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Understanding and Forecasting Chatbot Adoption: An SEM-ANN Methodology

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Abstract

This study introduces an innovative and integrated research model, synthesizing components from the established Technology Acceptance Model (TAM) with key elements like content richness and personal innovativeness, essential for Chatbot effectiveness. TAM serves as a foundation to identify factors influencing Chatbot adoption. A notable aspect of this research is its focus on Chatbot utiliza-tion for educational purposes, primarily aimed at augmenting the efficacy of inter-action between teachers and students. Our model highlights the direct correlation between TAM's perceived usefulness and perceived ease of use, and user satis-faction. Additionally, flow theory is integrated as an external factor, examining user involvement and control over Chatbot use. Data for this study was gathered from 824 education professionals, including teachers, administrators, and stu-dents. A novel hybrid analysis approach combining Structural Equation Model-ing (SEM) and an Artificial Neural Network (ANN) based on deep learning was employed. The study also utilized Importance-Performance Map Analysis (IPMA) to evaluate the significance and effectiveness of each factor. The findings from ANN and IPMA analyses pinpoint user satisfaction as the key determinant of Chatbot adoption intention. Structural equation modeling of the data reveals significant impacts of perceived usefulness and ease of use on the intention to use Chatbot. Furthermore, user satisfaction and flow experience emerge as pivotal in enhancing Chatbot adoption intention. Theoretically, our model offers compre-hensive insights into factors affecting Chatbot usage intention, particularly con-sidering internet service factors at the individual level. Practically, these results can guide decision-makers and practitioners in higher education to prioritize spe-cific factors and shape their strategies accordingly. Methodologically, this re-search demonstrates the deep ANN architecture's efficacy in elucidating complex, non-linear relationships within the theoretical model. The overarching conclusion indicates a high demand for Chatbots in education, serving as a prevalent com-munication medium between teachers and students, and significantly facilitating information exchange.

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1. Introduction

The integration of artificial intelligence in various domains has been a subject of intense research over the past few years, with Chatbots emerging as a significant area of focus, particularly in the educational sector. The Technology Acceptance Model (TAM) has been widely adopted to understand the factors influencing the acceptance and usage of technological innovations, including Chatbots (Davis, 1989). This model primarily hinges on two critical factors: perceived usefulness and perceived ease of use, which have been consistently validated across diverse technological contexts (Venkatesh et al., 2000).

In the realm of education, Chatbots represent a paradigm shift, offering novel ways to facilitate and enhance the interaction between teachers and students. Despite the growing interest and apparent potential of Chatbots in educational settings, there remains a paucity of comprehensive research that integrates TAM with other determinants like content richness, personal innovativeness, and flow theory – a concept focusing on the degree of user immersion and control (Csikszentmihalyi & Csikzentmihaly, 1990). These additional factors are pivotal in assessing the effectiveness of Chatbots in an educational context.

While existing literature provides insights into the general acceptance of technology in education, there is a noticeable gap in studies that specifically explore the amalgamation of TAM with other relevant factors in the context of Chatbot adoption in education. Furthermore, the interaction between user satisfaction, a critical outcome of technology acceptance, and these factors has not been adequately addressed. This study aims to bridge this gap by proposing an integrated model that combines TAM with content richness, personal innovativeness, and flow theory to comprehensively understand the determinants affecting the adoption of Chatbots in educational settings (Yas et al., 2022). Additionally, the study seeks to elucidate the relationship between these determinants and user satisfaction. The paper contributes to the existing body of knowledge by providing a holistic view of the factors influencing Chatbot adoption in education. Methodologically, it employs an innovative hybrid approach using Structural Equation Modeling (SEM) and an Artificial Neural Network (ANN) based on deep learning, showcasing the capability of these methods in uncovering complex interrelationships among variables. The findings are anticipated to offer practical insights for educators and policymakers in higher education, assisting them in making informed decisions about the integration of Chatbots and other AI technologies in teaching and learning processes (Aburayya et al., 2023; S. Salloum et al., 2023; Shwedeh, Aburayya, et al., 2022).

