LEX LOCALIS-JOURNAL OF LOCAL SELF-GOVERNMENT
ISSN:1581-5374 E-ISSN:1855-363X
VOL. 23, NO. S5 (2025)

AUTOMATING TECHNICAL SUPPORT PROCESSES TO INCREASE CHATBOT ACCEPTANCE AMONG THE FACULTY AND STUDENTS OF KING ABDULAZIZ UNIVERSITY (KAU) DURING THE COVID-19 PANDEMIC

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- **Abstract**

The Covid-19 pandemic affected the lives of people all over the world which lead to promote the demand for digital transformation in many businesses and services. Among the areas most greatly affected is the educational process. The transformation in the educational process from the physical to the digital mode represents a formidable challenge, particularly for less developed communities in the digital way. The King Abdulaziz University (KAU) presented a variety of approaches for equipping their instructors and students with the necessary expertise to bring about digital transformation in terms of online educational processes. Among the approaches employed to achieve digital transformation is Chatbot. Chatbot is based on the delivery of supporting materials to its users, including documents, photos, audio and video files, deriving from a variety of sources and databases to facilitate the learning process. This study delves into the main design and algorithms of Chatbot services, its level of acceptance by the targeted groups, and the effects arising from the engagement of this approach.

Keywords: Chatbot, Digital transformation, WhatsApp, technical support system

1. Introduction

The engagement of modern and appropriate technologies can facilitate the spread of digital transformation. Among these technologies are Chatbot and the use of machine language (ML) for semantic learning (SL). The benefits which come with the engagement of Chatbot include the capacity to reach the target audience through various social applications such as Facebook and WhatsApp [1]. Chatbot, which is making inroads in the fields of public transportation, education training, and healthcare, can be defined as human interaction algorithms facilitating the development of customer service departments [2].

Among the issues hindering good communication between government agencies and the community is the lack of technical support operations. As such, establishments such as Universal Studios, Plum Chat bot, Sephora chat bots, and Domino's Chatbot consider technical support operations an essential business investment [3-5]. Designed to simplify the interaction between humans and computers, Chatbots provide personalised services in complex situations to facilitate the decision-making process [6].

This study focuses on the factors which influence the customers' acceptance level of Chatbot use through the WhatsApp platform as well as the factors which serve to increase the accuracy of SL through the direct acquirement of essential information. The university is enthusiastically exploring various approaches to develop its public education infrastructure for its subsequent deployment in the public education sector, which will serve to boost the economy of the Kingdom of Saudi Arabia (KSA). This is in line with the sixteenth goal of the KSA's National Transformation Programme (Vision 2030), which is aimed at the introduction of private sector universities, which will contribute towards the growth in the volume of educational opportunities available. In this study, 25% of the estimated 100,000 students at KAU are subjected to online study or blended learning to determine the factors influencing the acceptance level of students and academic staff with regards to the Chatbot approach. This study also forwards recommendations for future studies aimed at expanding the utilisation of Chatbots.

1.1. Definition and type of Chatbot

Chatbot services surfaced in 2016, when robots were created to facilitate automated responses during messenger conversations. Over time, this interaction evolved into a fundamental marketing strategy for attracting potential customers [7]. Chatbots, which can be customised for a variety of languages, play a pivotal in exchange marketing role on the internet, providing visitors to websites and online applications, with the required assistance and support during their search for solutions to their queries. This will consequently serve to enhance the customers' online shopping and site visiting experiences [8, 9].

The classification of Chatbot types is based on different criteria, including programming language, learning methods, work methods, and applications. Chatbot robots rely on pre-set rules and available data for the delivery of responses to customer inquiries. In order to accurately identify the needs and requirements of customers, Chatbot robots are equipped with buttons for the selection of a quick response from a list of pre-determined options [10]. The expansion occurs when questions which did not exist previously are included for response by the support team. Chatbot robots do not require ML programmes as they are automatically fed with conversations at every stage, rendering any form of interpretation unnecessary [11-12].

Another kind of Chatbot is AI and ML-based Chatbots, that is simply searching for keywords, automated Chatbots draw conclusions from the interpretation of patterns. This mechanism, which employs high-quality AI techniques, facilitates the user's inclusion of various answers based on the queries forwarded by customers [1]. Chatbots utilise NLP to comprehend human speech by breaking down phrases into Objectives, Entities, and Context. The efficiency of Chatbot at the initial stage of its employment is hampered by the extensive preparation time required prior to its response to the target audience. Over time, however, the experience accumulated renders the response time shorter [13].

2. Literature review

Many studies have been conducted on the use of Chatbots in various domains. The emphasis of these studies is mainly on the development of an integrated knowledge space, providing primary information regarding digital transformation, and the automating of technical as well as non-technical processes. This literature review focuses on the factors influencing the acceptance of Chatbots from a scientific as well as practical perspective.

