Education and Information Technologies (2022) 27:8071–8091
https://doi.org/10.1007/s10639-022-10947-3

Understanding key drivers affecting students' use of artificial intelligence-based voice assistants

Jawaher Hamad Al Shamsi[1] · Mostafa Al-Emran[1] · Khaled Shaalan[1]

Received: 29 September 2021 / Accepted: 6 February 2022 / Published online: 1 March 2022

Abstract
Artificial intelligence (AI)-based voice assistants have become an essential part of our daily lives. Yet, little is known concerning what motivates students to use them in educational activities. Therefore, this research develops a theoretical model by extending the technology acceptance model (TAM) with subjective norm, enjoyment, facilitating conditions, trust, and security to examine students' use of AI-based voice assistants for instructional purposes. The developed model was then validated based on data collected from 300 university students using the PLS-SEM technique. The results supported the role of enjoyment, trust, and perceived ease of use (PEOU) in affecting the perceived usefulness (PU) of voice assistants. The empirical results also showed that facilitating conditions and trust in technology strongly influence the PEOU. Contrary to the extant literature, the results indicated that subjective norm, facilitating conditions, and security did not impact PU. Similarly, subjective norm and enjoyment did not affect PEOU. This research is believed to add a holistic understanding of the key drivers affecting students' use of voice assistants for educational purposes. It offers several theoretical contributions and practical implications on how to successfully employ these assistants.

Keywords Artificial intelligence · Voice assistant · Human-AI interaction · Technology acceptance · Drivers · Education

✉ Mostafa Al-Emran
mustafa.n.alemran@gmail.com

Jawaher Hamad Al Shamsi
joojyskj@gmail.com

Khaled Shaalan
khaled.shaalan@buid.ac.ae

[1] Faculty of Engineering & IT, The British University in Dubai, Dubai, UAE

1 Introduction

The prevalence of artificial intelligence (AI) applications in today's era allows individuals to interact and communicate with new non-human agents, such as voice assistants and robots. The literature witnessed an increasing interest in AI-based voice assistants, particularly in the last few years. Siri (from Apple), Cortana (from Microsoft), Alexa (from Amazon), Bixby (from Samsung), and Google Assistant (from Google) are some of the most frequently used AI-based voice assistants that are embedded in smartphones or smart speakers (McLean & Osei-Frimpong, 2019). These assistants have changed the way in which users search for information, use content, manage home automation devices, purchase products, and achieve tasks through exhibiting voice as the primary interface (Al-Kaisi et al., 2021). Through relying on AI-based algorithms, voice assistants record human speech, upload it to the cloud, parse the recording into commands, and send back the output to the user via a computer-generated message (Gouda et al., 2021). A recent report indicates that 27% of the global online population is using voice assistants on their smart mobile devices (McCue, 2018). These voice assistants are expected to replace the role of

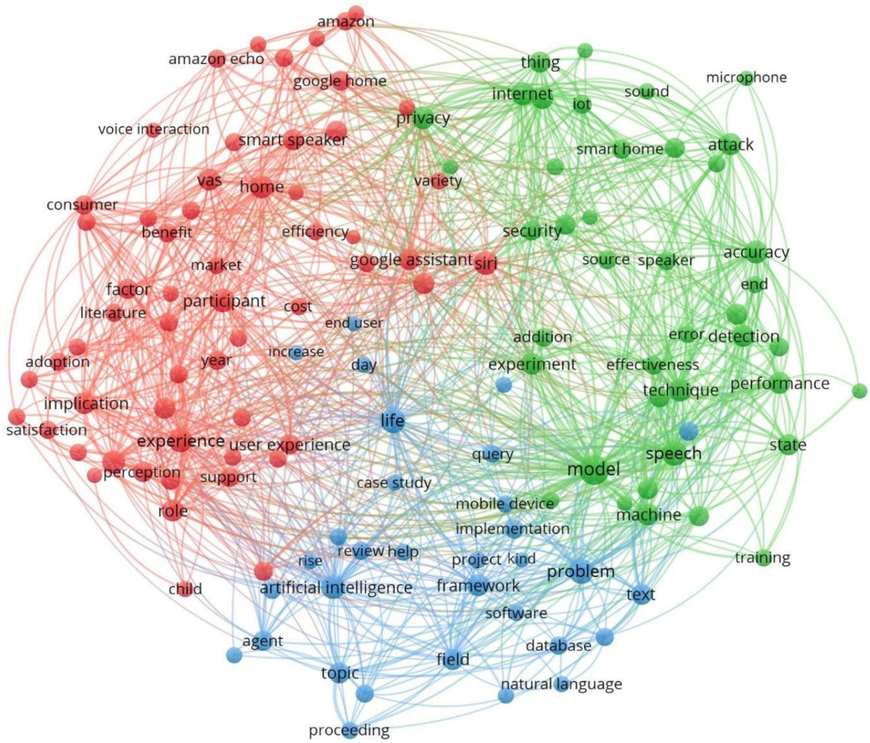

Fig. 1 Research focus of voice assistant studies

other technologies, such as laptops and PCs, specifically in utilitarian activities (Gartner, 2016).

In education, AI-based voice assistants offer a broad instructional potential for enhancing students' autonomous learning. For instance, students can ask questions and get answers instantly by accessing a large amount of online data. In classrooms, students can ask intelligent speakers-based voice assistants to read books for them by accessing thousands of audio books online. On the other side, instructors can use those assistants in designing specific interactions for several classroom activities, such as customized tests and quizzes. Voice assistants reinforce the concept of "contemporary learning", in which instructors can record their lectures and upload them as podcasts. Students can ask voice assistants to download the lectures at "anytime anywhere" settings (Shah, 2020).

To determine the research gap in the extant literature, this research conducted a bibliometric analysis on the studies published on voice assistants using the VOSviewer tool (Van Eck & Waltman, 2010). This was carried out in August 2021 by searching the Scopus database. Figure 1 shows the bibliometric analysis results, and it clearly depicts that voice assistant studies have mainly focused on three main themes. By inspecting the studies of each theme (cluster), it has been noticed that the focus of the studies under the first two clusters (green and blue) was mainly technical. In that, the green cluster concentrated on studies related to the use of machine learning algorithms in training and testing the data received through voice assistants. The cluster also covered studies that examine the security measures and voice attacks to voice assistants. The studies under the blue cluster concentrated on the implementation of voice assistants and the natural language processing of the textual data collected through those assistants. The studies under the red cluster focused on the human-computer interaction side, where the users' experience, perceptions, and voice assistant adoption were measured.

While the extant literature witnessed a growing number of studies on voice assistants (Kendall et al., 2020), the bibliometric analysis results provided evidently several research gaps. First, understanding what impacts the actual use of voice assistants is still in its infancy stage and requires extensive research efforts (Ostrom et al., 2019). Second, most of the previous adoption studies focused on the consumers' use of voice assistants in utilitarian services (Ostrom et al., 2019; Vimalkumar et al., 2021), and ignored what affects their use for educational purposes. Third, while the role of subjective norm, enjoyment, facilitating conditions, trust, and security in examining the adoption of voice assistants has been discussed in some of the previous individualistic societies, there is a scarce of knowledge regarding their impact in collectivistic contexts.

