Online Health Communities: The Impact of AI Conversational Agents on Users

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Abstract. The literature lacks evidence on the acceptability of AI conversational agents (chatbots) and the motivations for their adoption in healthcare industry. This paper aims to examine the acceptance of these chatbots based on the UTAUT model in Online Health Communities (OHCs) and to explore what kind of impact these particular features have on the users' intentions, and the actual use of these communities. Based on a quantitative methodology approach, we rely on the UTAUT model to study OHCs users' behavior and intentions towards such AI conversational agents/chatbots. The study shows that the UTAUT has proved to be a strong and reliable model for evaluating the adoption and application of AI conversational agents (chatbots) in OHCs. A questionnaire was employed to collect data, and respondents are chosen using the cluster sampling approach. On a 7 Likert scale, respondents were asked to select which choice best suited their reaction to any of the topics presented. A total of 632 answers from 62 countries were received, with 443 of them being complete. Many tests were used to examine the data such as the bivariate and multivariate analysis. Since the returned p-value for most of the hypotheses tested was 0.05, the majority of the hypotheses tested were accepted. Findings showed the interrelations between AI conversational agents/chatbots and OHCs on users' Behavioral Intention (BI). The main constructs of the UTAUT model (Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions) had a significant impact on the participants' BI and Usage Behavior (UB) for AI conversational agents/chatbots in OHCs. As for moderators, gender and age had no effect on BI and UB. Understanding the main factors that have a significant impact on users' intentions to use chatbots in OHCs determines the significance of those results.

Keywords: Online Health Communities · AI conversational agents · Chatbots · UTAUT

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1 Introduction

Healthcare undergoes a continuous transformation and faces many challenges; incidents of miscommunication between health professionals and friends or family of patients, misinformed patient about health-related issues on social media platforms, without forgetting the upheaval caused by the recent COVID-19 pandemic. In fact, healthcare providers usually need lots of time to address such challenges on their own and surely better coordination and communication between all healthcare stakeholders (patients, practitioners, patients' family or friends…) would positively contribute to the all involved stakeholders' experience.

With this regard, the advancements in Artificial Intelligence (AI) are expected to have a positive impact on the healthcare industry, whereas the informational requirements and the need for online health communication is intensified [1]. Indeed, AI conversational agents or Chatbots are considered a promising development to that respect. Chatbots are a class of AI applications that rely on Deep Learning (DL) to assist provision of information [2], gather information or perform routine tasks and are being implemented in the Online Health Communities (OHCs) as an alternative means to provide information instead of human healthcare personnel [3]. Chatbots are accessible through different digital hubs: websites, mobile and messaging applications, SMS, etc. It is estimated that there will be an increase in the deployment of chatbots in the health sector in the future. However, a number of questions in relation to the intentions to use health-related AI conversational agents is not fully exploited in the literature.

In view of the above, the aim of this research is to examine the intention of using health chatbots applications in OHCs and to explore what kind of impact these particular features have on the users' intentions, and the actual/potential use of these communities. The focus of the article is therefore to study such intention of use and its impact on users' behavior in OHCs through one of the most used models (UTAUT) that analyzes the behavioral intention to adopt any system related to technology [4].

For this purpose, we will first sum up the related literature covering OHCs and AI agents/chatbots. Then we shall present the UTAUT model with the related technology acceptance studies applied in health organizations and the proposed model and hypotheses to be tested. Afterwards, we will briefly explain the methodology used and present our results through a proper discussion of the findings. Finally, we shall conclude our work with our contributions, managerial implications, and limitations.

2 Contextual Background: OHCs AI Agents/Chatbots

Online health communities (OHCs) - a special case of virtual communities - offer opportunities to patients, friends or family to post and explain their concerns, ask questions, receive feedback, or share their experiences. Users/patients can choose a physician and interact only with him/her to protect their privacy [5].

OHCs' positioning is reinforced through the adoption of AI and DL techniques. As digital health innovation continues to improve, it has initiated changes in providing care by changing the doctor-patient relationship with shared decision-making, communication, health management, and cost-effectiveness [6]. OHCs have three diversions based on the users' perspective: i) an OHC could aim healthcare subjects through discussion forums and sharing ideas and experiences; ii) address patients and physicians for exchange of support and information; or iii) designed only for physicians in order to share their professional knowledge and experiences.