2. The Theoretical Framework

2.1 Users' Satisfaction

Satisfaction typically denotes an emotional state where an individual's feelings align with their anticipations based on previous experiences. This state is intimately linked with the overall positive or negative impressions that technology elicits upon its usage. In essence, when individuals perceive technology as beneficial, efficient, and user-friendly, it triggers both their internal and external motivational factors (Khudhair, H. Y et al., 2019). Consequently, their confidence in their abilities and willingness to innovate surpass their initial expectations. Satisfaction is realized when these expectations are met (Bhatt et al., 2020; Oliver, 1981; Venkatesh & Davis, 2000). On the other hand, user satisfaction plays a pivotal role in the adoption of products or services. The degree of user contentment directly correlates with the level of satisfaction attained. Researchers have identified a strong connection between the ongoing willingness to use technology and the level of satisfaction, which significantly influences the long-term use of technological solutions (Ambalov, 2018; Bhattacherjee, 2001; Nascimento et al., 2018). Based on these insights, the following hypothesis is proposed:

H1: The level of user satisfaction (UST) has a positive impact on the adoption of Chatbots in educational contexts.

2.2 The Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM) has been extensively utilized in various studies to assess technology adoption, acceptance, and usage intentions across diverse sectors (Al-Maroof R.A., Arpaci I., Al-Emran M., Salloum S.A., 2021; Al-Maroof R.S., 2021). In this particular study, we concentrate on two fundamental aspects of TAM, which are believed to have a direct influence on the adoption of Chatbot as wearable technology (El Nokiti et al., 2022; Shwedeh et al., 2021; Shwedeh, Hami, et al., 2022). The first aspect, perceived usefulness, refers to the user's belief in the extent to which the technology will be beneficial. The second aspect evaluates the degree to which technology is perceived as effortless from the user's point of view (Davis, 1989; Davis et al., 1989). Based on these premises, we propose the following hypotheses:H2: The perceived usefulness (PU) has a positive impact on the adoption of Chatbots in educational contexts.

H3: The perceived ease of use (PEU) has a positive impact on the adoption of Chatbots in educational contexts.

2.3 Flow Theory

Originally, the concept of flow is characterized by feelings of control, deep involvement, and enjoyment. Users are more inclined to consistently engage with technology when it offers complete enjoyment and satisfaction. This engagement activates their thoughts, attention, and behaviors, leading to positive emotional responses that enhance the flow experience in technology usage (Csikszentmihalyi, 1988; Fredrickson et al., 2003; Hung et al., 2012). As users immerse themselves in this flow state, they often lose track of time and are driven by intrinsic motivation. This phenomenon results in an online flow state, described as a continuous and interactive experience marked by pleasure, immersion, and engagement (Hoffman & Novak, 1996, 2009). Recently, the flow experience has become a significant factor in the adoption of IT systems, including e-learning, internet, and entertainment activities (Ravikumar et al., 2022; Salameh et al., 2022; Shwedeh, Adelaja, et al., 2023). It is often characterized by a seamless integration into the technology experience, transcending self-awareness (Ang et al., 2007). Consequently, flow theory has emerged as a valuable predictor of technology adoption. Based on this understanding, the following hypothesis is proposed:

H4: Flow experience (FLE) has a positive impact on the adoption of Chatbots in educational contexts.

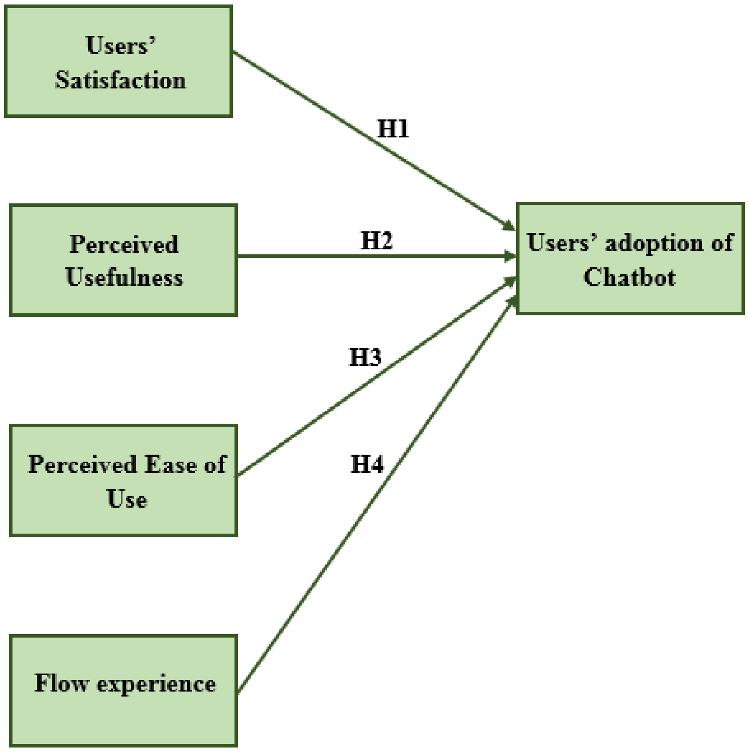

Fig 1. Research model.