To bridge the aforementioned research gaps, this study goes a step further by developing a theoretical research model for understanding the students' actual use of voice assistants for educational purposes in a new collectivistic context. The developed model extends the technology acceptance model (TAM) (Davis, 1989) with other external variables, including subjective norm, enjoyment, facilitating conditions, trust, and security. These external factors are central to using voice assistants in collectivistic societies, and their exploration is essential to understanding technology strengths and weaknesses. Accordingly, this research aims to achieve the following objectives:

- To develop a theoretical model by extending the TAM with other external factors, including subjective norm, enjoyment, facilitating conditions, trust, and security, to examine the use of AI-based voice assistants for educational purposes.
- To evaluate the developed theoretical model using the PLS-SEM technique.

2 Theoretical framework and research hypotheses

By analyzing the existing literature on AI-based voice assistants, it has been noticed that there is a scarcity of knowledge concerning what impacts the use of these technologies for educational purposes. Therefore, this research develops a research model based on the Technology Acceptance Model (TAM) and extended with several factors that are believed to affect the students' use of voice assistants in instructional activities. The selection of TAM as the basis in this research stems from several reasons. First, while it was developed in 1989 (Davis, 1989), a recent study showed that the model is still valid and that the number of TAM-based studies is still progressing on a yearly basis (Al-Emran & Granić, 2021). Second, there is little empirical support on how TAM can be employed to evaluate the use of AI-based voice assistants.

Figure 2 shows the developed research model. It is suggested that perceived usefulness (PU) and perceived ease of use (PEOU) are influenced by subjective norm, enjoyment, facilitating conditions, and trust. It is also anticipated that PU is influenced by security and PEOU. The behavioral intention (BI) to use voice assistants is affected by both PU and PEOU, which in turn, affects the students' actual use of those assistants in higher education.

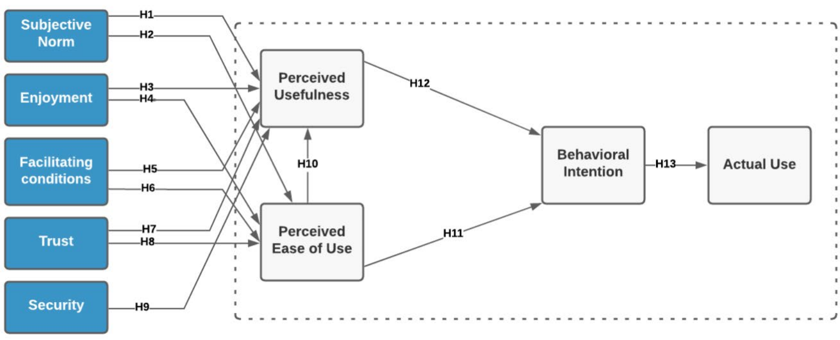

Fig. 2 Research model

2.1 Subjective norm

Subjective norm (SN) refers to "an individual's perception of how important others in his or her social environment wish or expect him or her to behave in a certain way" (Moan & Rise, 2006). The definition of subjective norm is also used to represent social influence (Bloemendaal, 2018). Earlier research claimed that subjective norm impacts the perceived usefulness and ease of using voice assistants (Moriuchi, 2019; Song, 2019). Accordingly, the following hypotheses are put forward:

H1 Subjective norm positively influences the perceived usefulness of voice assistant technology.

H2 Subjective norm positively influences the perceived ease of use of voice assistant technology.

2.2 Enjoyment

Enjoyment is defined as "the activity of using a specific system is perceived to be enjoyable in its own right, aside from any performance consequences resulting from system use" (Venkatesh, 2000). When the user feels that using a particular device is enjoyable, he/she would have positive feelings toward that device and would be more likely to use it (Basak et al., 2015). The simplicity of starting the system or how effective the voice technology in delivering simple responses improves the user's enjoyment (Sorensen, 2019). The extant literature showed that enjoyment is a strong predictor of the perceived usefulness and ease of use (Al-Qaysi et al., 2021; Chu, 2019; Liu et al., 2021). Thus, the following hypotheses are proposed:

H3 Enjoyment positively influences the perceived usefulness of voice assistant technology.

H4 Enjoyment positively influences the perceived ease of use of voice assistant technology.

2.3 Facilitating conditions

Facilitating conditions (FC) refers to "the degree to which an individual believes that an organizational and technical infrastructure exists to support the use of the system" (Venkatesh et al., 2003). The use of any technology requires specific resources, skills, and infrastructure (Albanna et al., 2022). In this context, FC refers to the attributes such as accessibility and efficiency of smartphones and other supporting technologies that impact the usage of voice assistants. Prior research endorsed the role of FC in influencing the perceived usefulness and perceived ease of use (Bloemendaal, 2018; Li et al., 2021). Consequently, this leads to the following:

H5 Facilitating conditions positively influences the perceived usefulness of voice assistant technology.

H6 Facilitating conditions positively influences the perceived ease of use of voice assistant technology.

2.4 Trust

Trust is described as "a psychological state comprising the intention to accept vulnerability based upon positive expectations of the intentions or behavior of another" (Rousseau et al., 1998). In this context, trust is viewed as the users' beliefs towards whether the voice assistants are secure in protecting their personal data (Chu, 2019). The existing literature showed that trust has positively affected the perceived usefulness and ease of using voice assistants (Alharithi, 2019; Chu, 2019; Zeng, 2020). Thus, the following hypotheses are suggested:

H7 Trust positively influences the perceived usefulness of voice assistant technology.

H8 Trust positively influences the perceived ease of use of voice assistant technology.

2.5 Security

Security (SE) refers to "users' perspectives toward the protection level against the potential threats" (Park et al., 2017). Security is believed to be a significant factor in influencing the use of voice assistants. This stems from the fact that those technologies typically gather information from their users, such as users' names, ages, genders, and voice recordings, to provide them with the best user experience. Previous studies showed that security significantly impacts perceived usefulness (Chu, 2019; Neumann, 2018). Therefore, the following hypothesis is formulated:

H9 Security positively influences the perceived usefulness of voice assistant technology.

2.6 Perceived ease of use

Perceived ease of use (PEOU) is defined as "the degree to which a person believes that using a particular system would be free from effort" (Davis, 1989). Users must have the impression that technological innovations in their workplace are simple to operate (Chu, 2019) and effort-free in performing the intended tasks (Lin & Chen, 2015). PEOU is found to be the fundamental element that affects the perceived usefulness and the behavioral intention to use voice assistants (Moriuchi, 2019; Song, 2019; Sorensen, 2019). Therefore, the following hypotheses are proposed:

H10 Perceived ease of use positively influences the perceived usefulness of voice assistant technology.

H11 Perceived ease of use positively influences the behavioral intention to use voice assistant technology.

