A Model for Predicting User Intention to Use Voice Recognition Technologies at the Workplace in Saudi Arabia

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ABSTRACT

The use of voice recognition technologies (VRTs) has been expanding, and these are currently used at workplaces. This study tested a model for predicting users’ intention to use VRTs at workplaces. The model extended the technology acceptance model (TAM) and considered four additional factors—perceived privacy, perceived security, perceived trust, and social norms—and four variables—age, education level, gender, and nationality. The authors validated the model based on responses from 300 employees working in Saudi Arabia. The results indicated a medium level of acceptance and a valid TAM in its original form. Further, perceived privacy and perceived security are significant predictors of perceived trust, and perceived trust is an important predictor of attitudes and intention to use VRTs. The social norms variable was a significant predictor of intention to use and accept VRTs. The results also showed that age and education level significantly affect users’ attitudes toward VRT adoption.

KEYWORDS

Behavioral Intention, Perceived Ease of Use, Perceived Privacy, Perceived Security, Perceived Trust, Perceived Usefulness, Speech Recognition, Social Norms

INTRODUCTION

Voice recognition technologies (VRTs) are a computer software or hardware device with the ability to decode the human voice. Several terms have been used in the literature to refer to a software or a hardware that uses voice as the primary interface to interact with them. These terms include voice user interfaces, conversational agents, intelligent or virtual personal assistants, interactive voice systems, and conversational interfaces (Corbett & Weber, 2016; Gardner-Bonneau & Blanchard, 2007; Kepuska & Bohouta, 2018; McTear, Callejas, & Griól, 2016; Myers, Furqan, Nebolsky, Caro, & Zhu, 2018; Porcheron, Fischer, Reeves, & Sharples, 2018).

Voice recognition applications have grown significantly and are increasingly used among individuals as part of their daily interaction with technologies (Getsmarter, 2019; Myers et al., 2018). This growth is because of the substantial investment by major companies, such as Amazon, Google, Microsoft, and Apple, in speech recognition technologies (Myers et al., 2018), and the production of advanced voice-activated technologies that support many languages around the world. An example of the products of these companies is the “smart speakers” or the autonomous screenless voice gadgets, such as Alexa by Amazon, Google Home, Cortana by Microsoft, and HomePod by Apple (PWC, 2018).

Many voice-based applications have also been made available to users in many devices, such as desktops/laptops, tablets, smart TVs, smartphones, and smartwatches (PWC, 2018). One category
of these applications is the intelligent voice assistants, such as Apple Siri, Google Assistant, and Samsung Bixby Voice (Pew Research Center, 2017; PWC, 2018). Voice interaction has also become a feature in many modern web and mobile applications. For instance, the speech-to-text feature has been embedded into several word processors (e.g., Google Docs and Apple Pages) and translation applications (e.g., Google Translate).

Many VRTs have been adopted in private and government organizations (Simon, 2007). These are used in areas such as human resources, sales, marketing, customer relationship management, education and healthcare (Forbes Technology Council, 2018; Getsmarter, 2019; Simon, 2007). Voice-activated technology can be used in several ways in the workplace—for example, by integrating with business applications and for improving efficiency of search engines, increasing productivity, increasing effectiveness of meetings, enabling easy access to big data, increasing the effectiveness of financial services, and making IT operations smarter and faster (Forbes Technology Council, 2018). Many studies have found that voice recognition systems are efficient, effective, and increase productivity when tested in organizations (Simon, 2007). However, despite all the benefits of VRTs, it has been found that there is still some resistance to accepting them in organizations (Costanzo, 2003).

Although numerous studies have been conducted on VRTs, most of these were technical-oriented studies (Porcheron et al., 2018; Simon, 2007). The literature has only a few user studies on VRTs in spite of the fact that users play an important role in the success and failure of technologies. In addition, some of the current user studies have been conducted primarily in workplaces in the United States and Europe (e.g., Kocielnik, Avrahami, Marlow, Lu, & Hsieh, 2018; Simon, 2007), and have not considered countries that have workplace cultures that differ from those found in the West. Saudi Arabia is one such country where the understanding of users’ acceptance of VRTs at the workplace is limited.

Therefore, we developed a model to predict users’ intention to use VRTs at the workplace in Saudi Arabia. The basis of our model is the technology acceptance model (TAM) (Davis, 1985, 1989), which is one the most popular acceptance models used in determining users’ intentions to accept and use a new technology (Al-Gahtani, 2001; Pikkarainen, Pikkarainen, Karjaluoto, & Pahnila, 2004). The model has been extended to include additional factors believed to affect the users’ acceptance of VRTs in the researched context. We validated the model based on a study of users’ acceptance of VRTs in public and private organizations in Saudi Arabia. Therefore, our study offers two contributions: (a) It proposes a model to predict users’ intention to use VRTs at the workplace in Saudi Arabia, and (b) it reveals the current acceptance level of VRTs at these workplaces in Saudi Arabia in general. Overall, our model for predicting users’ intention to use VRTs and the research context (workplaces in Saudi Arabia) make the contribution of this study new and different from the contributions of related studies.