3. Research Methodology

3.1 Data collection

An online survey was conducted with students from various educational institutions across the United Arab Emirates (UAE). This data collection effort began on March 10, 2023, and concluded on May 15, 2023. The research team distributed 900 surveys randomly, achieving an impressive 91.5% response rate, highlighting the strong engagement of the participants in this study. Of the responses received, 824 were complete and usable, while 76 were discarded due to incompleteness. The number of valid responses, 824, is within the recommended sample size of 285 for a population of 1100, as suggested by (Krejcie & Morgan, 1970). This sample size, smaller than the baseline recommendation, was deemed sufficient for conducting a structural equation modeling analysis (Chuan & Penyelidikan, 2006), enhancing the credibility and strength of the study's hypotheses. A notable aspect of this study is its integration of historical developments in artificial intelligence (Abdallah et al., 2022; Dahu et al., 2022; Khadragy et al., 2022a; Ravikumar et al., 2023). The research utilized Structural Equation Modeling (SEM) through the advanced Smart-PLS Version 3.2.7 platform, allowing for a detailed assessment of the measurement model (Yas et al., 2023). The Final Path Model was carefully developed to address complex variables and interactions. Further, this study planned to implement the PLS-SEM & ANN algorithm for validating the proposed theoretical model. The use of PLS-SEM was chosen for its ability to simultaneously analyze both the measurement and structural models, leading to more accurate outcomes (Alshurideh et al., 2020; Barclay et al., 1995). Additionally, the study employed a deep ANN algorithm via SPSS to predict the dependent variables in the conceptual framework. This dual-analytical method offers a unique contribution to information systems (IS) literature, especially as one of the few instances where a deep ANN algorithm is applied to predict technology usage in a medical setting.

3.2 Demographic information

Figure 2 presents a detailed breakdown of the participant demographics and individual characteristics. The composition of the survey respondents was nearly gender-balanced, with 61% female and 39% male participants. In terms of age distribution, a majority (76%) were in the 18 to 29 age bracket, with the rest being 29 years old or older. Examining their educational qualifications, the data shows that 5% held a diploma, 4% an advanced diploma, a significant 72% had an undergraduate degree, 16% had completed postgraduate studies, and 3% had attained a doctoral degree. The researchers employed a "purposive sampling method", as recommended by (S. A. Salloum & Shaalan, 2018), particularly when participants expressed a willingness to engage in the study. This approach allowed for a varied sample, incorporating individuals from different academic backgrounds and spanning a broad age range, thereby enriching the study with diverse educational perspectives. To analyze this demographic data thoroughly, the research team used IBM SPSS Statistics version 23, ensuring a comprehensive and detailed evaluation of the participant profiles.

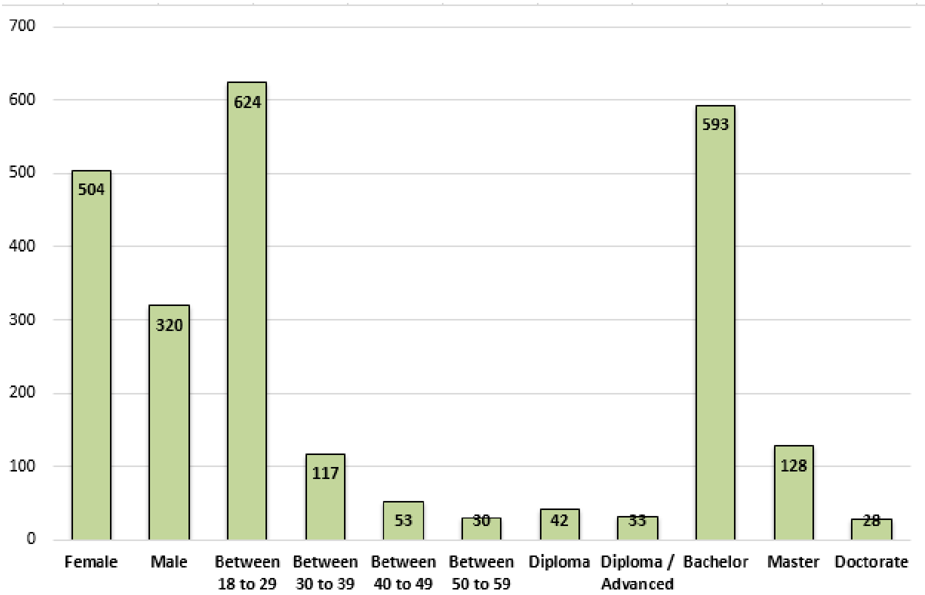

Fig 2. Demographic information of the participants (n=824).