2.1. Level of Chatbot acceptance in various management systems and marketplace

The virtual assistant, a recently developed educational Chatbot application for educators and pupils, is utilised for acquiring answers to education-related queries and to perform tasks that are routine. Other than perceived ease of use (PEOU) and practicality, also the survey conducted by [29] considered the social language used, proactivity, the age of the participants, and their digital skills to determine the acceptance level and usage frequency of educators with regards to Chatbots. Among their findings is that the use of a formal language in the Chatbot system elevates the level of intent in terms of usage frequency. The acceptance factors investigated during their undertaking will facilitate the development of an appropriate Chatbot design for the education community.

In a study aimed at improving consumer experiences with e-commerce response systems, Araújo & Casais detected a change in consumer purchasing behaviour brought about by the engagement of innovative Chatbot technologies [14]. Their study delved into the use of Chatbots as digital assistants in the e-commerce digital marketing domain and they influenced by advertisements delivered through mobile phones.

Rese and others investigated the use of NLP for enhancing the customer experience in the retail domain. The answers to shopping-related questions were received in NLP without the involvement of a salesperson or other inquiry options [37]. Their undertaking involved the integration of the technology acceptance model (TAM) conceptual framework with the less popular uses and gratification (U&G) theory in the pre-purchase phase of fashion items on online retail platforms. According to their findings, utility factors; namely perceived usefulness (PU) and authenticity of conversation; positively influenced Chatbot acceptance. The study mentioned that the PU is among the main factors influencing the level of acceptance with regards to Chatbots.

The direct relationship between development and business intelligence has been examined by several researchers. According to Araújo and Casais, Chatbots are highly efficient when it comes to product sales, concern for customers, and the enhancement of the customer purchasing experience [14]. The advancement of e-commerce is stymied by the long period the customer has to endure before receiving a response from the customer service representative, particularly in a live chat situation. This delay is caused by the customer-sales representative communicating with several customers simultaneously. As such, alterations to specific Chatbot features are required to facilitate the immediate delivery of responses to users based on a frequently asked questions (FAQs) dataset by way of SA of a word and its roots as well as artificial intelligence mark-up language (AIML) and latent semantic analysis (LSA) [5 & 15].

Chatbot systems were assessed for their capacity to accelerate the delivery of meaningful, comprehensive, and informative customer responses [15,16]. The methods used to develop the chatbots are based on pre-written rules and templates. The emergence of DL and neural network models gave rise to a formidable generation-based model for problem-solving and conversational responsiveness [16]. Enholm and others identified three factors determining the capacity of Chatbots, DL, and SA for increasing commercial value: (a) the challenges faced in adopting the use of AI, (b) the synchronising of AI with the organisational and institutional framework, and (c) the effects of AI and its branches on the business [12].

During the Covid-19 pandemic, many companies turned to innovative strategies in order to adapt to this unanticipated scenario and remain competitive. Therefore, Many chatbots have been made that development of smart technologies with the capacity to independently provide customers with the information they require during the decision-making process [2]. While the Chatbot system comes with the capacity to deliver accurate responses to queries, the use of this technology is not without its drawbacks. one of them is related to ethics and privacy concerns, which need to be overcome in order to promote the sustainability and acceptance of chatbot systems [9].

2.2. Using an expert system with Chatbot

Expert systems are increasingly linked to Chatbots for the provision of various services in an unprecedented manner. In this segment, we examine the relationship between expert systems and Chatbots in the context of the healthcare and tourism industries.

It has been established that the application of AI technologies can lead to improvements in the quality of various services. Azimi and others developed a seven-step methodology for the application of expert systems and Chatbots for the management of library services [7]. While healthcare is important for improving and maintaining the quality of human life, attaining information on health issues can often prove to be difficult. In view of this situation, Athota and others developed a medical robot linked to expert systems, which comes with the capacity to diagnose diseases and deliver basic information regarding their causes and effects prior to the user’s consultation with a doctor [6].

Other than providing access to medical information, this service will also serve to decrease the costs of healthcare. This medical Chatbot system involves the calculation for similarity in sentences and answers suggested by n-gram, term frequency-inverse document frequency (TF-IDF), and cosine similarity to attain more similar responses to the query submitted by the expert systems. The extended period involved the use of conventional diagnostic methods can lead to inaccuracies in the final results. Taking this into consideration, they developed a Chatbot which can diagnose disease severity based on user textual questions and used the NLP model to process meaning extraction by way of decision trees and probable disease characterisation.