This paper begins with a brief description about VRTs and TAM. Next, we present the research model and hypothesis, the methodology, and the results. Then, we discuss the results and provide recommendations that would help to increase acceptance of VRTs at the workplace in Saudi Arabia. We also discuss the limitations of the study and the potential future research.

**BACKGROUND**

**Voice Recognition Technologies**

VRTs or speech recognition technologies have evolved over the past decades to reach an advanced stage currently. The accuracy of voice recognition has reached high levels in many voice-enabled applications, in particular the commercial ones, as reported by Alapetite, Andersen, and Hertzum (2009). The usage of voice recognition devices or systems provides many advantages, including freeing human hands for other tasks, increasing the data entry rate, improving spelling accuracy and easing the access by people with physical disabilities or with lack of typing skills to computer systems (Lai, 2000; Simon, 2007).
In the many studies on VRTs, the focus was primarily on topics such as computational sociolinguistics, dialogue systems, and natural language processing (Nguyen, Doğruöz, Rosé, & de Jong, 2016). Thus, relatively less research has been conducted on user acceptance and experience of the technology (Porcheron et al., 2018; Simon, 2007). As regards the adoption of VRTs, Simon (2007) investigated user acceptance of a voice recognition device in the United States Navy. The study used the TAM and added elements of the theory of planned behavior (TPB). It analyzed data from 270 participants and found that around 90% of the model variance can be predicted, and that social pressure had a significant effect on behavioral intention to use the technology. Another field study explored the adoption of speech recognition technology by individuals with disabilities (Goette, 2000). It found that the key factor for successful adoption of VRT is the use of the technology for a trial period. They also found that the unsuccessful adoption of VRT was due to factors such as the environment, and the limitations associated with disability. Our research has a similar aim in that we designed a model to predict user intention to use VRTs, using it to investigate user acceptance of VRTs in organizations in Saudi Arabia.

Technology Acceptance Model

The TAM has been developed by Davis (1985) to predict users’ intention to accept and use technologies. Its main aim is to determine factors influencing the acceptance of technology and information systems. The model is accepted widely in information system research and has been used in numerous studies across different domains, such as information and cyber security (Al-Harby, Qahwaji, & Kamala, 2009; James, Pirim, Boswell, Reithel, & Barkhi, 2006), internet banking (Al-Sharaf, Arsha, Abu-Shanab, & Elayah, 2016; Giovanis, Binioris, & Polychronopoulos, 2012; Lee, 2009), cloud computing (Alharbi, 2012; Park & Kim, 2014), and VRT (Simon, 2007). Studies have proved that the TAM can predict an individual’s intention to use an information system better than other models, such as the TPB (Mathieson, 1991). In addition, Mathieson (1991) found that TAM is easier to apply than other models when seeking to acquire general information on users’ opinions about a system.

TAM (Figure 1) consists of two factors that are critical for computing acceptance: perceived usefulness and perceived ease of use. Davis, Bagozzi, and Warshaw (1989) defined perceived usefulness as “the prospective user’s subjective probability that using a specific application system will increase his/her job performance within an organizational context.” Perceived ease of use was defined as the degree to which users expect the use of information system to be easy and effortless (Davis, 1989; Davis et al., 1989).

Figure 1. Technology acceptance model

The model assumes that perceived usefulness and perceived ease of use significantly affect users’ attitudes toward using the technology. Perceived ease of use is assumed to influence perceived
usefulness. The model also posits that behavioral intention to accept and use a system is influenced by the individual’s attitude and perceived usefulness of the computer system. In the model, the actual use of the system is determined by the behavioral intention.

RESEARCH MODEL AND HYPOTHESIS

The Traditional Technology Acceptance Model

The baseline for our research model is TAM (Figure 1). Hence, our proposed research model consists of the constructs in the original TAM (Figure 2). We used behavioral intention as a dependent variable in our study, similar to many other studies (Alharbi, 2012; Amoako-Gyampah & Salam, 2004; Chau, 1996; Davis, 1989). Thus, the following hypotheses are established:

H1: The perceived usefulness is positively related to the attitude toward voice recognition technologies in organizations in Saudi Arabia.

H2: The perceived ease of use is positively related to the attitude toward voice recognition technologies in organizations in Saudi Arabia.