2.7 Perceived usefulness

Perceived usefulness (PU) refers to "the degree to which a person believes that using a particular system would enhance his/her job performance" (Davis, 1989). PU is considered to be the most motivational factor in IT adoption (Basak et al., 2015). When the user intends to use new technology, his/her intention is proved to be influenced by the usefulness of that technology (Cacho-Elizondo et al., 2012; Chu, 2019). The existing literature supported the relationship between PU and the users' behavioral intention (Chai et al., 2020; Elfeky & Elbyaly, 2021; Liu et al., 2021). Therefore, the following hypothesis is suggested:

H12 Perceived usefulness positively influences the behavioral intention to use voice assistant technology.

2.8 Behavioral intention

Behavioral intention (BI) refers to the degree of intensity of users' intention to perform a particular behavior (Davis, 1989). Users who use voice assistants would have an optimistic behavior if the assistant recognized their voices and replied accurately to their requests (Sorensen, 2019). Prior research showed a strong association between behavioral intention and the actual use of a specific technology (Afonso, 2019; Mohammadi, 2015). Based on that, the following hypothesis is formulated:

H13 Behavioral intention positively influences the actual use of voice assistant technology.

3 Methodology

To examine the students' use of AI-based voice assistants, we have collected data from students studying at four private and public universities in the United Arab Emirates (UAE) using online questionnaire surveys. The targeted participants are those who adapted the voice assistant technology. A compulsory filtering question was added at the beginning of the survey to be ticked by the actual users of voice assistants for educational purposes. As there is no sampling frame for such types of users, we have employed the purposive sampling technique for collecting responses from those universities. The selection of the four universities is because most of their students are actual users of voice assistants.It is imperative to mention that the participants have used voice assistants by posting questions to them and getting answers through accessing a large amount of online data. They have also used these assistants by asking them to download learning materials, including lecture notes, e-books, and

Table 1 Items' description and their resources

Constructs	Items	Item description	References
Perceived usefulness	PU1	"I think voice assistant technology can improve my productivity."	(Lin & Chen, 2015; Pal, Arpnikanondt, Funilkul, & Chutimaskul, 2020; Pal, Arpnikanondt, Funilkul, & Razzaque, 2020)
	PU2	"I think voice assistant technology can increase my performance."	
	PU3	"I think voice assistant technology can encourage me to finish my tasks quickly."	
	PU4	"Overall, using voice assistant technology is useful."	
Perceived ease of use	PEU1	"Learning how to use voice assistant technology is easy to me."	(Jennifer & Sofroniev, 2020; Sorensen, 2019; Teo & Zhou, 2014)
	PEU2	"My interaction with a voice assistant technology is clear and understandable."	
	PEU3	"I find voice assistant technology to be easy to use."	
Behavioral intention	BI1	"I intend to use a voice assistant in the future."	(Chowdhury, 2018; Lee & Choi, 2017; Wagner et al., 2019)
	BI2	"I will recommend using voice assistant technology to my friends and family."	
	BI3	"I will keep myself updated with the latest voice assistant technology."	
Actual use	AU1	"I use the voice assistant technology frequently."	(Afonso, 2019; Easwara Moorthy & Vu, 2015; Pal & Patra, 2020)
	AU2	"I prefer to use voice assistant technology."	
Subjective norm	SN1	"People who are close to me recommend using a voice assistant technology."	(Bloemendaal, 2018; Moriuchi, 2019; Song, 2019)
	SN2	"People around me use voice assistant technology."	
	SN3	"People who are close to me would guide me to use a voice assistant technology."	
Enjoyment	ENJ1	"I enjoy interacting with the voice assistant technology."	(Basak et al., 2015; Cacho-Elizondo et al., 2012; Chu, 2019)
	ENJ2	"The conversation with the voice assistant is interesting."	
	ENJ3	"My creativity can be stimulated when using a voice assistant."	
Facilitating conditions	FC1	"I have the knowledge to use a voice assistant."	(Easwara Moorthy & Vu, 2015; Neumann, 2018; Schudzich, 2019)
	FC2	"I have the required skills to use voice assistant technology."	
	FC3	"I can get assistance from others when I get trouble using a voice assistant."	
Trust	TR1	"Voice assistants are trustworthy."	(Alharithi, 2019; Neumann, 2018; Zeng, 2020)
	TR2	"I think voice assistants are reliable."	
	TR3	"I believe that voice assistants are honest."	
Security	SE1	"I am concerned about voice assistant technology on leaking my personal information without my authorization."	(Chu, 2019; Neumann, 2018; Schudzich, 2019)
	SE2	"Using voice assistant might threaten my personal privacy."	
	SE3	"I am afraid that voice assistant technology might collect my personal information without my acknowledgment."	

tutorials. As the medium of instruction inside the targeted universities is English and given that the voice assistants do not support the Arabic language (i.e., the native language of participants), students interacted and communicated with these assistants using the English language. The participants were introduced to the aim of the research, and they were informed that their participation is voluntary and that their entries will be used only for research purposes. A total of 300 valid responses were collected.

The survey consisted of 27 items that were used to measure the nine constructs in the proposed research model. The items were adopted from the previous relevant literature and revised to reflect the study's aim and objectives. The description of the items, along with their resources, are listed in Table 1.

To evaluate the proposed hypotheses in this research, the partial least squares-structural equation modeling (PLS-SEM) is employed via SmartPLS (Ringle et al., 2015). The reason behind using PLS-SEM (variance-based SEM) rather than the covariance-based SEM (CB-SEM) is attributed to two main points. First, PLS-SEM works better than CB-SEM if the research objective is to develop an existing theory (Hair et al., 2011), which is the scenario in this study. Second, since this research focuses more on exploring the determinants influencing the use of voice assistants rather than confirming them, PLS-SEM is regarded as the suitable technique in such situations (Hair et al., 2011).

Table 2 Participants' demographics

Characteristics	Items	Frequency	Percentage
Gender	Female	243	81%
	Male	57	19%
Age	18 - 21	171	57%
	22 - 26	100	33.3%
	27 - 30	11	3.7%
	31 - 35	10	3.3%
	36 - 40	4	1.3%
	Above 40	4	1.3%
Level of education	Diploma	20	6.7%
	Higher diploma	19	6.3%
	Bachelor	240	80%
	Master	20	6.7%
	Doctorate	1	0.3%
Voice assistant types	Siri (Apple)	134	44.7%
	Google	140	46.7%
	Cortana (Microsoft)	2	0.7%
	Alexa (Amazon)	13	4.3%
	Others	11	3.7%

4 Results

4.1 Participants' demographics

The participants' demographic characteristics are shown in Table 2. It can be seen that 81% were females, while 19% were males. It is imperative to mention that females represent the vast majority of students in the four targeted universities. The majority of participants were in the age group of 18-21, with 57%. For the educational level, 240 (80%) were bachelor's degree students, followed by 20 (6.7%) diploma and master's students, 19 (6.3%) higher diplomas, and 1 (0.3%) doctorate. Concerning the type of voice assistants, 46.7% of the students are using Google as their voice assistant. This is followed by 44.7% who use Siri, 4.3% who use Alexa, 3.7% who use other assistants, and 0.7% who use Cortana.