In the context of technological developments in the tourism industry, Sperli proposes a framework that accumulates information on tangible and intangible sites in a unified data model to support the tourist journey with a conversational agent based on the Seq2Seq model [18]. Enterprise Service Bus is recommended for the automatic collection of future events by means of NLP through promotional websites or manually through organisations operating in this domain. As portrayed in their study, the advancement of the tourism industry is significantly dependent on the support of expert systems for attaining logical and digital solutions.

2.3. Chatbots factors that affect customer acceptance

Zumstein and Hundertmark considered three issues for their assessment of Chatbots: adequate responsiveness to customer conversations, empathy, and assistance through DL; and concluded that Chatbots use triple feedback measurement to reply to customers [19]. They found no differences between DL-based Chatbot and human agents in terms of empathy for emotional requests as it provided responses such as "I'm sorry that you to feel that way." Chatbots can provide such responses as many organisations build their Chatbot personas by adding their personalities, which is an accurate representation of the type and characteristics of the customers of these organisations. A Chatbot is expected to provide an immersive and engaging interaction with customers, which ultimately culminates in a business relationship based on trust [20, 21].

Among the key factors mentioned in relevant literature regarding the acceptance level of Chatbots is trust [19]. According to Følstad and others, the relationship between trust and commitment is important as commitment plays a significant role in the maintenance of customer loyalty. While some studies in this area delved into the issues of service quality, customer satisfaction, customer trust, and customer loyalty, as well as the humanising of Chatbot [21], others focused on the importance of increasing the trust in the security, reliability, and interoperability of Chatbots with existing bots [10, 19]. Therefore, the main factors to be considered for increasing the level of confidence in Chatbots are security, reliability, and accuracy. It is anticipated that young customers, who are unsurprisingly more familiar with mobile shopping, will benefit most from the use of Chatbots.

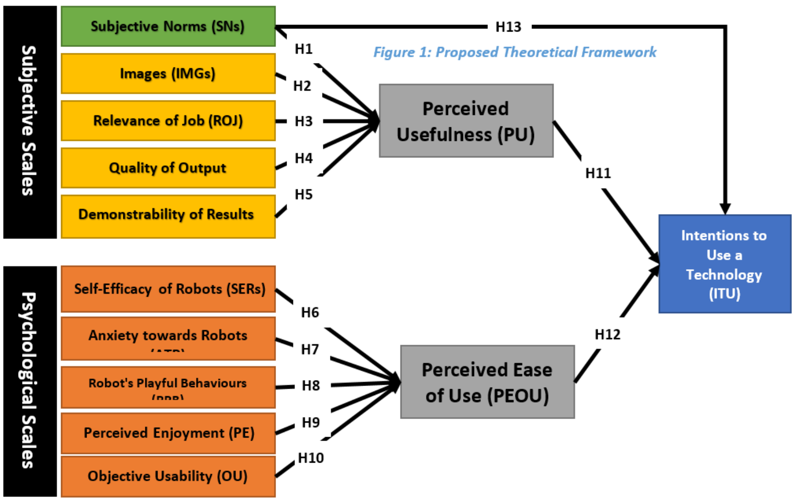

Figure 1: Proposed Theoretical Framework

Several researchers stressed on the importance of PU, pleasure, and PEOU as the drivers of user acceptance for automated response systems, such as Chatbots. According to Elkhani with others and Isaac and others (2018), flexibility and the PEOU are the factors to be considered during efforts aimed at increasing the acceptability level for Chatbots [23]. They are also of the opinion that conventional methods do not satisfactorily meet the needs of users. . Isaac conducted a pilot study using Chatbot characteristics that were based on the real-time responses that employees provided in electronic systems and linking it to autoresponder services [24]. The study found a correlation between the PEOU a Chatbots by measuring the level of compatibility, PEOU, and net benefits [23 & 24]. Thus, PEOU and further innovation of the Chatbot system, subsequent to its integration with DL and ML, will serve to promote the acceptance of this system in various areas [25].

In a survey conducted by Brandtzaeg and Følstad, 42% of the respondents were impressed at the capacity of Chatbots to quickly and efficiently access data. There were also respondents who consider the relationship between Chatbots and humans an avenue for the enhancement of human interactions through the social media [26].

3. Theoretical framework

The main constructs in the theoretical framework are presented together with the fundamental hypotheses applied. The compatibility of the theoretical framework with regards to the target audience in the KSA is also discussed.

Various factors, including as age and gender, influence the training and acceptance of Chatbots [28]. Kuberkar and Singhal examined the significance of Chatbots in emerging technologies and smart cities with the emphasis on travel ticket purchasing and accessibility to information on the status of roads in terms of traffic flow [3]. They exploited UTAUT's theoretical framework to conduct a preliminary survey to identify the factors which would encourage citizens to use public transportation instead of their own vehicles. The findings derived through their study can serve to significantly reduce the occurrence of crowds, travel delays, and air pollution in densely populated cities of the KSA; such as Riyadh, Jeddah, and Dammam; as well as during religious events; such as the Hajj and Ramadan. While studies applying the UTAUT framework are diverse and focus on perceived value with expected performance and expected effort, they lack several key aspects, which were highlighted in the theoretical framework of TAM3, to accurately gauge the acceptance level with regards to Chatbots.