H3: The perceived ease of use is positively related to the perceived usefulness of voice recognition technologies in organizations in Saudi Arabia.

H4: The perceived usefulness is positively related to the behavioral intention to use voice recognition technologies in organizations in Saudi Arabia.

H5: The attitudes toward adoption is positively related to the behavioral intention to use voice recognition technologies in organizations in Saudi Arabia.

Perceived Privacy, Security, and Trust

Several studies have extended specific TAMs by integrating trust into the models (e.g., Al-Sharaf et al., 2016; Alharbi, 2014; Gefen, Karahanna, & Straub, 2003; J. B. Kim, 2012). In addition, our review of the literature showed that many factors influence the trust regarding a system in each technological domain. For example, it has been found that customer satisfaction, reliability, empathy, perceived security, perceived privacy, information quality, initial trust, and perceived risk affect trust in internet banking (Chandio, 2011; Feizi & Ronaghi, 2010; K. Kim & Prabhakar, 2000; Yousafzai, Foxall, & Pallister, 2010). In the domain of voice recognition, many concerns have been raised regarding security and privacy (Alepis & Patsakis, 2017; Chung, Iorga, Voas, & Lee, 2017; Easwara Moorthy & Vu, 2015; Hoy, 2018; Knote, Janson, Eigenbrod, & Söllner, 2018; Saffarizadeh, Boodraj, & Alashoor, 2017), which can affect users’ trust of the technology.

A prior work on the voice user interfaces in the Arab world suggests that researchers should conduct some studies that focus on privacy and security concerns, and trust issues regarding voice user interfaces among Arab users, assuming that these factors may affect user acceptance of these technologies in the region (Majrash & Al-Megren, 2019). Therefore, we added three constructs to our model: perceived privacy, perceived security, and perceived trust; see Figure 2. The basic assumption is that perceived privacy and perceived security positively affect perceived trust of the voice recognition system, which directly affect users’ attitudes toward the technology and influence behavioral intention to use and accept the technology. Thus, the following hypotheses are tested:

H6: The perceived privacy is positively related to the perceived trust of voice recognition technologies in organizations in Saudi Arabia.

H7: The perceived security is positively related to the perceived trust of voice recognition technologies in organizations in Saudi Arabia.

H8: The perceived trust is positively related to the attitude toward the voice recognition technologies in organizations in Saudi Arabia.
**H9:** The perceived trust is positively related to the behavioral intention to use the voice recognition technologies in organizations in Saudi Arabia.

**Age, Education, Gender, and Nationality**

Several external variables have been found to significantly affect users’ attitudes toward the adoption of new technologies in Saudi Arabia. For example, it has been found that variables such as age, education level, and nationality significantly affect users’ attitudes toward the adoption of cloud computing (Alharbi, 2012). Therefore, four external variables (age, education level, gender, and nationality) that are believed to affect the attitude toward the VRTs were added to the model. Thus, the following hypotheses are tested:

**H10:** Age has a significant effect on the attitude toward voice recognition technologies in organizations in Saudi Arabia.

**H11:** Gender has a significant effect on the attitude toward voice recognition technologies in organizations in Saudi Arabia.

**H12:** Education level has a significant effect on the attitude toward voice recognition technologies in organizations in Saudi Arabia.

**H13:** Nationality has a significant effect on the attitude toward voice recognition technologies in organizations in Saudi Arabia.

**Subjective/Social Norm**

The TAM was grounded on both the theory of reasoned action (Fishbein & Ajzen, 1975) and the TPB (Ajzen, 1985). However, a social factor termed subjective norm—which is an important determinant of intention and behavior in both theories—was not included in the TAM because of theoretical and measurement concerns (Davis et al., 1989). The subjective norm refers to “the perceived social pressure to perform or not to perform the behavior” (Ajzen, 1991). As highlighted by Simon (2007), many studies have proved that subjective norms significantly contribute to model predictability (Hartwick & Barki, 1994; Mathieson, 1991; Venkatesh & Davis, 2000). In addition, Simon (2007) found that the subjective norm is a significant determinant in the adoption of a voice recognition system, and could have an impact similar to that of perceived usefulness. For the purpose of this study, we added subjective norm as a construct in our research model. Therefore, the following hypothesis is tested:

**H14:** Social/subjective norms is positively related to the behavioral intention to use voice recognition technologies in organizations in Saudi Arabia.