4.2 Common method bias

To ensure that the collected data did not contain common method bias (CMB), Harman's single-factor with nine variables (subjective norm, enjoyment, facilitating conditions, trust, security, perceived usefulness, perceived ease of use, behavioral intention, and actual use) was conducted (Podsakoff et al., 2003). The nine variables were then loaded into a single variable. The analysis results showed that the largest variance explained by the single variable is accounted for 21.39%, which is below the threshold value of 50% (Podsakoff et al., 2003). This indicates that the collected data do not raise any issues concerning CMB.

4.3 Measurement model assessment

To evaluate the measurement model, it is required to test the reliability and validity. The reliability of the variables can be measured using Cronbach's alpha and composite reliability (CR), while the validity can be measured through convergent validity and discriminant validity. As per the results shown in Table 3, the Cronbach's alpha values are ranged between 0.821 and 0.899, indicating that all values are above 0.7 (Hair et al., 2019). The results in Table 3 also reveal that the CR values are ranged between 0.894 and 0.937, which exceeds the threshold value of 0.7 (Hair et al., 2020). It can, therefore, be suggested that the reliability is confirmed.

The convergent validity is measured by testing the factor loadings and average variance extracted (AVE) (Hair et al., 2019). As per the readings in Table 3, the values of all factor loadings are greater than the suggested value of 0.7. Furthermore, the values of AVE are ranged between 0.736 and 0.864, which exceeds the threshold value of 0.5. This indicates that the convergent validity is confirmed. The discriminant validity measures how far one construct varies from the other constructs in the theoretical framework (Chin, 1998). This type of validity is assessed by examining the Fornell-Larcker criterion, the cross-loadings, and the Heterotrait-Monotrait ratio (HTMT). The Fornell-Larcker criterion analysis is shown in Table 4. It is evident that the square roots of AVEs (i.e., bold diagonal values) are greater than the correlations among the latent variables (i.e., off-diagonal values) for all columns and

Table 3 Reliability and convergent validity results

Variables	Items	Factor loading	Cronbach's Alpha	CR	AVE
Perceived usefulness	PU1	0.846	0.881	0.918	0.736
	PU2	0.852			
	PU3	0.857			
	PU4	0.877			
Perceived ease of use	PEU1	0.905	0.899	0.937	0.832
	PEU2	0.913			
	PEU3	0.919			
Behavioral intention	BI1	0.911	0.888	0.931	0.818
	BI2	0.939			
	BI3	0.862			
Actual use	AU1	0.919	0.843	0.927	0.864
	AU2	0.940			
Subjective norm	SN1	0.903	0.884	0.928	0.811
	SN2	0.900			
	SN3	0.899			
Enjoyment	ENJ1	0.923	0.895	0.935	0.827
	ENJ2	0.918			
	ENJ3	0.886			
Facilitating conditions	FC1	0.909	0.821	0.894	0.739
	FC2	0.885			
	FC3	0.779			
Trust	TR1	0.897	0.872	0.921	0.796
	TR2	0.913			
	TR3	0.867			
Security	SE1	0.882	0.870	0.920	0.793
	SE2	0.889			
	SE3	0.901			

Table 4 Fornell-Larcker criterion

	AU	BI	ENJ	FC	PEU	PU	SE	SN	TR
AU	**0.929**								
BI	0.799	**0.905**							
ENJ	0.679	0.748	**0.909**						
FC	0.616	0.737	0.748	**0.860**					
PEU	0.660	0.808	0.666	0.785	**0.912**				
PU	0.707	0.818	0.732	0.667	0.732	**0.858**			
SE	0.433	0.429	0.463	0.466	0.413	0.448	**0.891**		
SN	0.748	0.703	0.650	0.657	0.579	0.607	0.383	**0.901**	
TR	0.688	0.732	0.693	0.706	0.666	0.678	0.444	0.668	**0.892**

rows (Fornell & Larcker, 1981). For the cross-loadings, it can be seen from Table 5 that the factor loadings belonging to each construct are greater than the loadings of its corresponding constructs. Concerning the HTMT, Table 6 shows that all HTMT values are less than the threshold value of 0.85, with an exception to 7 values. Since the reliability and convergent validity were ascertained (Al-Emran et al., 2020), these

Table 5 Cross-loadings results

	AU	BI	ENJ	FC	PEU	PU	SE	SN	TR
AU1	**0.919**	0.684	0.562	0.531	0.564	0.573	0.360	0.698	0.595
AU2	**0.940**	0.793	0.692	0.610	0.656	0.730	0.440	0.694	0.678
BI1	0.694	**0.911**	0.661	0.662	0.758	0.746	0.440	0.598	0.643
BI2	0.747	**0.939**	0.697	0.711	0.795	0.769	0.366	0.645	0.694
BI3	0.726	**0.862**	0.670	0.624	0.633	0.703	0.360	0.667	0.650
ENJ1	0.653	0.714	**0.923**	0.710	0.682	0.677	0.419	0.602	0.633
ENJ2	0.546	0.657	**0.918**	0.647	0.610	0.651	0.399	0.506	0.597
ENJ3	0.653	0.666	**0.886**	0.682	0.514	0.670	0.448	0.669	0.663
FC1	0.519	0.657	0.695	**0.909**	0.735	0.596	0.356	0.537	0.579
FC2	0.525	0.631	0.661	**0.885**	0.671	0.562	0.447	0.552	0.555
FC3	0.549	0.612	0.568	**0.779**	0.612	0.563	0.403	0.611	0.695
PEU1	0.579	0.730	0.585	0.718	**0.905**	0.643	0.377	0.495	0.537
PEU2	0.641	0.735	0.617	0.714	**0.913**	0.653	0.351	0.574	0.651
PEU3	0.585	0.745	0.618	0.715	**0.919**	0.705	0.400	0.515	0.633
PU1	0.612	0.658	0.641	0.589	0.600	**0.846**	0.389	0.512	0.591
PU2	0.577	0.658	0.611	0.566	0.577	**0.852**	0.412	0.484	0.559
PU3	0.581	0.717	0.581	0.530	0.606	**0.857**	0.324	0.516	0.570
PU4	0.651	0.765	0.677	0.604	0.716	**0.877**	0.412	0.565	0.604
SE1	0.500	0.423	0.388	0.438	0.424	0.412	**0.882**	0.380	0.444
SE2	0.328	0.361	0.411	0.439	0.327	0.362	**0.889**	0.336	0.362
SE3	0.323	0.360	0.439	0.372	0.347	0.418	**0.901**	0.307	0.377
SN1	0.692	0.644	0.578	0.566	0.490	0.554	0.346	**0.903**	0.587
SN2	0.650	0.659	0.595	0.659	0.582	0.530	0.329	**0.900**	0.617
SN3	0.681	0.596	0.581	0.547	0.488	0.556	0.361	**0.899**	0.599
TR1	0.651	0.689	0.611	0.610	0.599	0.603	0.352	0.673	**0.897**
TR2	0.655	0.690	0.632	0.635	0.635	0.658	0.441	0.561	**0.913**
TR3	0.526	0.575	0.613	0.649	0.544	0.545	0.394	0.555	**0.867**

Table 6 HTMT results

	AU	BI	ENJ	FC	PEU	PU	SE	SN	TR
AU									
BI	0.919								
ENJ	0.776	0.838							
FC	0.741	0.864	0.871						
PEU	0.754	0.902	0.738	0.912					
PU	0.811	0.922	0.824	0.785	0.818				
SE	0.500	0.488	0.526	0.556	0.465	0.509			
SN	0.868	0.794	0.732	0.774	0.648	0.686	0.437		
TR	0.794	0.829	0.786	0.841	0.749	0.769	0.507	0.760	

values do not raise any issues related to discriminant validity. Hence, it can be argued that there are no issues in terms of the discriminant validity in this study.