The emergence of AI applications significantly altered the digital transformation domain. Several studies applied the TAM framework to determine the level of acceptance with regards to modern technologies. Chocarro and others examined the acceptability of text-based Chatbots assistants in the education sector [29]. Their findings indicate that PU and PEOU promote the acceptance of Chatbots. Much like chat language that is formal, the extensive vocabulary of a Chatbot and its ability to learn increases its acceptance among educators. According to Araújo and Casais, the Chatbots present the opportunity to exploit social networks through relationship marketing in the digital environment [14]. They explained the use of the TAM model in e-commerce to measure the factors that positively influence the acceptance of Chatbots and the intention to invest in Chatbots. Ashfaq et al. (2020) applied Chatbots as native text-based conversation agents to interact with many different types of users. They considered the factors such as satisfaction, acceptance of users, and intention of continuity with regards to customer service based on Chatbots. Among the models proposed is the expectation-confirmation model while the components proposed include service quality and information quality. According to their findings, PEOU and perceived enjoyment (PE) are significant indicators of intentions to continue using Chatbots. Their study also revealed that user satisfaction, in terms of Chatbot service, is an important factor for determining users' aptitude regarding Chatbots. Thus, the level of acceptance determines the quality of Chatbot services as well as user satisfaction in the organisational sector.

3. 1. Proposed framework

The proposed theoretical framework, which takes into consideration previous studies using TAM3, focuses on three main areas. Firstly, the relationship between components [14, 29, 30], secondly, PEOU and PU [31 - 33], and thirdly, expansion of the TAM3 framework through the addition of components [34 - 36]. The level of acceptance is measured by way of the ground theory or through open ended questions [34 -36]. In this study, we investigated the aspects associated to the activation of DL systems and AI. The theoretical framework (Figure 1) focuses on two main groups of fundamental components: the subjective and psychological scales. Each of these fundamental components comprises five sub-components. The subjective scale component comprises the sub-components of subjective norms (SNs), images (IMGs), relevance of job (ROJ), quality of output (QOO), and the demonstrability of results (DOR) while the psychological scale comprises the sub-components of self-efficacy of the robots (SERs), anxiety towards robots (ATR), robot's playful behaviours (RPB), perceived enjoyment (PE), and objective usability (OU). These ten sub-components are referred to for measuring the degree of correlation between PEOU, PU, and the intention to use a technology (ITU), which are the three basic components for measuring the acceptance and coping level with regards to electronic systems.

3. 2. Main components for measuring the level of Chatbot acceptance

The following are the fundamental components for measuring the level of acceptance with regards to the use of Chatbots.

Subjective Norms (SNs): This component focuses on the compliance to employ Chatbots. It considers the individual’s opinion regarding the applicability of Chatbots to the beneficiary audience [34]. Therefore, the SNs correlate to two main components; PU and ITU; in accordance with the following hypotheses:

H1. Subjective norms (SN) positively influence perceived usefulness (PU).

H13. Subjective norms (SN) positively influence intentions to use a technology (ITU).

Images (IMGs): This is the degree to which the individual realises that innovation and technical transformation will enhance his/her position in the social administrative system [38]. The IMGs component is an important aspect in the acceptance of technology in general and the acceptance of Chatbots in particular [2]. Thus, the relationship between IMGs and PU is according to the following hypothesis:

H2. Images (IMGs) positively influences perceived usefulness (PU).

Relevance of Job (ROJ): This is the degree to which the individual is convinced that the Chatbot system is applicable to the job which it was designed for [35]. This component focuses on defining the scope of work that was performed during the information gathering, design, and implementation phases of Chatbot. The relationship between ROJ and PU is according to the following hypothesis:

H3. Relevance of Job (ROJ) positively influences perceived usefulness (PU).

Quality of Output (QOO): This is the degree to which the individual is convinced that the system performs its functions well [35]. The QOO component focuses on the quality of the outputs and the materials provided to the target audience. The output of expert systems with Chatbot at their core comes in two parts: (a) the initial inputs and algorithms for the future learning of the robot and (b) the periodic measurements of the level of user satisfaction to achieve the required quality. Both these parts represent the main pillars of expert systems [7]. Thus, the relationship between QOO and PU is according to the following hypothesis:

H4. Quality of Output (QOO) positively influences perceived usefulness (PU).