The integration of heterogeneous systems is crucial for enterprise preparedness during a crisis [7]. The COVID-19 pandemic promoted healthcare delivery solutions and healthcare apps based on blockchain and AI [8]. The outcome of digitalization produces benefits for the healthcare systems and electronic medical test records improve the access to the health records both for patients and health practitioners [9]. DL algorithms is capable of feature extraction with no human interaction. It exploits a structure imitating a human's neuronal structure of the brain [10].

Within the same context of OHCs, chatbots are AI applications based on DL able to interact and converse with a human through text, voice, and animation [11]; they are software applications created to reproduce and imitate human interaction and communication through or into speech or text [12]. In the context of healthcare, personalized health and therapy information are being provided by chatbots or healthbots to provide support to patients by suggesting diagnoses and treatments based on patient indications [13].

Interactive conversational agents, digital assistants, artificial conversation entities, and smart bots are also defined as chatbots. These chatbots are considered more attractive and user-friendly. They provide users with an efficient and comfortable communication by offering accurate information and assistance to their questions and problems [14].

Limitation in healthcare resources such as medical professionals and facilities usually impedes people living in remote areas from receiving professional medical advice and having access to real-time and efficient health care services [15]. Thus, patients generally opt for other options [16]. In fact, some of the motivations for using chatbots include the novelty of such interaction, social factors and entertainment, but most importantly efficiency. In a business context, these applications became commonly used because they minimize service costs and can deal with several consumers at the same time [14].

Forty-one different chatbots have been used for different purposes in mental health. Mental disorders, stress, depression, and acrophobia could be managed by using chatbots, and this idea was proven by twelve studies that demonstrated the efficiency of automation and use of chatbots [17].

Finally, the COVID-19 has had the largest impact on technological advancements and acceptance. In the next section we shall introduce the UTAUT model and our research methodology.

3 The Impact of AI Agents/Chatbots on OHCs' Users

3.1 The Proposed UTAUT Model and Our Main Hypotheses

Understanding the reasons for rejecting or adopting each new technology has become critical. As a result, technology acceptance concepts, theories, and models expect to bring the idea of how individuals may accept, understand, and use the latest technology. Venkatesh [4] proposed the **Unified Theory of Acceptance and Use of Technology** (UTAUT) framework to explore and analyze the acceptance of technology and its reasons in information systems (IS) research; it is one of the most widely used technology acceptance frameworks that investigates and explains the intention to use technology in organizational contexts [4].

In fact, the UTAUT model has been used in a variety of fields including near-field communication technologies [18], interactive whiteboards [19], e-health [20], and ERP software acceptance [21], and home telehealth services [22]. Many factors influence people's decision-making process in relation to the adoption of new technologies. Research has been presented in various contexts [4, 23]. To the best of authors' knowledge there is limited research on this research area.

The UTAUT model presents four independent constructs: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC) that predict technology acceptance. According to many authors [4, 18–20], these constructs are directly associated with Behavioral Intentions (BI) which is defined as users' intention to use the system, and Use Behavior (UB). User demographics such as gender and age have been conceptualized as moderators in the UTAUT framework [24].

In our article we shall study the impact of these constructs on the level of the acceptance of health AI agents/chatbots in OHCs through the UTAUT model [4]. The choice of this model is explained by the fact that it provides a comprehensive synthesis of users' intentions to adopt new technologies. The following table will present the basic UTAUT model including the interrelations between the six main constructs and two moderators (Gender and Age) (Fig. 1).

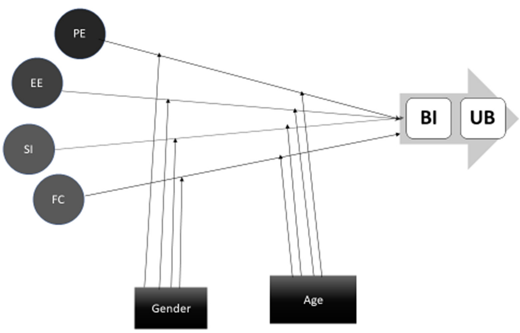


Fig. 1. Basic UTAUT model. Source [4]

The following table will present the variables and moderators of the UTAUT model (Table 1).