4.4 Structural model assessment

We have tested the collinearity between the factors before evaluating the structural model to ensure no lateral collinearity issues (Ramayah et al., 2018). The variance inflation factor (VIF) is one of the standard measures used for assessing collinearity. As per the readings in Table 7, all the VIF values are less than 5 (Hair et al., 2011), indicating no multicollinearity. The assessment of the structural model is performed through a bootstrapping procedure of 5000 re-samples by measuring the *t*-values, standard beta (β), coefficient of determination (R^2), effect size (f^2), and predictive relevance (Q^2) (Hair et al., 2017). R^2 is a common indicator for measuring the structural model and a predictor for all the endogenous variables in the research model. It has been argued that the R^2 values above 0.67 are categorized as "High", values between 0.33 and 0.67 are categorized as "Moderate", and values between 0.19 and 0.33 are categorized as "Weak" (Chin, 1998). The results indicated that the R^2 values for the actual use (0.638), perceived ease of use (0.645), and perceived usefulness (0.667) are within the range of 0.33 and 0.67, which means that the predictive power of the variables is "Moderate". Further, the R^2 value for the behavioral intention to use AI-based voice assistants is discovered to be 0.763, which implies that the predictive power of the variable is "High".

Table 7 shows the path coefficient results for all the proposed hypotheses in the conceptual model. According to the data analysis, 8 out of the 13 hypotheses were supported in this research, while the rest were not accepted by the empirical data. In that, the findings demonstrated that subjective norm has an insignificant positive influence on perceived usefulness (β=0.090, t = 1.387) and perceived ease of use (β=0.017, t = 0.315) of voice assistants. Hence, H1 and H2 are rejected. The results showed that enjoyment has a significant positive influence on perceived usefulness (β=0.350, t = 5.780), while it has an insignificant positive impact on perceived ease of use (β=0.104, t = 1.127). Thus, H3 is accepted, and H4 is rejected.

The results indicated that facilitating conditions has an insignificant effect on perceived usefulness (β = -0.109, t = 1.156), while it has a significant positive effect on perceived ease of use (β=0.567, t = 8.124). This means that H5 is rejected and H6 is accepted. Trust is shown to have a significant positive influence on perceived usefulness (β=0.155, t = 2.574) and perceived ease of use (β=0.183, t = 2.397). Therefore, H7 and H8 are accepted. The results revealed that security has an insignificant positive correlation with perceived usefulness (β=0.068, t = 1.553), which indicates the rejection of H9.

The findings also pointed out that perceived ease of use has a positive association with perceived usefulness (β=0.401, t = 6.051) and behavioral intention (β=0.450, t = 9.614), which means that H10 and H11 are accepted. In addition, perceived usefulness has a strong positive correlation with the behavioral intention to use (β=0.488, t = 10.772), which shows the acceptance of H12. The results also indicated that the behavioral intention has a significant positive influence on the students' actual use of voice assistants (β=0.799, t = 29.279). Thus, H13 is accepted.

We have also tested the effect sizes (f^2), as shown in Table 7, by following the recommendations of Cohen (1988). Values of 0.02, 0.15, and 0.35 indicate small, medium, and large effects, respectively (Cohen, 1988). The analysis shows that sub-

Table 7 Hypotheses testing results

Hypothesis	Relationship	Std. Beta	*t*-value	*p*-value	f^2	VIF	Decision
H1	SN → PU	0.090	1.387	0.166	0.011	2.157	Not Supported
H2	SN → PEU	0.017	0.315	0.753	0.000	2.155	Not Supported
H3	ENJ → PU	0.350	5.780	0.000	0.132	2.787	Supported
H4	ENJ → PEU	0.104	1.127	0.260	0.011	2.709	Not Supported
H5	FC → PU	-0.109	1.156	0.248	0.009	3.762	Not Supported
H6	FC → PEU	0.567	8.124	0.000	0.322	2.816	Supported
H7	TR → PU	0.155	2.574	0.010	0.027	2.630	Supported
H8	TR → PEU	0.183	2.397	0.017	0.038	2.506	Supported
H9	SE → PU	0.068	1.553	0.121	0.010	1.351	Not Supported
H10	PEU → PU	0.401	6.051	0.000	0.171	2.822	Supported
H11	PEU → BI	0.450	9.614	0.000	0.397	2.152	Supported
H12	PU → BI	0.488	10.772	0.000	0.468	2.152	Supported
H13	BI → AU	0.799	29.279	0.000	1.759	1.000	Supported

jective norm has a small effect size on perceived usefulness and perceived ease of use with the values of 0.011 and 0.000, respectively. Perceived enjoyment has a small effect size on perceived usefulness and perceived ease of use with the values of 0.132 and 0.011, respectively. Facilitating conditions has a small effect size on perceived usefulness (f^2 = 0.009), but it has a medium effect on perceived ease of use (f^2 = 0.322). Trust has a small effect size on perceived usefulness and perceived ease of use with the values of 0.027 and 0.038, respectively. Perceived security has a small effect size on perceived usefulness with the value of 0.010. Perceived ease of use has a medium effect size on perceived usefulness (f^2 = 0.171), but it has a large effect on behavioral intention (f^2 = 0.397). Perceived usefulness has a large effect size on behavioral intention with a value of 0.468. The behavioral intention has a large effect size on actual use with the value of 1.759.

Regarding predictive relevance (Q^2), Q^2 values greater than 0 indicate that the exogenous constructs have predictive relevance for the endogenous construct under consideration (Hair et al., 2016). The analysis reveals that Q^2 values were all greater than 0 (actual use Q^2 = 0.541, behavioral intention Q^2 = 0.618, perceived ease of use Q^2 = 0.529, and perceived usefulness Q^2 = 0.480).

5 Discussion

The rapid growth of information technologies has changed the way through which students communicate at "anytime anywhere" settings (Al-Emran et al., 2018; Alshurideh et al., 2020). AI-based voice assistants have exposed significant progress, and their potential is improving. While the existing literature witnessed several studies on the applications of voice assistants in different instructional activities, little is known concerning the determinants affecting the students' use of those assistants (Kim et al., 2020). Hence, this study aimed at examining the key factors that are believed to influence students' use of AI-based voice assistants in educational activities. In that, we developed a research model by extending the TAM with other external factors, including subjective norm, enjoyment, facilitating conditions, trust, and security.