**METHODOLOGY**

For the purpose of this study, we used a survey consisting of a set of questions in three sections: respondent’s profile, organization profile, and adoption of VRTs. Thirty-six items were used in the instrument to investigate the adoption of VRTs (see Table 1). Most of the survey items are derived from validated measures in the literature (e.g., Al-Gahtani, Hubona, & Wang, 2007; Al-Sharaf et al., 2016; Simon, 2007). For all question items, we used a 7-point Likert scale, ranging from 1, labelled “strongly agree,” to 7, labelled “strongly disagree.” The methodology of this study is presented in three phases.
Pre-Testing Phase

In the first phase, we used a set of techniques to test the validity and reliability of the survey items. We used expert reviews, which is a common pre-testing technique (Yan, Kreuter, & Tourangeau, 2012), that involves expert individuals (Willis, Schechter, & Whitaker, 1999), or a group of experts (an expert panel), to review questionnaires (T. Demaio & Landreth, 2004). An expert in survey design completed the survey and was asked about the understanding of terms, clarity of instructions and any other potential misunderstanding (T. J. DeMaio & Rothgeb, 1996). Then, the instrument was improved based on the expert’s feedback. We also conducted cognitive testing for the instrument. The cognitive testing involved think-aloud and verbal probing techniques (Draugalis, Coons, & Plaza, 2008; Fowler, 1995; Willis, 2004). Three experts in human–computer interaction were asked to complete the survey and to verbalize their thoughts while answering in the presence of the researcher. Probes were used when the experts did not sufficiently verbalize their thoughts or when necessary to obtain additional information. Some examples of the probes used: “I noticed you hesitated before you answered what were you thinking about?” and “What does the term X mean to you?” (Collins, 2003). Then, the instrument was improved based on the results obtained through the cognitive testing.
The second phase is the pilot study, which we conducted to examine the reliability of the instrument. We randomly selected 40 employees at a large organization in Saudi Arabia and asked them to complete the pilot version of the instrument. We used the Cronbach’s alpha as a measure of the internal consistency of the instrument. The results showed that Cronbach’s alpha values were all above 0.82, which is higher than the acceptable level of 0.7 (Cronbach, 1951), and the covariation among items for the same factors were higher than among those for different factors. The evidence obtained from the first and second phases about the validity and reliability of the instrument justified the execution of the main study. The final instrument items are presented in Table 1.

### Table 1. The Instrument Items

| PU1: | Using voice recognition technologies will increase my productivity. |
| PU2: | Using voice recognition technologies will enable me to accomplish tasks more quickly. |
| PU3: | Using voice recognition technologies will improve my performance. |
| PU4: | Using voice recognition technologies will enhance my effectiveness. |
| PU5: | Using voice recognition technologies will make my job easier. |
| PU6: | I think voice recognition technologies will be useful in my job. |

| PEOU1: | Learning to use voice recognition technologies will be easy for me. |
| PEOU2: | I will find it easy to get voice recognition technologies to do what I want them to do. |
| PEOU3: | My interaction with voice recognition technologies will be clear and understandable. |
| PEOU4: | I will find voice recognition technologies flexible to interact with. |
| PEOU5: | It will be easy for me to become skilled with voice recognition technologies. |
| PEOU6: | I will find voice recognition technologies easy to use. |
| PEOU7: | I will find that voice recognition technologies don’t require a lot of mental effort. |

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| PP1: | I think voice recognition technologies will comply with personal data protection laws. |
| PP2: | I think that I will feel safe when I make voice interaction with voice recognition technologies. |
| PP3: | I think voice recognition technologies will only store voice data that are necessary to improve the systems’ ability to understand my voice better. |
| PP4: | I think voice recognition technologies will respect users’ right when obtaining personal information. |
| PP5: | I think voice recognition technologies will not provide my stored voice data to other parties without my consent. |
| PP6: | I think voice recognition technologies will ensure the privacy of any stored voice files. |
| PP7: | I think voice recognition technologies will show concern for the privacy of their users. |

| PS1: | I think voice recognition technologies will have mechanisms to ensure safe transmission of voice data. |
| PS2: | I think voice recognition technologies will show great concern for the security of any voice interaction. |
| PS3: | I think voice recognition technologies will have sufficient technical capacity to ensure that no other organization will supplant its identity. |
| PS4: | I think voice recognition technologies will ensure the security of any stored voice files. |

| PT1: | I think voice recognition technologies will keep their promises. |
| PT2: | I think voice recognition technologies will be trustworthy. |
| PT3: | Overall, I will trust voice recognition technologies. |

| SN1: | I think people who are important to me will use voice recognition technologies. |
| SN2: | I think my friends will use voice recognition technologies. |
| SN3: | I think people whose opinions I value would prefer me to use voice recognition technologies. |

| AT1: | I think it would be very good to use voice recognition technologies in my organization. |
| AT2: | In my opinion, it would be very desirable to use voice recognition technologies in my organization. |
| AT3: | Overall, I like the idea of using voice recognition technologies. |

| BI1: | If my organization provides a voice recognition technology, I think that I would use it. |
| BI2: | To the extent possible, I will use voice recognition technologies to do various tasks. |
| BI3: | I will use any voice recognition technology that can help in making my job easier. |

Notes: PU = perceived usefulness, PEOU = perceived ease of use, PP = perceived privacy, PS = perceived security, PT = perceived trust, SN = Social/subjective norms, AT = attitude, BI = behavioral intention.