Table 1. Presentation of UTAUT main constructs

Variables/Moderators	Description [4]
PE	The degree to which a person believes that using the system would improve job performance. The acceptance framework has been utilized in various studies to explain end-users' BIs for adopting new technologies in the healthcare business [25]
EE	The level of ease in relation with the use of the system. It comprises three variables: complexity, ease of use, and perceived ease of use. EE is seen in the context of the health industry as the perceived level of ease in adopting a healthcare system
SI	The degree to which a person believes that other people believe he or she should adopt the new system. Along with increased support from friends, volunteers, and family, E-Health applications are viewed as a valuable instrument for achieving the technology use [26]
FC	The degree to which a person believes that an organizational and technological infrastructure has been developed to support the system's use. FC is also presented as the perception that resources will be available to complete the task [27]
BI	BI relates to how people intend to use technology in the future
Gender	One of the main moderating variables in the UTAUT. Guo [28] investigated the moderating role of gender in the adoption of mobile social networking sites and to recognize gender differences
Age	Age is identified as a moderator on BI and technology use. In the adoption of IS, the impact of PE on BI has been shown to be larger for males than females

The following table will also present the main hypotheses adopted for the use of chatbots in OHCs (Table 2).

Table 2. Table of hypotheses

Hypothesis
H1. PE posits a positive relationship towards BI to use platforms/chatbots in OHCs
H2. EE posits a positive relationship towards BI to use platforms/chatbots in OHCs
H3. SI posits a positive relationship towards BI to use platforms/chatbots in OHCs
H4. FC will have a significant effect on BI to use platforms/chatbots in OHCs
H5. BI posits a positive relationship towards UB
H1a, H1b, H1c and H1d: Gender will moderate the relationship between PE, EE, SI, and FC respectively, to use chatbots in OHCs
H2a, H2b, H2c and H2d: Age will moderate the relationship between PE, EE, SI, and FC respectively, to use chatbots in OHCs

3.2 Research Methodology

As a philosophy, positivism complies to the view that only "factual" knowledge collected through observation, including measurements, is trustworthy [29–31]; the researchers are working with precise frameworks or models (the UTAUT) while presuming that these frameworks or models are solid and sustainable [32], with a philosophical realism adhering to the hypothetico-deductive approach. Indeed, after addressing the theoretical perspectives based on the UTAUT framework and after proposing the hypotheses, the survey is generated to collect data and test the validity of the hypotheses. In fact, it is noted by IS publications that most of IS researches are positivistic [32], and most of the quantitative researches in IS used hypothetico-deductive approach [33].

Statistical analysis was performed using IBM SPSS version 25. In fact, a descriptive analysis was enrolled, and the variables were presented as per their type. All the scores followed a Likert scale from 1 to 7 (from 1 "strongly disagree" to 7 "strongly agree"). Reliability test was done for each score in order to validate the score (Cronbach alpha value was higher than 0.7 for all the scores).

Bivariate analysis was enrolled in order to test the correlation between UTAUT scores (PE, EE, SI, FC, BI, and UB) and the variables considered as moderators (gender, age). In the bivariate settings we used Student t-test and ANOVA test. Linear regression test was used to test the correlation between UTAUT scores and BI and between BI and UB. Furthermore, a multivariate analysis was enrolled in order to test the factors affecting BI. A statistically significant correlation was set at 5% (p-value less than 0.05).

Our statistical analysis was performed on a convenience sample of 443 participants (OHCs members). A total of 632 responses have been received of which 443 were complete. The completion rate is about 70% and the responses came from 62 countries. The data collection started on March 15th, 2021 and lasted until April 25th, 2021 for a total duration of 40 days.

4 Results, Findings and Discussion

This part presents the statistical analysis performed on the complete sample; based on the results, we shall analyse the hypotheses and the correlations between the main constructs of UTAUT model with BI and UB with a proper discussion; then, we will address the analysis of the main moderators defined by Venkatesh [4].

Participants were almost evenly distributed: 49% females and 46% males (Appendix A). The mean age was 34.3 (minimum 18 - maximum 68 years). However, one interesting finding was recorded that out of the 443 participants, 57.8% had limited experience in the use of Chatbots and/or online communities, and only 3.6% considered themselves experts in the use of chatbots in OHCs (Appendix B); These low experience levels that there is too much to do regarding this matter; this finding will be further emphasized in the managerial implication part.