The research findings showed that subjective norm has an insignificant impact on perceived usefulness and ease of use of voice assistants. However, this contradicts with the results found in prior research (Moriuchi, 2019; Song, 2019). This might be caused by the people surrounding the students, who find the technology hard to use, or those who are not familiar with voice assistants specifically for learning activities. Furthermore, the outcomes revealed that enjoyment has a significant positive influence on the perceived usefulness of voice assistants, which confirms the findings observed in earlier research (Al-Qaysi et al., 2021; Chu, 2019; Liu et al., 2021). This indicates that students find the voice assistant as an enjoyable tool, which enhances their learning performance.

While the previous literature supported the relationship between enjoyment and perceived ease of use (Al-Qaysi et al., 2021; Chu, 2019; Liu et al., 2021), the research findings pointed out that enjoyment has an insignificant influence on the perceived ease of use of voice assistants. This shows that students find the voice assistants hard to use due to their complexity. Therefore, it can be argued that students did not find any enjoyment while using the system in their learning process. Contrary to what has been observed in the existing literature (Bloemendaal, 2018; Li et al., 2021), the results of this study did not support the correlation between facilitating conditions and perceived usefulness. This might be attributed to the reason that students have less knowledge and skills in using voice assistants in their instructional activities, which hinders the usefulness of those tools in such activities. However, the results revealed that facilitating conditions positively impact the perceived ease of use of voice assistants, which aligns with the results found previously (Bloemendaal, 2018; Li et al., 2021). This indicates that finding assistance regarding the use of voice assistants from others would facilitate the use of those assistants in instructional activities.

While 41% of voice assistant users have concerns about trust (Perez, 2019), the research findings found that trust has a positive influence on perceived usefulness and perceived ease of use of voice assistants in learning activities. This confirms the results found in previous studies (Alharithi, 2019; Chu, 2019; Zeng, 2020). This indicates that voice assistants would be useful and user-friendly if students find them reliable while searching and gathering information related to their studies. Further, the results showed that security has no significant impact on the perceived usefulness of voice assistants, which contradicts the outcomes observed in earlier studies (Chu, 2019; Neumann, 2018). This means that students might consider the voice assistants useless if they expose their personal information without authorization and threaten their privacy.

In line with the TAM assumptions (Davis, 1989) and the conclusions drawn in previous studies (Moriuchi, 2019; Song, 2019; Sorensen, 2019), the results found that perceived ease of use has a significant positive impact on perceived usefulness and the behavioral intention to use voice assistant technologies. This indicates that the higher the easiness of voice assistants, the higher the advantages of getting students' attention to realize the usefulness of those assistants in performing learning activities and the intention to use them in the future. The research findings also showed that perceived usefulness has a significant positive correlation with the behavioral intention to use voice assistants, which comes in line with the conclusions drawn in prior studies (Chai et al., 2020; Elfeky & Elbyaly, 2021; Liu et al., 2021). This shows that students' behavioral intention is increased for those who found the technology useful in their learning activities. The results demonstrated that behavioral intention strongly influences the actual use of voice assistants, which supports the results found in previous studies (Afonso, 2019; Mohammadi, 2015). This indicates that the actual use of voice assistants for educational purposes would increase if students exposed higher positive intentions toward those assistants.

6 Conclusions

6.1 Theoretical contributions

Stemming from the empirical data analysis, this research provides four theoretical contributions. First, this research developed an integrated theoretical model by extending the TAM with several external factors that are believed to influence the students' use of AI-based voice assistants for instructional purposes. Unlike the previous studies that mainly examined the use of voice assistants in the western individualistic contexts (e.g., (Fernandes & Oliveira, 2021; Pitardi & Marriott, 2021)), the developed model was tested in a collectivistic society like the UAE. This is believed to add a thorough understanding of the determinants affecting the use of voice assistants in unexplored contexts, such as the UAE, and open the door for further research in the domain. Second, this research contributes to the extant literature on AI-based voice assistants in general and the educational sector in specific, which is still in its infancy stage. While the study used the TAM, which has been widely used in the past, understanding the underlying TAM constructs and the other external factors in examining the use of voice assistants in learning purposes is believed to add a significant value to the TAM on one side and the research domain of voice assistants on the other side.

Third, most of the extant empirical studies have focused on the consumers' use of voice assistants (e.g., (Fernandes & Oliveira, 2021; Vimalkumar et al., 2021)) and ignored their role in educational activities. Thus, engaging the students in this research and understanding the factors affecting their use of voice assistants is believed to add value to the educational technology literature. Fourth, the developed model explained 63.8% of the variance in the actual use of voice assistants, which proves that the model is suitable for new collectivistic contexts like the UAE.

6.2 Practical implications

This research offers several practical implications. First, decision-makers can rely on the findings of this research to better understand the determinants affecting students' use of voice assistants to effectively use these technologies for learning purposes. Second, given the insignificant role of subjective norm in affecting the usefulness and ease of use of voice assistants, decision-makers need to organize awareness campaigns and training sessions to guide students on how to use those assistants in learning activities.Ensuring and maintaining specific guidelines for using those assistants would socially communicate their benefits among the students.

Third, the empirical results did not support the role of security in influencing the usefulness of voice assistants by students. This is mainly because those assistants need to collect a massive amount of data from users to perform competently and provide the best user experience. Students can expose their personal information only when they feel that the information is secure and the service provider is trustworthy. Therefore, service providers need to be transparent on how the data are collected and used. Further, practitioners need to educate students about their privacy and how to protect their personal information. Fourth, stemming from the nature of voice assistants in collecting users' data, educational institutions need to have strong policies and procedures to deal with students' data breaches.

6.3 Limitations and future work

This study is limited in several ways. First, the developed model was tested on data collected from university students only, without considering educators' responses. Further research might look into the determinants affecting the use of voice assistants from the lenses of educators. Second, the developed model was based on extending the TAM with external factors and did not consider the role of moderating variables, such as gender and age, in examining the use of voice assistants. Examining the role of moderators is believed to add a significant value for potential work in the future. Third, this research relied on a quantitative approach through the use of questionnaire surveys, which does not allow an in-depth exploration of students' use of voice assistants. Further trials are encouraged to employ an in-depth mixed method to draw a better and deeper exploration of the topic.

Fourth, this study is cross-sectional, and therefore, a time-lag research approach is suggested to discover whether the responses of different participants of similar age at different points in time would change or not. Fifth, this research did not include the course through which voice assistants were used, which is due to the nature of the study in examining the general educational purposes of these assistants. Therefore, it is suggested to investigate the role of the course in future studies to understand how voice assistants are used across different courses. Sixth, the selection of participants in terms of the educational level was uneven. Therefore, future studies should consider this issue to approach neutral samples from various educational levels.

Acknowledgements This work is a part of a research study submitted to The British University in Dubai.