**Pilot Study Phase**

The second phase is the pilot study, which we conducted to examine the reliability of the instrument. We randomly selected 40 employees at a large organization in Saudi Arabia and asked them to complete the pilot version of the instrument. We used the Cronbach’s alpha as a measure of the internal consistency of the instrument. The results showed that Cronbach’s alpha values were all above 0.82, which is higher than the acceptable level of 0.7 (Cronbach, 1951), and the covariation among items for the same factors were higher than among those for different factors. The evidence obtained from the first and second phases about the validity and reliability of the instrument justified the execution of the main study. The final instrument items are presented in Table 1.
Main Study Phase

In the third phase, we collected the data for the main study and conducted tests to further ensure the reliability and validity of the instrument. The survey was distributed via email to employees working in public and private organizations in Saudi Arabia. The emails were sent directly to the employees by the researcher or by the human resources or public relations departments in their organizations. The survey was available online and accessible to the public using Google forms for three months starting on 15th of February 2019. The survey was also posted on social media to target more employees, especially in organizations that did not provide an accessible mailing list. In the survey, we highlighted the anonymity of responses to encourage participation.

A total of 335 responses to the survey were received. We excluded 30 responses because these were from participants who declared that they were “currently not employed”. Five responses were excluded because participants did not answer all the survey questions. After applying the exclusion criteria, we obtained 300 responses. Of these, 220 were by employees working in public organizations and 80 by employees in private organizations. Participants were from different sectors, including education and training, healthcare and social assistance, financial and insurance services, transportation, information and communications technology, and municipalities. Other participant demographics are shown in Table 2.

Table 2. Participants’ Demographics

| Measure         | Item      | Frequency | Percentage |
|-----------------|-----------|-----------|------------|
| Age             | 20–29     | 100       | 33.3       |
|                 | 30–39     | 100       | 33.3       |
|                 | 40–49     | 80        | 26.7       |
|                 | 50–59     | 20        | 6.7        |
| Education Level | High School | 30       | 10.0       |
|                 | Diploma   | 70        | 23.3       |
|                 | Bachelor  | 120       | 40.0       |
|                 | Master    | 60        | 20.0       |
|                 | PhD       | 20        | 6.7        |
| Gender          | Male      | 200       | 66.7       |
|                 | Female    | 100       | 33.3       |
| Nationality     | Saudi     | 160       | 53.3       |
|                 | Non-Saudi | 140       | 46.7       |

We used the Cronbach alpha test on the items of each construct to assess the validity of the survey and internal consistency. The results showed that the Cronbach’s alpha value for each construct exceeded the acceptable level of 0.7 that Cronbach (1951) suggested, proving the internal consistency of the questionnaire. Factor analysis with principal component analysis as an extraction method and varimax rotation was also performed to ascertain that perceived usefullness, perceived ease of use, attitude, perceived privacy, perceived security, perceived trust, social/subjective norms, and behavioral intention are distinct constructs. The 36 items were analyzed at the level of eight factors. Table 3 shows that each item scored higher in its related construct and that items within their constructs had
scores above 0.50, representing an acceptable level of convergent and discriminant validity (Fornell & Larcker, 1981).

Table 3. Factor analysis.