The impact of the UTAUT variables was tested; all four variables were supported in the multivariate analysis. The study findings matched most of the hypothesized interrelations with UTAUT variables (H1, H2, H3, H4, and H5). Through linear regression, the findings showed that the variables of the conceptual model have a positive correlation on the BI to use chatbots in OHCs (PE: $p = 0.000$, EE: $p = 0.001$, SI: $p = 0.000$, and

FC: $p = 0.001$). These variables were considered as very important in determining the acceptance of using technology in the healthcare context through various researchers [34, 35].

The following Tables 3 and 4 are showing the multivariate analysis of the main UTAUT constructs and their correlations with BI, and the representation of the main UTAUT score categories (Table 5).

Table 3. Multivariate analysis of UTAUT main constructs

	Unstandardized Coefficients		Standardized Coefficients	t	P.value
Study population	B	Std. Error	Beta		
(Constant)	1.872	0.930		2.014	0.045
PE	0.292	0.036	0.341	8.019	0.000
SI	0.126	0.026	0.235	4.867	0.000
FC	0.118	0.036	0.165	3.249	0.001
EE	0.130	0.040	0.139	3.210	0.001
Dependent variable : BI					

Table 4. Representation of UTAUT score categories

UTAUT constructs	Representation and score categories (%)		
	Poor	Good	Very good
PE	**60.9**	26.9	12.2
EE	38.8	**31.4**	**29.8**
SI	**83.1**	8.8	8.1
FC	58	**28**	**14**
BI	**56.9**	21.9	21.2
UB	**93.2**	3.8	2.9

Regarding PE (a 5-item scale with a mean of 21.6 ± 7.23 over 35, and a median of 23 with a minimum of 5 and a maximum of 35) (Appendix C), participants almost agree that using chatbots enhances productivity and facilitates the accomplishment of tasks more quickly. Having 60.9% in the poor area means that a great potential exists to enhance the awareness and promote the use of these technologies. So, PE is very important to the use of online platforms. In fact, users are always interested to enhance their performance through the use of these technologies. Accordingly, this variable is considered as one of the strongest one on BI [4, 34, 36].

According to regression analysis, PE is positively correlated to BI ($p < 0.001$) to use chatbots in OHCs. From a user perception, this finding confirms that using the system will enhance performance, attitude, and intention to use the system in the healthcare context [4, 37]. It also confirms previous literature that showed PE as a strong predictor of BI to adopt healthcare technology [22, 38]. In summary, when PE increase, BI increase and the null hypothesis is rejected. In other words, when users or patients find that the use of chatbots/OHCs increases their productivity and enhances their health, they increase their intentions to use them.

Regarding EE (a 5-item scale with a mean of 25.46 ± 6.61 over 35, and a median of 26, with a minimum of 5 and a maximum of 35), participants highly agree that the process of learning and becoming familiar in using Chatbots is easy for them. Having 61.2% in the Good and Very Good area means that the users are already considering that EE is highly important to use these technologies. EE is considered as a crucial step to the use of these online platforms. According to regression analysis, EE (H2) is significantly correlated to BI ($p = 0.001$) as in many other researchers [35, 39, 40]. It implies that the ease of using chatbots in the healthcare field is more likely to have an impact on the perception of BI [19]. This finding confirms [41], that EE has a positive impact on the BIs of patients interacting with physicians in OHCs.

In summary, when users' or patients find that the use of chatbots in OHCs is easy, they will increase their intentions to use them.

As for SI (a 7-item scale with a mean of 22.88 ± 11.52 over 49, and median of 22 with a minimum of 7 and a maximum of 49), participants highly disagree that the majority of friends or colleagues surrounding them use or believe that they should use chatbots. Having 83.1% in the poor area means that the users are already considering that SI is not affecting them to use these technologies. In fact, a statistically significant and positive correlation was found between SI (H3) and BI in the regression analysis ($p < 0.001$). Although health is always a personal thing but patients are not experts. So, their BI and UB in OHCs are influenced by their social relationships mainly other patients in the family, friends or even family members nurse, doctors, technician etc. [34, 35, 40].

In other words, when users' friends, family, and colleagues (who matter), propose to users that they should use chatbots in OHCs, the users increase their intentions to use OHCs.

Finally for FC (a 4-item scale with a mean of 18.67 ± 4.61 over 28, and a median of 19 with a minimum of 4 and a maximum of 28), participants highly agree that they have the necessary resources (laptops, smartphones, etc.) to use chatbots for getting support on all levels. Also, they highly agree that they have the necessary knowledge to use chatbots for getting support on all levels. Having 42% in the Good and Very Good areas means that the users are already considering that FC is highly important to use these technologies. Also, having 58% in the poor area means that this factor is highly important to increase the BI.