Funding There is no funding received for this study.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

References

Afonso, G. F. M. (2019). *Understanding smart-speakers adoption in Portugal: a unified theory of acceptance and use of technology applied in the Portuguese consumer market*. University Institute of Lisbon

Al-Emran, M., Al-Maroof, R., Al-Sharafi, M. A., & Arpaci, I. (2020). What impacts learning with wearables? An integrated theoretical model. *Interactive Learning Environments*. https://doi.org/10.1080/10494820.2020.1753216

Al-Emran, M., & Granić, A. (2021). Is It Still Valid or Outdated? A Bibliometric Analysis of the Technology Acceptance Model and Its Applications From 2010 to 2020. In *Recent Advances in Technology Acceptance Models and Theories*. https://doi.org/10.1007/978-3-030-64987-6_1

Al-Emran, M., Mezhuyev, V., Kamaludin, A., & AlSinani, M. (2018). Development of M-learning Application based on Knowledge Management Processes. *2018 7th International Conference on Software and Computer Applications (ICSCA 2018)*, 248–253

Al-Kaisi, A. N., Arkhangelskaya, A. L., & Rudenko-Morgun, O. I. (2021). The didactic potential of the voice assistant "Alice" for students of a foreign language at a university. *Education and Information Technologies*, 26, 715–732. https://doi.org/10.1007/S10639-020-10277-2

Al-Qaysi, N., Mohamad-Nordin, N., & Al-Emran, M. (2021). Developing a comprehensive theoretical model for adopting social media in higher education. *Interactive Learning Environments*. https://doi.org/10.1080/10494820.2021.1961809

Albanna, H., Alalwan, A. A., & Al-Emran, M. (2022). An integrated model for using social media applications in non-profit organizations. *International Journal of Information Management*, 63, 102452. https://doi.org/10.1016/J.IJINFOMGT.2021.102452

Alharithi, F. (2019). *Detecting Conflicts among Autonomous Devices in Smart Home*. Florida Institute of Technology

Alshurideh, M., Al Kurdi, B., Salloum, S. A., Arpaci, I., & Al-Emran, M. (2020). Predicting the actual use of m-learning systems: a comparative approach using PLS-SEM and machine learning algorithms. *Interactive Learning Environments*. https://doi.org/10.1080/10494820.2020.1826982

Basak, E., Gumussoy, C. A., & Calisir, F. (2015). Examining the factors affecting PDA acceptance among physicians: an extended technology acceptance model. *Journal of Healthcare Engineering*, 6(3), 399–418. https://doi.org/10.1260/2040-2295.6.3.399

Bloemendaal, R. H. (2018). The Internet of Things in home environments: Building customer relationships: a study of customer attitude and intention to use in the context of IoT in home environments. *Master's Thesis, University of Twente*

Cacho-Elizondo, S., Shahidi, N., & Tossan, V. (2012). *Educational Mobile Coaching: Exploring Adoption Patterns and Barriers*

Chai, C. S., Wang, X., & Xu, C. (2020). An extended theory of planned behavior for the modelling of chinese secondary school students' intention to learn artificial intelligence. *Mathematics*, 8(11), 1–18. https://doi.org/10.3390/math8112089

Chin, W. W. (1998). The partial least squares approach to structural equation modeling. *Modern Methods for Business Research*, 295(2), 295–336

Chowdhury, S. (2018). *Avoidance Attitudes towards Virtual Assistants*. Coventry University

Chu, L. (2019). *Why would I adopt a smart speaker?: Consumers' intention to adopt smart speakers in smart home environment*. Master's thesis, University of Twente

Cohen, J. (1988). Statistical power analysis for the behavioral sciences. In *NJ: Lawrence Earlbaum Associates*. Hilsdale. https://doi.org/10.1234/12345678

Davis, F. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319–340. https://doi.org/10.2307/249008

Easwara Moorthy, A., & Vu, K. P. L. (2015). Privacy Concerns for Use of Voice Activated Personal Assistant in the Public Space. *International Journal of Human-Computer Interaction*, 31(4), 307–335. https://doi.org/10.1080/10447318.2014.986642

Elfeky, A. I. M., & Elbyaly, M. Y. H. (2021). The use of data analytics technique in learning management system to develop fashion design skills and technology acceptance. *Interactive Learning Environments*, 1–18. https://doi.org/10.1080/10494820.2021.1943688

Fernandes, T., & Oliveira, E. (2021). Understanding consumers' acceptance of automated technologies in service encounters: Drivers of digital voice assistants adoption. *Journal of Business Research*, 122, 180–191. https://doi.org/10.1016/J.JBUSRES.2020.08.058

Fornell, C., & Larcker, D. F. (1981). Evaluating Structural Equation Models With Unobservable Variables and Measurement Error. *Journal of Marketing Research*, 18(1), 39–50. https://doi.org/10.2307/3151312

Gartner (2016). *Gartner Says Digital Assistants Will Serve as the Primary Interface to the Connected Home*. Gartner. https://www.gartner.com/en/newsroom/press-releases/2016-06-20-gartner-says-digital-assistants-will-serve-as-the-primary-interface-to-the-connected-home

Gouda, P., Ganni, E., Chung, P., Randhawa, V. K., Marquis-Gravel, G., Avram, R. … Sharma, A. (2021). Feasibility of Incorporating Voice Technology and Virtual Assistants in Cardiovascular Care and Clinical Trials. *Current Cardiovascular Risk Reports*, 15, 1–8. https://doi.org/10.1007/S12170-021-00673-9

Hair, J. F., Howard, M. C., & Nitzl, C. (2020). Assessing measurement model quality in PLS-SEM using confirmatory composite analysis. *Journal of Business Research*, 109, 101–110. https://doi.org/10.1016/J.JBUSRES.2019.11.069

Hair, J. F., Hult, G. T. M., Ringle, C., & Sarstedt, M. (2016). *A primer on partial least squares structural equation modeling (PLS-SEM)*. Sage Publications

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed a silver bullet. *Journal of Marketing Theory and Practice*, 19(2), 139–152. https://doi.org/10.2753/MTP1069-6679190202

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, 31(1), 2–24. https://doi.org/10.1108/EBR-11-2018-0203

Hair, J., Hollingsworth, C. L., Randolph, A. B., & Chong, A. Y. L. (2017). An updated and expanded assessment of PLS-SEM in information systems research. *Industrial Management & Data Systems*, 117(3), 442–458. https://doi.org/10.1108/IMDS-04-2016-0130

Jennifer, P., & Sofroniev, G. (2020). *Exploring Voice-Controlled System: Services and Consumer Preferences towards future usage within the Food Industry*. Jönköping University

Kendall, L., Chaudhuri, B., & Bhalla, A. (2020). Understanding technology as situated practice: everyday use of voice user interfaces among diverse groups of users in urban India. *Information Systems Frontiers*, 22, 585–605. https://doi.org/10.1007/s10796-020-10015-6

Kim, J., Merrill, K., Xu, K., & Sellnow, D. D. (2020). My Teacher Is a Machine: Understanding Students' Perceptions of AI Teaching Assistants in Online Education. *International Journal of Human–Computer Interaction*, 36(20), 1902–1911. https://doi.org/10.1080/10447318.2020.1801227

Lee, S. Y., & Choi, J. (2017). Enhancing user experience with conversational agent for movie recommendation: Effects of self-disclosure and reciprocity. *International Journal of Human Computer Studies*, 103(January), 95–105. https://doi.org/10.1016/j.ijhcs.2017.02.005