|   | 1   | 2   | 3   | 4   | 5   | 6   | 7   | 8   |
|---|-----|-----|-----|-----|-----|-----|-----|-----|
| PU1| 0.666 | 0.224 | 0.327 | 0.195 | 0.247 | 0.174 | 0.272 | 0.339 |
| PU2| 0.678 | 0.218 | 0.407 | 0.227 | 0.302 | 0.114 | 0.255 | 0.213 |
| PU3| 0.847 | 0.175 | 0.345 | 0.278 | 0.167 | 0.065 | 0.09  | 0.04  |
| PU4| 0.685 | 0.258 | 0.444 | 0.205 | 0.293 | 0.196 | 0.221 | 0.205 |
| PU5| 0.85  | 0.159 | 0.284 | 0.277 | 0.224 | 0.122 | 0.041 | 0.089 |
| PU6| 0.78  | 0.231 | 0.243 | 0.237 | 0.305 | 0.219 | 0.21  | 0.087 |
| PEOU1| 0.414 | 0.256 | 0.669 | 0.258 | 0.265 | 0.242 | 0.252 | 0.138 |
| PEOU2| 0.446 | 0.33  | 0.671 | 0.273 | 0.278 | 0.179 | 0.153 | 0.175 |
| PEOU3| 0.44  | 0.311 | 0.636 | 0.284 | 0.328 | 0.211 | 0.134 | 0.203 |
| PEOU4| 0.431 | 0.365 | 0.707 | 0.287 | 0.191 | 0.137 | 0.148 | 0.123 |
| PEOU5| 0.432 | 0.333 | 0.659 | 0.329 | 0.251 | 0.147 | 0.165 | 0.189 |
| PEOU6| 0.372 | 0.316 | 0.742 | 0.188 | 0.299 | 0.092 | 0.175 | 0.128 |
| PEOU7| 0.442 | 0.332 | 0.668 | 0.325 | 0.24  | 0.202 | 0.122 | 0.137 |
| PP1| 0.467 | 0.342 | 0.427 | 0.231 | 0.562 | 0.159 | 0.148 | 0.194 |
| PP2| 0.404 | 0.365 | 0.381 | 0.276 | 0.335 | 0.214 | 0.22  | 0.25  |
| PP3| 0.418 | 0.367 | 0.361 | 0.292 | 0.592 | 0.189 | 0.22  | 0.12  |
| PP4| 0.446 | 0.393 | 0.355 | 0.269 | 0.59  | 0.211 | 0.151 | 0.162 |
| PP5| 0.432 | 0.371 | 0.346 | 0.301 | 0.576 | 0.245 | 0.173 | 0.159 |
| PP6| 0.418 | 0.367 | 0.361 | 0.292 | 0.592 | 0.189 | 0.22  | 0.12  |
| PP7| 0.431 | 0.364 | 0.316 | 0.274 | 0.624 | 0.237 | 0.129 | 0.188 |
| PS1| 0.165 | 0.817 | 0.27 | 0.187 | 0.17 | 0.123 | 0.183 | 0.049 |
| PS2| 0.151 | 0.793 | 0.325 | 0.112 | 0.241 | 0.16  | 0.09  | 0.056 |
| PS3| 0.213 | 0.891 | 0.148 | 0.162 | 0.174 | 0.094 | 0.088 | 0.149 |
| PS4| 0.156 | 0.914 | 0.153 | 0.164 | 0.146 | 0.094 | 0.078 | 0.149 |
| PT1| 0.254 | 0.491 | 0.349 | 0.313 | 0.338 | 0.535 | 0.18  | 0.176 |
| PT2| 0.403 | 0.324 | 0.267 | 0.3  | 0.333 | 0.638 | 0.162 | 0.072 |
| PT3| 0.249 | 0.49 | 0.324 | 0.315 | 0.332 | 0.538 | 0.194 | 0.209 |
| AT1| 0.28  | 0.357 | 0.334 | 0.484 | 0.311 | 0.143 | 0.185 | 0.536 |
| AT2| 0.285 | 0.363 | 0.315 | 0.475 | 0.309 | 0.158 | 0.166 | 0.551 |
| AT3| 0.284 | 0.437 | 0.33 | 0.473 | 0.208 | 0.128 | 0.171 | 0.527 |
| BI1| 0.507 | 0.166 | 0.291 | 0.673 | 0.21  | 0.254 | 0.176 | 0.134 |
| BI2| 0.4  | 0.198 | 0.301 | 0.742 | 0.239 | 0.216 | 0.151 | 0.123 |
| BI3| 0.278 | 0.31  | 0.26  | 0.758 | 0.22  | 0.093 | 0.161 | 0.172 |
| SN1| 0.399 | 0.341 | 0.353 | 0.356 | 0.28  | 0.194 | 0.562 | 0.181 |
| SN2| 0.421 | 0.326 | 0.35  | 0.352 | 0.294 | 0.196 | 0.554 | 0.18  |
| SN3| 0.412 | 0.325 | 0.379 | 0.346 | 0.289 | 0.188 | 0.557 | 0.159 |

PU = perceived usefulness, PEOU = perceived ease of use, PP = perceived privacy, PS = perceived security, PT = perceived trust, SN = Social/subjective norms, AT = attitude, BI = behavioral intention.
RESULTS

User Acceptance of Voice Recognition Technologies

The results showed an overall medium level of user acceptance of VRTs in organizations in Saudi Arabia; see Table 4. The averages ranged between 3.51 with perceived ease of use and 4.43 with behavioral intention. The average of perceived usefulness was 4.40, which is higher than the averages of the other factors, except the behavioral intention. The average of attitude toward the VRTs was 3.70. The averages of perceived privacy and perceived security were similar, 4.00 and 3.96 respectively.

