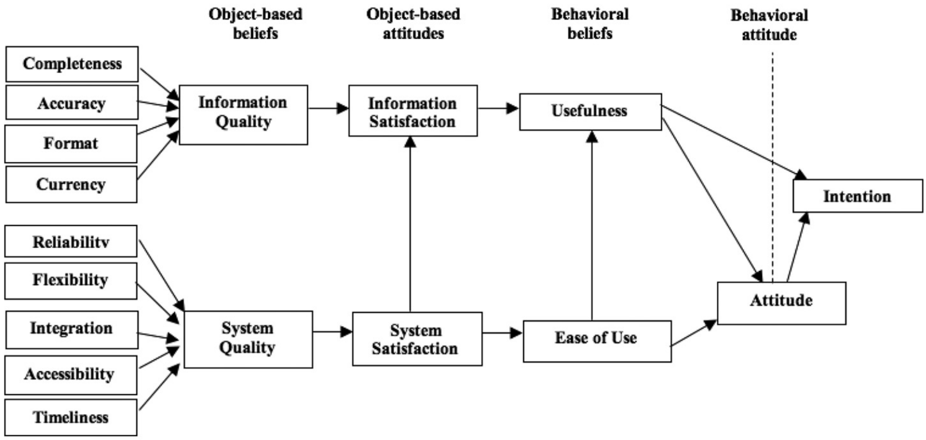
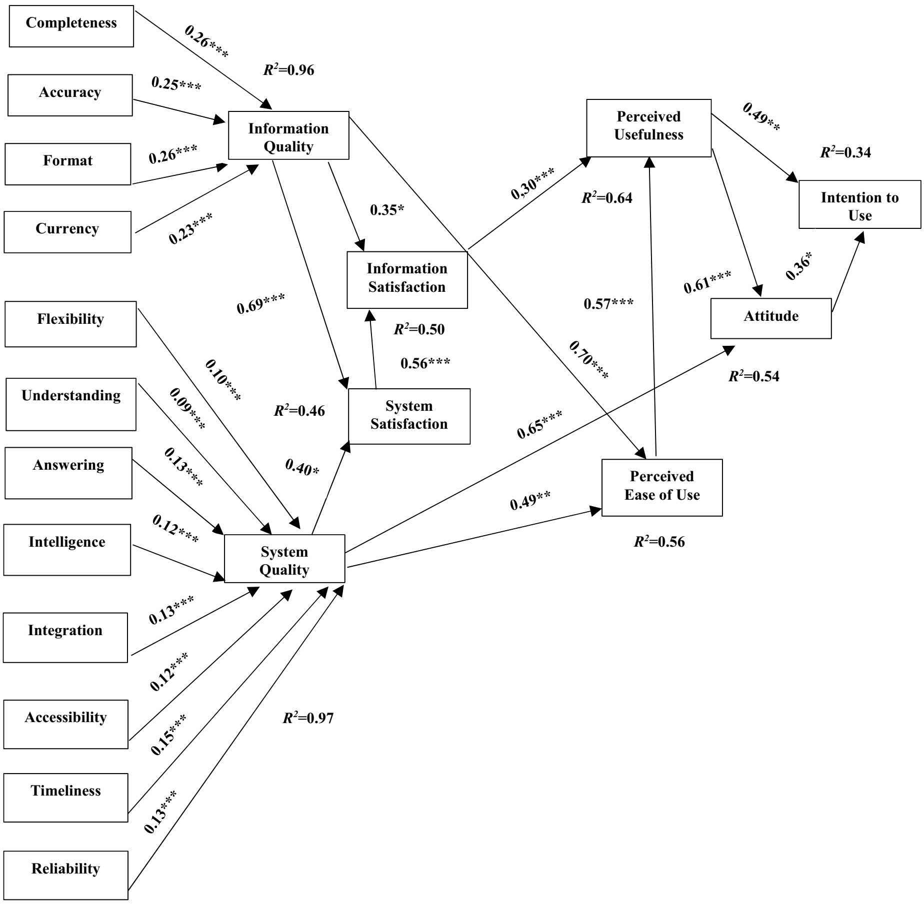


Figure A1. Integrated model of user satisfaction and technology acceptance

Source: Wixom and Todd (2005, p. 90)

Appendix 3



Notes: *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$

Figure A2.
Structural model

Corresponding author

Mine Bertan Yılmaz can be contacted at: minebertan@gmail.com