Demonstrability of Results (DOR): This is the degree to which the individual is convinced that the results derived from the use of the system are tangible, observable, and transferable [38]. As such, the stability of systems is essential for their attainment of practical maturity as well as for their future transfer and expansion. Thus, the relationship between DOR and PU is according to the following hypothesis:

H5. Demonstrability of results (DOR) positively influences perceived usefulness (PU).

Self-efficacy of Robots (SERs): This is the capacity of a system in terms of managing its own capabilities [35]. This component facilitates the delivery of appropriate and useful answers, measures the closeness of the answer to the required accuracy, and provides the user with the best answer [24]. The hypothesis is as follows:

H6. Self-efficacy of Robots (SERs) positively influences perceived ease of use (PEOU).

Anxiety towards Robots (ATR): The escalation in anxiety and natural resistance with regards to Chatbot use are to be expected with the engagement of any new system [35]. This component focuses on lowering the level of resistance to acceptance stemming from anxiety to reduce the human presence required for the automation and digital transformation processes [2]. Thus, the relationship between ATR and PEOU is according to the following hypothesis:

H7. Anxiety towards robots (ATR) positively influences perceived ease of use (PEOU).

Robot's Playful Behaviours (RPB): The pleasure derived from interacting with a Chatbot is the intrinsic motivation associated with the use of any new system [35]. During the engagement of electronic systems, the level of acceptance increases in tandem with the level of delight attained [6]. The hypothesis is as follows:

H8. Robot's playful behaviours (RPB) positively influences perceived ease of use (PEOU).

Perceived Enjoyment (PE): This is the degree of enjoyment associated to the use of a specific system subsequent to gaining sufficient experience regarding its usage [36]. Sanny and others. concurs by stating that the PE component focuses on the enjoyment associated to the use of the Chatbot system stemming from the attainment of sufficient experience and knowledge regarding its usage [21]. The repeated use of Chatbots will increase the enjoyment required to develop a good relationship between human and machine while promoting the usage sustainability of these machines [19]. Thus, the relationship between PE and PEOU is according to the following hypothesis:

H9. Perceived enjoyment (PE) positively influences perceived ease of use (PEOU).

Objective usability (OU): The OU focuses on the PEOU following the attainment of sufficient experience by an individual regarding the use of a new system [36]. This component emphasises on the importance of PEOU by providing an adequate and useful Chatbot usage experience [39]. The use of the OU component within the TAM3 framework will facilitate an increase in the level of use and, consequently, promote the acceptance and expansion of Chatbot systems [26]. Thus the relationship between OU and PEOU is according to the following hypothesis:

H10. Objective usability (OU) positively influences perceived ease of use (PEOU).

Perceived Usefulness (PU): The PU component determines the value gained by users of a specific technology. It is defined as the degree to which an individual is convinced that the use of particular system will enhance its functionality [40]. The five independent components associated with PU are known as SN scales. These are the standards which focus on the tangible aspects and are measured according to user’s degree of acceptance [27]. Thus, the relationship between PU and ITU is according to the following hypothesis:

H11. Perceived usefulness (PU) positively influences intentions to use a technology (ITU).

Perceived Ease of Use (PEOU): This is the degree of effort expended during the use of a particular technology or the extent to which the user craves for effort-free technology during the use of a particular system [41]. The five independent components associated to the PEOU component, which focuses on the psychological aspects of the user. Thus, the relationship between PEOU and ITU is according to the following hypothesis:

H12. Perceived ease of use (PEOU) positively influences intentions to use a technology (ITU).

Intentions to Use a Technology (ITU): The acceptance of a technology and intentions to use it in the future are determined by the behaviour of the user [35].

4. Methodology

In this study, involving the employees of KAU, the quantitative approach is used to identify the factors which can facilitate the acceptance and usage of Chatbots. The KAU is considered among the leading educational establishments in terms of the application of distance learning for university programmes. Several privacy and sustainability criteria were established to assess the customer acceptance value and, subsequently, transform this value into a product, which can be applied and measured by the target audience.

The date collection is conducted through e-mail and WhatsApp messages were employed for the accumulation of data. E-mail invitations were sent to all employees of the university through the university's e-mail system. The conventional snowball sample technique was used for the collection of data through questionnaires from groups involved in the automation and digital transformation process.

The Likert scale was applied for the 44 items in the questionnaire. The scale consists of five levels ranging from 5 denoting 'strongly agree' to 1 denoting 'strongly disagree'. The data is accumulated through a self-managed electronic approach accessible through Google services. The data gathering process was completed within a period of nine months.