Hypotheses Testing

We used linear regression tests for testing the hypotheses in our study. The results of the tests are presented in Table 5. Hypotheses 1–5 tested the relationships between the original TAM constructs (perceived usefulness, perceived ease of use, users’ attitudes, and behavioral intention). The results showed that perceived usefulness can account for 58.2% of the variance in users’ attitudes. The effect of perceived usefulness on users’ attitudes was significant. The results also demonstrated that perceived ease of use can predict 68.2% of the variance in users’ attitudes, with a significant effect of perceived ease of use on such attitudes. When entering the two variables (perceived usefulness and perceived ease of use) in a single block as predictors, the results showed they can account for 68.9% of variance in users’ attitudes, with F(2, 297) = 328.498, p < 0.001. The results also showed that perceived ease of use can predict 76.8% of variance in perceived usefulness; the effect was significant. In addition, perceived usefulness and users’ attitudes can explain 63.5% and 73.7% of variance in behavioral intention respectively. Both variables have significant effects on behavioral intention. Overall, the results provided evidence in support of hypotheses 1–5.

Hypothesis 6 and 7 tested the effects of perceived privacy and perceived security on perceived trust. The results indicated that perceived privacy and perceived security can predict 78.6% and 57.7% of variance in perceived trust respectively. The effects of both variables on perceived trust were significant. Therefore, hypotheses 6 and 7 are supported. When entering both perceived privacy and perceived security as predictors, they explained 81% of variance in perceived trust, with F(2,297) = 650.079, p < 0.001.

Hypotheses 8 and 9 tested the effect of perceived trust on users’ attitudes and behavioral intention. The results showed that perceived trust significantly affected both. The results also showed that perceived trust can explain 65.9% of variance in users’ attitudes and 63.1% of variance in behavioral intention. Thus, hypotheses 8 and 9 are also supported.

Table 4. Mean and Standard Deviation for Each Construct

| Construct               | No of items | Mean | SD  |
|-------------------------|-------------|------|-----|
| Perceived usefulness    | 6           | 4.40 | 1.36|
| Perceived ease of use   | 7           | 3.51 | 1.52|
| Perceived privacy       | 7           | 4.00 | 1.65|
| Perceived security      | 4           | 3.96 | 0.98|
| Perceived trust         | 3           | 3.84 | 1.86|
| Social/subjective norms | 3           | 4.13 | 1.69|
| Attitude                | 3           | 3.70 | 1.38|
| Behavioral intention    | 3           | 4.43 | 1.95|
Hypotheses 10–13 tested the effect of the external variables (age, education level, gender, and nationality) on users’ attitudes. Entering all external variables into one block, the results showed that they can account for 57.4% of variance in users’ attitudes, with F(4, 295) = 99.438, \( p < 0.001 \). However, when testing the relationship between each individual external variable and users’ attitudes, we found significant effects of age and educational level, but no significant effects of gender and nationality. Age and education level can predict 39.4% and 29.7% of variance in users’ attitudes respectively. Hence, Hypotheses 10 and 11 are supported, while hypotheses 12 and 13 are rejected.

Hypothesis 14 tested the effect of SN on behavioral intention. The results showed that SN explained 69.3% of variance in behavioral intention, and the effect was significant. Therefore, hypothesis 14 is supported.

We also tested the effect of a set of variables on users’ attitudes and behavioral intention. On entering the variables of perceived usefulness, perceived ease of use, perceived trust, age, education level, gender, and nationality in one block, the results showed they can predict 75.8% of the variance in users’ attitudes, with F(7, 292) = 130.589, \( p < 0.001 \). Moreover, when perceived usefulness, users’ attitudes, perceived trust, and social/subjective norms were entered in a single block to predict the variance in behavioral intention, the results presented a high percentage of variance (79.9%), with F(4, 295) = 292.864, \( p < 0.001 \).

**DISCUSSION**

Our results showed an overall medium level of user acceptance of VRTs in organizations in Saudi Arabia. The results also confirmed the relationships in the original TAM (see Figure 3). We found that users’ attitude toward adopting VRTs was significantly affected by perceived usefulness and perceived ease of use. Further, perceived usefulness and attitude significantly affected the behavioral intention to use VRTs in organizations in Saudi Arabia. Therefore, the organizations should increase the awareness of their employees regarding the usefulness and ease of use of VRTs to increase the level of user acceptance of such technologies. In addition, during the development of voice-activated...
systems, the designers should ensure the ease of use of the voice interface and apply an appropriate voice interaction design, to support the acceptance of the systems.