Li, L., Paudel, K. P., & Guo, J. (2021). Understanding Chinese farmers' participation behavior regarding vegetable traceability systems. *Food Control*, *130*. https://doi.org/10.1016/J.FOODCONT.2021.108325

Lin, H. F., & Chen, C. H. (2015). Design and application of augmented reality query-answering system in mobile phone information navigation. *Expert Systems with Applications*, 42(2), 810–820. https://doi.org/10.1016/j.eswa.2014.07.050

Liu, Y., Sun, J. C., & Chen, S. (2021). Comparing technology acceptance of AR-based and 3D map-based mobile library applications: a multigroup SEM analysis. *Interactive Learning Environments*, 1–15. https://doi.org/10.1080/10494820.2021.1955271

McCue, T. (2018). *Okay Google: Voice Search Technology And The Rise Of Voice Commerce*. Forbes. https://www.forbes.com/sites/tjmccue/2018/08/28/okay-google-voice-search-technology-and-the-rise-of-voice-commerce/?sh=25a6a2ec4e29

McLean, G., & Osei-Frimpong, K. (2019). Hey Alexa … examine the variables influencing the use of artificial intelligent in-home voice assistants. *Computers in Human Behavior*, 99, 28–37. https://doi.org/10.1016/J.CHB.2019.05.009

Moan, I. S. V., & Rise, J. (2006). Predicting smoking reduction among adolescents using an extended version of the theory of planned behaviour. *Psychology and Health*, 21(6), 717–738. https://doi.org/10.1080/14768320600603448

Mohammadi, H. (2015). Social and individual antecedents of m-learning adoption in Iran. *Computers in Human Behavior*, 49, 191–207. https://doi.org/10.1016/j.chb.2015.03.006

Moriuchi, E. (2019). Okay, Google!: An empirical study on voice assistants on consumer engagement and loyalty. *Psychology and Marketing*, 36(5), 489–501. https://doi.org/10.1002/mar.21192

Neumann, N. (2018). *The Acceptance of Smart Home Technology* [University of Twente]. https://doi.org/10.1007/978-3-030-61140-8_1

Ostrom, A. L., Fotheringham, D., & Bitner, M. J. (2019). Customer Acceptance of AI in Service Encounters: Understanding Antecedents and Consequences. *Handbook of Service Science, Volume II* (pp. 77–103). Cham: Springer. https://doi.org/10.1007/978-3-319-98512-1_5
Pal, D., Arpnikanondt, C., Funilkul, S., & Chutimaskul, W. (2020). The Adoption Analysis of Voice-Based Smart IoT Products. *IEEE Internet of Things Journal*, 7(11), 10852–10867. https://doi.org/10.1109/JIOT.2020.2991791
Pal, D., Arpnikanondt, C., Funilkul, S., & Razzaque, M. A. (2020). Analyzing the adoption and diffusion of voice-enabled smart-home systems: empirical evidence from Thailand. *Universal Access in the Information Society*, *0123456789*. https://doi.org/10.1007/s10209-020-00754-3
Pal, D., & Patra, S. (2020). University Students' Perception of Video-Based Learning in Times of COVID-19: A TAM/TTF Perspective. *International Journal of Human-Computer Interaction*, 00(00), 1–19. https://doi.org/10.1080/10447318.2020.1848164
Park, E., Hwang, B., Ko, K., & Kim, D. (2017). Consumer Acceptance Analysis of the Home Energy Management System. *Sustainability*, 9(12), 1–15. https://doi.org/10.3390/SU9122351
Perez, S. (2019). *41% of voice assistant users have concerns about trust and privacy, report finds*. TechCrunch. https://techcrunch.com/2019/04/24/41-of-voice-assistant-users-have-concerns-about-trust-and-privacy-report-finds/
Pitardi, V., & Marriott, H. R. (2021). Alexa, she's not human but… Unveiling the drivers of consumers' trust in voice-based artificial intelligence. *Psychology & Marketing*, 38(4), 626–642. https://doi.org/10.1002/MAR.21457
Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, 88(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879
Ramayah, T., Cheah, J., Chuah, F., Ting, H., & Memon, M. A. (2018). *Partial Least Squares Structural Equation Modeling (PLS-SEM) using SmartPLS 3.0: An Updated Guide and Practical Guide to Statistical Analysis (2nd Edition)* (2nd ed.). Kuala Lumpur, Malaysia: Pearson
Ringle, C. M., Wende, S., & Becker, J. (2015). *SmartPLS 3. Bönningstedt: SmartPLS*. http://www.smartpls.com
Rousseau, D. M., Sitkin, S. B., Burt, R. S., & Camerer, C. (1998). Not So Different After All: A Cross-Discipline View Of Trust. *Academy of Management Review*, 23(3), 393–404. https://doi.org/10.5465/AMR.1998.926617
Schudzich, T. (2019). *Music Consumers' Adoption of Smart Speakers in the Field of Music: How do music consumers adopt towards (musical) smart speakers with reference to music marketing?*. University of Twente
Shah, K. (2020). *7 Super Smart Ways of Using Voice Technology in The Classroom*. Thirdrocktechkno. https://www.thirdrocktechkno.com/blog/7-super-smart-ways-of-using-voice-technology-in-the-classroom/
Song, Y. W. (2019). *User acceptance of an artificial intelligence (AI) virtual assistant: an extension of the technology acceptance model*. The University of Texas at Austin
Sorensen, K. N. (2019). *Millennials' Acceptance of Voice Activated Shopping*. University of Nebraska - Lincoln
Teo, T., & Zhou, M. (2014). Explaining the intention to use technology among university students: A structural equation modeling approach. *Journal of Computing in Higher Education*, 26(2), 124–142. https://doi.org/10.1007/s12528-014-9080-3
Van Eck, N. J., & Waltman, L. (2010). Software survey: VOSviewer, a computer program for bibliometric mapping. *Scientometrics*, 84(2), 523–538. https://doi.org/10.1007/s11192-009-0146-3
Venkatesh, V. (2000). Determinants of perceived ease of use: Integrating control, intrinsic motivation, and emotion into the technology acceptance model. *Information Systems Research*, 11(4), 342–365. https://doi.org/10.1287/isre.11.4.342.11872
Venkatesh, V., Morris, M., Davis, G., & Davis, F. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 27(3), 425–478. https://doi.org/10.2307/30036540
Vimalkumar, M., Sharma, S. K., Singh, J. B., & Dwivedi, Y. K. (2021). 'Okay google, what about my privacy?': User's privacy perceptions and acceptance of voice based digital assistants. *Computers in Human Behavior*, *120*. https://doi.org/10.1016/J.CHB.2021.106763
Wagner, K., Nimmermann, F., & Schramm-Klein, H. (2019). Is It Human? The Role of Anthropomorphism as a Driver for the Successful Acceptance of Digital Voice Assistants. *Proceedings of the 52nd Hawaii International Conference on System Sciences*, 1386–1395. https://doi.org/10.24251/hicss.2019.169

Zeng, D. (2020). *An Investigation of Mature Travelers'Usage Intention of Intelligent Voice Assistants in Hotels*. Purdue University