Table 1: Frequency of Responses of the Examined Means, SDs, Skewness, and Kurtosis

Group of Factor Code	Mean	SD	Skew	Kurtosis	Cronbach's alpha	CR	AVE	Rotated Factor Loadings
SN	**3.9124**	**0.7980**	**0.0723**	**1.288**	**0.8053**	**0.6320**	**0.8591**	**0.8822**
IMG	**3.908**	**0.7832**	**0.7324**	**0.6557**	**0.8445**	**0.6548**	**0.9008**	**0.7766**
REL	**3.7106**	**0.7618**	**0.5791**	**-0.9177**	**0.7672**	**0.6748**	**0.8184**	**0.7766**
Out	**3.465**	**0.7484**	**0.2915**	**0.4514**	**0.8106**	**0.6859**	**0.8647**	**0.7787**
RD	**3.4782**	**0.9756**	**-0.2389**	**0.8373**	**0.8081**	**0.6838**	**0.8621**	**0.7744**
RSE	**4.0322**	**0.7003**	**-0.0187**	**0.6802**	**0.8404**	**0.6848**	**0.8965**	**0.7766**
RANX	**3.6067**	**0.8343**	**0.0601**	**-0.6807**	**0.8733**	**0.6871**	**0.9316**	**0.7851**
RPLAY	**3.6097**	**0.9834**	**0.4814**	**0.9526**	**0.8449**	**0.6873**	**0.9013**	**0.7595**
ENJ	**3.1075**	**0.9262**	**0.4446**	**1.2521**	**0.7826**	**0.6934**	**0.8348**	**0.8096**
OU	**4.0001**	**0.7406**	**0.3428**	**1.0141**	**0.8009**	**0.6646**	**0.8543**	**0.6816**
PU	**3.7523**	**0.7737**	**-0.5565**	**0.5256**	**0.8232**	**0.7299**	**0.8781**	**0.7712**
PEOU	**3.9358**	**0.7551**	**0.6823**	**0.8457**	**0.8603**	**0.6784**	**0.9177**	**0.7947**
ATU	**3.8441**	**0.7644**	**0.5694**	**0.8857**	**0.8418**	**0.6852**	**0.8981**	**0.7851**

The Sample size of this study is depended on the number of staff and student that is taken from the General Authority of Statistics of the KSA. It is approximately 120,000 [42]. The participants in this survey are required to be employees or students of KAU for a period not less than three years, with a minimum of six months' experience in the use of Chatbot services. The Raosoft equation was used to calculate the sample size with a margin of error of 6.0% and a confidence level of 90%. The appropriate sample size was calculated as not less than 188 participants [43]. The total sample for this survey was recorded as 196 responses, with 54%

deriving from male participants and the remainder from female participants. Table 2 displays Cronbach's alpha values for the theoretical framework of this study, which ranges between 0.601 to 0.880, indicating high internal consistency and reliability of the data extracted from the questionnaire.

5. Data Analysis and Descriptions

The demographic questions were classified into four main groups. The first group focused on the basic characteristics of the participants and includes four questions referring to gender, age, current occupation, and educational level. The second group focused on the background of technical support services users at the university and the extent to which they benefited from their use of Chatbot services. The third group focused on the practical experiences of the participants, with an emphasis on their level of knowledge in terms of the blackboard educational process management systems at the university, the methods of Internet connection, and the purpose of this Internet connection. And the fourth group focused on the devices most frequently used to cope with the educational process as well as the various technical support methods made available through the technical services at KAU.

The standard deviation (SD) in this study, the SD did not exceed 0.9834 [44]. It is essential that the skewness and kurtosis measures of the normal distribution are in an acceptable area for measurement and that their value is between 0 and +1.50 [45]. In this study, the skewness and kurtosis were -0.9177 to 1.2880, respectively, which were within the acceptable region for analysis (Table 1).

Table 2: Total Variance Explained

Component	Initial Eigenvalues			Extracted Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	15.215	40.874	35.125	15.215	40.874	35.125
2	3.568	9.91	50.784	3.568	9.91	50.784
3	2.965	7.145	57.929	2.965	7.145	57.929
4	1.632	3.512	61.441	1.632	3.512	61.441
5	1.443	3.015	64.456	1.443	3.015	64.456
6	1.332	3.007	67.463	1.332	3.007	67.463
7	1.276	2.932	70.395	1.276	2.932	70.395
8	1.119	2.536	72.931	1.119	2.536	72.931
9	1.003	2.21	75.141	1.003	2.21	75.141
10	0.812	1.901	77.042	0.812	1.901	77.042
11	0.732	1.532	78.574	0.732	1.532	78.574
12	0.613	1.213	79.787	0.613	1.213	79.787
13	**0.632**	**1.109**	**80.896**	**0.632**	**1.109**	**80.896**
14	0.352	1.007	81.903			
Note: Extraction method – PCA – Eight components extracted						