Regarding FC (H4), a statistically significant and positive correlation was found between FC and BI in the regression analysis ($p = 0.001$). The literature confirmed as per the findings of this study that FC has a significant influence on BI [40]. According to [39], the BI to adopt this tool is related to the specific devices that sometimes need technical support more than other ones. In other words, having laptops, smartphones and the necessary knowledge and experts available for assistance, increase the users' BI to use chatbots in OHCs. When users receive more FCs to use chatbots, they will increase their intentions to use them.

The following table is showing the significant correlation between BI and UB. It highlights that UB is positively correlated with BI ($p < 0.001$), and UB will increase with the increasing of BI ($B = 0.514$).

As for BI (a 4-item scale, with a mean of 17.88 ± 6.19 over 28, and a median of 18 with a minimum of 4 and a maximum of 28), participants agree that they are planning to use chatbots in OHCs in the future, provided that they have access to these online platforms. However, 56.9%, of participants are located in the poor area, highlighting the need to understand the motivations and discover the opportunities to increase the acceptance of using chatbots in OHCs. Regarding H5, a statistically significant correlation was found between BI and UB in the linear regression ($p < 0.001$). This finding is associated with the findings of the literature review that found all variables having a significant correlation [41].

Additionally, the categorization of answers in this study showed that almost 45% of responders currently do not consider that becoming familiar with the use of chatbots is easy for them. Hence, having this significant correlation between BI and UB is a great potential to get people more involved into employing this technology.

Finally, for UB (a 3-item scale with a mean of 10.84 ± 3.48 over 21, and a median of 11 with a minimum of 3 and a maximum of 21), participants do not agree that they are currently or frequently using chatbots in OHCs. It is indicative that 93.2% are located in the poor area. Further researches are required to understand the factors and examine opportunities that lead to UB.

To conclude, once we have a significant correlation between BI and UB, the variables that had a direct significant correlation on BI should have an indirect correlation with UB (Table 5). So, once participants are having the intention to use chatbots in OHCs, it will not be hard to convince them using these applications. Multiple strategies must be defined and aligned with the independent variables that had a direct impact on BI. In other words, when users' have more intention in using chatbots in OHCs, they use them more frequently.

Henceforth the 5 main hypotheses (H1, H2, H3, H4 and H5) were validated.

Finally, a detailed analysis was conducted about the role of UTAUT moderators in the use of chatbots in OHCs. In fact, Venkatesh [4] included many moderators in the UTAUT framework such as gender and age. So, we analyzed all the related hypotheses.

In general, the factor gender did not show any significant correlation with independent variables in this study (ANOVA Test). The chosen sample is in fact more familiar with

Table 5. Correlation between BI and UB

	Unstandardized Coefficients		Standardized Coefficients	t	P.value
	B	Std. Error	Beta		
(Constant)	5.675	0.435		13.046	0.000
Behavioral Intention	0.289	0.023	0.514	12.570	0.000
Dependent Variable: Use Behavior					

technology. The same analysis was applied for the age moderator. The findings do not correlate with the literature. In other terms, age does not have any impact on the use of chatbots in OHCs. In the bivariate analysis, a statistically non-significant correlation was found between Age and PE, EE, SI, FC and UB. Other researchers identified that the age is the most significant moderator in the healthcare context due to the fact that older patients may have some challenges when using technology [20, 22].

As mentioned before, the participants are already technology users'; their age does not increase or decrease their intentions to use chatbots in OHCs.

5 Contributions, Conclusion, Limitations and Future Research

In this article, we tried to highlight and examine the intention of using health AI agents/chatbots applications through the UTAUT model in OHCs. Based on the UTAUT framework, the technology use experience of OHCs members was showed through the intention of using AI conversational agents/chatbots in OHCs. BI and UB are highly correlated with the main constructs of UTAUT and play a major role in affecting the relationship between the variables and BIs of the participants.

The study showed that when PE, EE, SI, and FC increase, BI will increase. In other terms, when productivity is enhanced, the users will increase their intentions to use chatbots in OHCs. Also, these applications must be user friendly as it will increase participants BIs to use them. Apparently, family members, friends and colleagues have a major impact on the intentions of our participants. When the participants are well equipped with technology, they certainly increase their BIs to use these applications.