3.3 Study Instrument

In this study, a survey instrument was designed and implemented to validate the hypotheses. This survey comprised 13 items, specifically aimed at evaluating the five constructs outlined in the questionnaire. To enhance the research's relevance and validity, questions from previous studies were carefully reviewed and restructured before being incorporated into the survey. The origins of the constructs utilized are detailed in Table 1.

Table 1. Assessment Indicators.

Constructs	Items	Instrument	Sources
Users' adoption of Chatbot	ADP1	It is advisable to utilize Chatbots in educational settings.	(Davis et al., 1989; Rai & Selnes, 2019; Venkatesh et al., 2003)
	ADP2	Employing Chatbots in interactions with my students and colleagues enhances my professional development.	
Perceived Ease of Use	PEU1	I believe that Chatbot offers user-friendly interaction for both	(Huang et al., 2012; Larsen et

		teachers and students.	al., 2009)
	PEU2	I believe that due to its ease of use, Chatbot has the potential to supplant other technologies.	
	PEU3	I perceive Chatbot as a complex tool that requires significant cognitive effort to use.	
Perceived Usefulness	PU1	I believe that using Chatbot aids in enhancing my technical skills.	(Huang et al., 2012; Larsen et al., 2009)
	PU2	I believe that Chatbot enhances my motivation to acquire new information consistently.	
	PU3	I consider Chatbot to be a valuable source of educational information for both teachers and students.	
User satisfaction	UST1	Overall, my experience with Chatbot, whether as a teacher or a student, has been fulfilling.	(Oliver, 1981)
	UST2	Generally speaking, my experience with Chatbot has been promising and met all my requirements satisfactorily.	
	UST3	Overall, my experience with Chatbot has been less than satisfactory.	
Flow Experience	FLE1	I find myself fully immersed each time I use the Chatbot device.	(Bilgihan et al., 2014; Csikszentmihalyi, 1988; M.-C. Lee & Tsai, 2010)
	FLE2	Whenever I use Chatbot, my attention is solely focused on it.	

4. Findings and Discussion

4.1 Data Analysis

This study diverges from previous empirical research that predominantly relied on single-stage SEM analysis. Instead, it adopts a two-phase hybrid SEM-ANN methodology grounded in deep learning for verifying the hypothesized interconnections within the research model. The first phase involves applying the partial least squares-structural equation modeling (PLS-SEM) using SmartPLS (Ringle et al., 2015). The rationale for choosing PLS-SEM is its suitability for exploratory models, especially in the context of limited preceding literature. This approach aligns with established guidelines for PLS-SEM in information systems research (Al-Emran et al., 2018) and adheres to the recommended two-step process of evaluating both the measurement and structural models, as outlined in previous studies (Simpson, 1990). Additionally, this research incorporates importance performance map analysis (IPMA) within PLS-SEM to assess the significance and effectiveness of each construct. The second phase features the deployment of Artificial Neural Networks (ANN) to supplement and validate the PLS-SEM findings, focusing on the impact of independent variables on the dependent variable(Alkashami et al., 2023; Shwedeh, 2024; Shwedeh et al., 2020). The ANN is ideal for complex, non-linear relationships between inputs and outputs. It encompasses three key elements: network architecture, learning rule, and transfer function (S. A. Salloum et al., 2021; Simpson, 1990) further branching into specific types like radian basis, feed-forward multilayer perceptron (MLP) network, and recurrent network (S. A. Salloum et al., 2017; Sim et al., 2014). This study specifically utilizes the MLP neural network, which is noted for its layered structure, including input and output layers interconnected through hidden nodes. These layers process data through neurons (independent variables) and synaptic weights, with the outputs determined by an activation function, commonly the sigmoidal function (Asadi et al., 2019; Sharma & Sharma, 2019). Thus, the MLP neural network is employed here for training and testing the proposed research model.