Indicators of the CFA Test	
Test	Actual Result
X^2	6321.82
Df	245
X^2/df	12.03
GFI	0.954
TLI	0.963
NFI	0.921
CFI	0.974
IFI	0.912
AGFI	0.852
RMR	0.023
RMSEA	0.041

Exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) facilitate the analysis of each component in the framework to determine the strength of the groups and the relationship of their elements to each other as well as the strength of each item and their association with the components [45]. The implementation of the EFA testing procedures requires the execution of several comprehensive tests to verify the basic constructs in the theoretical framework. Namely, these tests are the the Kaiser-Meyer-Olkin (KMO) test, Bartlett's B test, and the eigenvalue. Previous investigations in this area indicate that the KMO for social studies must exceed 68.13% for the test sample. In this study, the KMO of the test sample was 80.896 (Figure 2). Additionally, the Bartlett's B test was 0.001, which is a significantly fitting value for testing the components in the framework. The CFA tests consider the links of relationships and structures to attain the general framework of SEM. In comparison to the EFA tests, the CFA tests deliver a more accurate interpretation of the framework [45]. The CFA and SEM results are presented in Table 3. Two additional tests were conducted to verify the results of the EFA: the composite reliability (CR) test and the average variance extracted (AVE) test. The CR test focuses on the composite reliability scale of two or more similar items in SEM and the extent of the relationship of the components in the model to each other [40]. The AVE is the amount of variance captured by a structure in relation to other framework entities [45]. As displayed in Table 1, the accepted value for measurement in CR is

0.6 while the accepted value for AVE is above 0.5 [45]. These results are deemed favourable as the structures and the relationship between them are highly correlated.

Among the methods for determining the suitability of the proposed framework is to measure the relationship between the components, which entails the testing of the hypotheses [45]. The hypotheses are assessed by way of three tests: t-value, p-value, and standardised regression coefficient. In this study, these three tests were conducted for each hypothesis to measure the strength of the relationship between the entities based on the previously proposed hypotheses. The values of the hypotheses, from H1 to H13, were recorded as between 0.9014 and 0.3926 and they were statistically significant at a level of 0.001. The t- ranged between 11.7526 to 6.5792. As seen in Table 3, all the results indicate that the tested hypotheses exceed the acceptance criteria set for this study, thus, meeting the main requirement for SEM. And therefore, the findings derived through our investigation reveal that the relationship between the components in the proposed framework meets the required degree of acceptance, indicating that in the context of the educational domain, the proposed framework is both appropriate and applicable. This framework can also be applied for increasing the level of acceptance and customer satisfaction in various other domains [49-53].

Table 3: Correlation Matrix and Discriminant Validity of the Measurement Model + Path Coefficients, t-values and p-values

R of Path	SN	IMG	REL	Out	RD	RSE	RANX	RPLAY	ENJ	OU	PU	PEOU	ATU	No. Hy.	Est.	t-value (R2)	Path	p-v.
SN	**0.813**													H1	0.7883	9.3035	SN → PU	***
IMG	.632**	**0.898**												H2	0.8406	6.5792	IMG → PU	***
REL	.294*	.589**	**0.883**											H3	0.7947	8.1856	REL → PU	***
Out	.323**	.692**	.607**	**0.838**										H4	0.687	10.688	Out → PU	***
RD	.195**	.705*	.579**	.632**	**0.772**									H5	0.7435	9.1691	RD → PU	***
RSE	.149*	.762**	.687**	.294*	.595*	**0.834**								H6	0.9014	10.3659	RSE → PEOU	***
RANX	.137*	.675**	.665**	.323*	.212*	.665**	**0.892**							H7	0.3926	7.7995	RANX → PEOU	***
RPLAY	.324**	.636*	.599**	.195*	.215*	.487**	.686**	**0.809**						H8	0.7446	11.0134	RPLAY → PEOU	***
ENJ	.568**	.523*	.218*	.349**	.421**	.565**	.748**	.446**	**0.834**					H9	0.7808	11.7526	ENJ → PEOU	***
OU	.585**	.481**	.381*	.175*	.662**	.578**	.686**	.454**	.728**	**0.853**				H10	0.7865	7.6967	OU → PEOU	***
PU	.446**	.558**	.537**	.324**	.509**	.607**	.558**	.512**	.607**	.575**	**0.821**			H11	0.7256	6.6302	PU → ATU	***
PEOU	.454**	.518**	.547**	.568**	.447**	.618**	.523**	.491**	.582**	.536**	.665**	**0.761**		H12	0.6962	8.3759	PEOU → ATU	***
ATU	.512**	.609**	.618**	.585**	.574**	.538**	.444**	.552**	.758**	.509**	.463**	.547**	**0.878**	H13	0.7947	6.6508	SN → ATU	***