The contribution of this study is twofold; first we contributed to theory by adding one more context to test the UTAUT model in OHCs for the usage of AI agents/chatbots. By testing the UTAUT model, this study has answered the demand for further research and empirical studies on intelligent automation in the healthcare industry. It also fills a gap in the current literature on the use of chatbot technology in healthcare. The UTAUT has once again proven to be a strong and reliable model for evaluating the adoption and application of new technology, since the findings revealed a better understanding of users' acceptability and readiness to use chatbots in OHCs. Therefore, this study advances the literature by offering key insights for practitioners and scholars interested in studying patients' behavior when it comes to the use of chatbots in OHCs.

Another contribution of this study is important information on the factors influencing the use of chatbots in OHCs. Technology developers should ensure that chatbots in OHCs interact in a variety of languages, providing customers with a user-friendly interface. The practitioners must ensure that chatbots do not cause any technology-related anxiety. Designers must create user-friendly chatbots in order to reduce patients' concerns about technology.

Patients can also use health chatbots to connect directly with physicians for diagnosis or treatment support by talking or texting smart algorithms as the first point of contact for primary care in the future. Physicians, nurses, or any other medical experts may be revealed from answering every single health question, including FAQ; instead, they will look to chatbots first. If the little medical assistant is unable to reply to the issues mentioned, the case will be transferred to a real-life doctor. Chatbot providers must ensure distinct and distinctive service features to meet the patients' needs and encourage patient usage. As for healthcare practitioners, chatbots must be developed with customization and personalization provisions based on the needs of patients in order for patients to feel at ease when using chatbots for health purposes.

Finally, although the literature review indicates that the UTAUT model is robust and has been validated in the literature, there are some intrinsic limitations need to be acknowledged; For instance, the intention-behavior gap and the external factors influence as identified by [42], should be taken into consideration in future studies. Furthermore, it is believed that other variables such as trust and FOTA, and other moderators such as technology experience, educational level, occupation, culture, and geographical zone, should be added to the UTAUT model in order to be tested in future studies and other contexts.

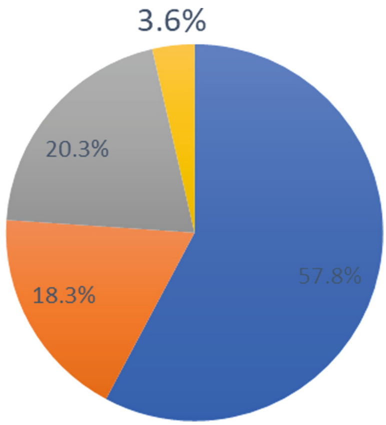
Finally, our research shows a methodological limit in terms of the generalization of the results; in fact, this research was carried out over a set length of time, therefore there is a need for a longitudinal evaluation in future research to guarantee UB. To conclude future research should explore the ethical principles and practical implications of chatbots, as well as the cultural and the regional impact on BI and UB.

Appendixes

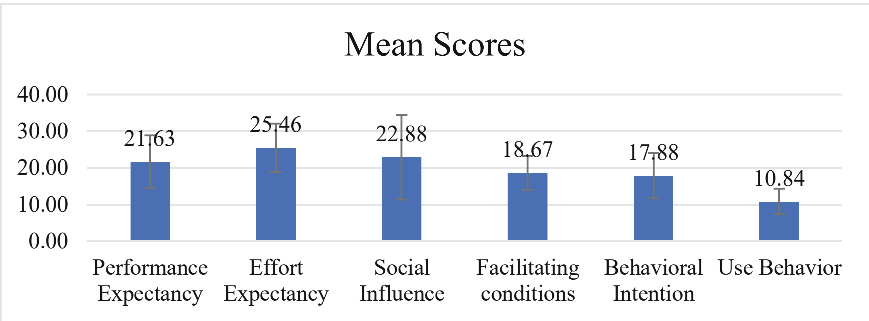
Appendix A: Demographic Characteristics of the Study Population

		Frequency	Percent
Gender	Female	217	49.0
	Male	204	46.0
	Prefer not to answer	22	5.0

Appendix B: Experience Related to the Use of Chatbots in OHCs



Appendix C: Descriptive Analysis of UTAUT Main Constructs



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