The results also confirmed our assumptions that perceived privacy and perceived security affect perceived trust, and perceived trust affects users’ attitudes toward the VRTs and influence behavioral intention to use and accept the technologies (see Figure 3). Therefore, the technology development entities should consider all aspects of privacy and security that affect the trust in VRTs when producing such technologies. In addition, when an organization wishes to adopt a VRT that has the desired level of security and privacy, the employees in the organizations need to be educated about the adequate level of privacy and security of the VRT, to increase their trust about it.

The results also indicated that age and education level have direct effects on the attitude toward the adoption of VRTs (see Figure 3). Our in-depth analysis of the age effect showed that younger employees tend to have a more positive attitude about VRTs than older employees. The analysis of the effect of the education showed that the higher the degree of the employees, the more likely they will have a positive attitude toward VRTs. Thus, when an organization is interested in utilizing a VRT, it should hold awareness programs, which it needs to design and direct to senior employees and employees with lower educational degrees (e.g., high school and diploma) to change their attitudes toward VRTs. However, the results showed that gender and nationality have no direct effects on attitudes toward VRTs. This means that both male and female, and Saudi and non-Saudi individuals, have a similar attitude toward VRT. Therefore, awareness programs might not be needed to target a specific group based on gender or nationality.

The social norms factor has been proved to significantly contribute to predictability of the acceptance of the VRTs at the workplace in Saudi Arabia (see Figure 3). This result is consistent with the finding of a prior study in which the subjective norm was found to be a significant determinant of the adoption of a voice recognition system (Simon, 2007). In our study, the social norms showed a higher impact than perceived usefulness on behavioral attention to use the systems. Therefore, the organization should use different techniques to influence the decision of employees to accept VRTs. For example, the organization can encourage employees whose opinions are valued by other employees to use these technologies to influence the others to use these as well.

Figure 3. The updated model with all significant relationships, **p < .001.
One limitation of our study is that our model did not encompass all the factors that may influence the behavioral intention to accept VRTs at the workplace in Saudi Arabia. Therefore, it is still required to investigate the effect of various factors such as workspace type (e.g., shared office vs. private office) and gender segregation in workplace (i.e., mixed-gender vs. single-gender workplaces) on user acceptance of VRTs. It is also necessary to investigate the effect of different levels of quality attributes of VRTs (e.g., system response, reliability, and accuracy of natural language processing) on behavioral intention to accept and to use VRTs. A future study may also focus on the effect of anthropomorphic design of VRTs on user acceptance.

In addition, our model was validated based on a sample consisted of individuals from several organizations across Saudi Arabia. However, future studies are still needed to validate our model at an organization level or with a more controlled sample of employees with an emphasis on specific job domains or particular VRTs. The model also needs to be validated by considering the culture at different workplaces across countries before generalizing the findings obtained in the present study. Further user acceptance studies of VRTs at workplaces based on objective measures are also needed to complement the findings from our study, which are based on self-reported measures.

The results of this research may also be limited by its reliance on an Internet-based data collection technique. The lack of a controlled setting, and the absence of personalization and social interaction with the researcher are potential problems associated with Internet data collection. Such problems may result in inattentive or careless responses, which affect the quality of data. Therefore, future studies should use other data collection techniques to re-validate our model and confirm the results related to the level of user acceptance of VRTs in organizations in Saudi Arabia.

CONCLUSION

This study presented a model to predict users’ intention to use VRTs at the workplace in Saudi Arabia. The model was validated based on a study of users’ acceptance of VRTs in public and private organizations in Saudi Arabia. We used the TAM with four additional factors—perceived privacy, perceived security, perceived trust, and social norms—and four external variables, age, education level, gender, and nationality. The results showed a medium level of acceptance of VRTs. The results also showed that the original TAM is valid when using it to test acceptance of VRTs at workplaces in Saudi Arabia. Further, the results showed that perceived privacy and perceived security are significant predictors of perceived trust. Perceived trust was an important determinant of attitudes and behavioral intention to use and accept VRTs. The results also showed that social norms significantly predict behavioral intention to use and accept these technologies. The results also highlighted that age and education level have a significant effect on users’ attitudes toward the adoption of VRTs but showed no effect of gender and nationality. The main dependent variable or output in our model is behavioral intention. The results demonstrated that perceived usefulness, attitude, perceived trust, and social norms predict around 80% of the variance in behavioral intention to use VRTs at the workplace in Saudi Arabia.

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AVAILABILITY OF DATA AND MATERIALS

The datasets used and/or analyzed during the current study are available from the author on reasonable request.
COMPETING INTERESTS

This research has only one author, so there are no competing interests.
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