6. Discussion and implications

The findings derived through this study provide useful information on the various components of the TAM3 framework, which correlate with the uses of AI and Chatbots in public educational organizations. Thus, institutions that lack AI resources will face difficulties when it comes to determining the best option for launching projects, managing employee issues, and performing administrative duties quickly and effectively [32, 46]. The early stage of AI adoption by an institutional organisation involves the formation of a strategy for the acquirement of initial resources. In this study, three out of every seven attempts to complete the conversation between the system and the end user was successful while the satisfaction level was recorded as 70%, which confirms the capacity of AI for facilitating the development of a Chatbot for accessing support from external partners who are equipped with the resources and skills that public organisations require but are in short supply of [47]. Subjective scales may not be equally successful for all forms of cooperation in public educational institutions as the appearance of psychological scales will provide additional value in terms of profit and pleasure. In terms of Chatbot use, the target audience is focused more on personal pleasure and benefits than on its impact on the organisation [37]. Therefore, the involvement of mentally prepared employees in projects is crucial for encouraging the public to continue with their engagement of extended and renewable services [46].

Firstly: For public sector organisations inexperienced in AI techniques, the implementation of AI projects with the assistance of external expertise will facilitate their engagement of AI in their daily operations. The global economic downturn brought about by the Covid-19 pandemic increased the awareness of public organisations regarding the benefits to be gained through digital transformation [47]. Organisations engaging the Chatbot system will be more efficient when it comes to issues such as workflow optimisation and the development of a competitive edge. Efforts to increase the acceptance level of Chatbots are significantly dependent on the feedback from internal customers and the willingness of external customers to support their usage. Agile practices that may aid the maturation of information, analysis, and adoption should be adopted in a manner that focuses on increasing customer satisfaction and their level of acceptance of Chatbot applications. [7].

Secondly: Organisations with average experience in AI techniques need to harness administrative support in order to acquire fundamental resources which are beyond the testing and verification stages. The capacity of internal resources to attain administrative support is based on the importance of the customer to the organisation. Technological advances in public sector organisations typically occur in stages, irrespective of their level of innovations maturity [48]. In the initial stage of these technical advances, innovators lead the way followed by the adopters of entrepreneurial projects; such as AI projects; during which organisations frequently simulate each other in their dealings with the consumer [49]. Thus, the significance of organisational factors in terms of the increase or decrease in maturity level is dependent on the allocation of resources as well the level of cooperation and coordination at the senior management level.

Thirdly: Organisations with extensive experience in digital transformation, automation, and AI should serve as a source of inspiration for organisations lacking expertise in these areas. State-owned companies can play an important role by creating a suitable environment for the development and expansion of AI technologies at all levels. Therefore, it is important to increase education and provide accurately and diverse options that ensure that AI applications safeguard public values; such as transparency, fairness, justice, and accountability [11].

7. Strengths, Limitations and conclusion

Generally, the strength of this study is threefold. Firstly, the utilisation of quantitative studies boosts the knowledge required for increasing the level of acceptance and cognitive maturity of the clients and end beneficiaries of Chatbots. Secondly, the promotion of understanding regarding the importance of acceptance with regards to AI approaches and techniques and the ability to distinguish their different stages facilitates the linking of management and strategic planning aspects with the scientific research of information systems. And thirdly, the identification of the factors that enhance the acceptance level for Chatbots will assist practitioners and developers during their search for the best means to identify the requirements of the target segment for the purpose of increasing the engagement of Chatbot and AI tools in public educational institutions.

There are three main limitations to this study. Firstly, while the participants of the survey are deemed to be on the same level, the reality is that the university community differs in terms of knowledge and skills. As such, it is recommended that future investigations in this area take the educational level, cognitive maturity in technology use, and age of the participants into consideration. These three factors might make a difference in the results derived from investigations to determine the level of acceptance regarding the use of modern technologies in educational institutions [50]. Secondly, the investigations conducted during the course of this study did not include an accurate assessment of the functional requirements of Chatbot users. In view of this discrepancy, impending studies should cover this aspect of Chatbot acceptance for the benefit of future investors in modern technologies. And thirdly, while this study focuses on the factors influencing the acceptance of Chatbot applications in the public sector, it does not consider the threats which come with the application of AI applications.

Thus, an independent study should be conducted to address the issues of transparency and fairness in relation to the use of AI applications and algorithms.

Although ML is challenging, the obstacles should be overcome with support and by adding a time dimension to observe the different stages of the maturation of Chatbot applications in AI. Public sector institutions, whether educational or otherwise, ought to consider the large-scale utilisation of AI technologies, which can successfully overcome longstanding problems previously considered unsolvable.

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