4.1.1 Convergent validity

The evaluation of the Measurement Model (Hair et al., 2017) was rigorously conducted, focusing on establishing construct validity, which includes assessments of both discriminant and convergent validity, as well as construct reliability. This latter aspect was measured using indicators like Cronbach's alpha (CA) and composite reliability (CR). A review of Table 2 shows Cronbach's alpha values ranging from 0.740 to 0.898, slightly under the widely accepted threshold of 0.7 (Akour et al., 2022; Nunnally & Bernstein, 1994). However, in contrast, the composite reliability scores, as depicted in Table 2, vary from 0.797 to 0.842, comfortably surpassing the established benchmark [51]. In assessing convergent validity, it is crucial to examine metrics such as average variance extracted (AVE) and factor loadings (Ahmad et al., 2021; Hair et al., 2017). Table 2 indicates that all factor loadings exceed the 0.7 threshold. Furthermore, the AVE values, as shown in Table 2, are well above the minimum requirement of 0.5, ranging from 0.534 to 0.701. Based on these findings, it can be confidently stated that the study has achieved a satisfactory level of convergent validity (Khadragy et al., 2022b; Shwedeh, Malaka, et al., 2023).

4.1.2 Discriminant validity

This research meticulously evaluated discriminant validity by employing the Heterotrait-Monotrait ratio (HTMT) and the Fornell-Larker criterion (Hair et al., 2017). According to the data presented in Table 3, the Fornell-Larker criterion was effectively applied, demonstrating that the square root of each Average Variance Extracted (AVE) has a stronger association with its respective construct than with others (Fornell & Larcker, 1981). Furthermore, as depicted in Table 4, the HTMT ratio results show that all construct values are below the threshold of '0.85' (Henseler et al., 2015). This indicates that the HTMT ratio meets the established standards, thereby reinforcing the discriminant validity of the study (Khudhair, H. Y., Mardani, A., Albayati, Y., Lootah, S. E., & Streimikiene, D., 2020). The findings affirm that the Measurement Model faces no significant challenges in terms of validity and reliability. This clean bill of health for the Measurement Model implies that the data is well-prepared for the next phase of analysis involving the structural model. The thoroughness in validating the Measurement Model's reliability and validity underscores the robustness of the research methodology. Such diligence in validation enhances confidence in the data used for the structural model analysis and, by extension, bolsters the credibility and accuracy of the study's overall findings.

Table 2. Convergent validity results.

Constructs	Items	Factor Loading	Cronbach's Alpha	CR	AVE
Users' adoption of Chatbot	ADP1	0.834	0.824	0.842	0.559
	ADP2	0.865			

Users' Satisfaction	UST1	0.863	0.893	0.797	0.534
	UST2	0.824			
	UST3	0.829			
Flow experience	FLE1	0.853	0.740	0.810	0.662
	FLE1	0.882			
Perceived ease of use	PEU1	0.860	0.898	0.825	0.699
	PEU2	0.822			
	PEU3	0.808			
Perceived usefulness	PU1	0.803	0.811	0.819	0.701
	PU2	0.805			
	PU3	0.866			

Table 3. Fornell-Larcker Scale.

	ADP	UST	FLE	PEU	PU
ADP	0.850				
UST	0.513	0.801			
FLE	0.374	0.663	0.794		
PEU	0.423	0.642	0.694	0.893	
PU	0.487	0.669	0.553	0.593	0.825

Table 4. Heterotrait-Monotrait Ratio (HTMT).

	ADP	UST	FLE	PEU	PU
ADP					
UST	0.593				
FLE	0.561	0.542			
PEU	0.388	0.469	0.596		
PU	0.540	0.622	0.648	0.540	

4.2 Hypotheses testing using SEM

Following the analysis of the measurement model, attention shifts to examining the structural model. This step includes assessing the coefficient of determination (R^2) and scrutinizing path coefficients via a rigorous bootstrapping process, involving 5,000 re-samples. Table 6 presents comprehensive details of the path coefficients, along with their corresponding t-values and p-values for each hypothesis within the path analysis. Remarkably, all hypotheses have garnered support from the research community . A detailed interpretation of the data reveals that hypotheses H1, H2, H3, and H4 are substantiated by empirical evidence, indicating a strong alignment between the theoretical predictions and the observed data. This alignment not only reinforces the validity of the model but also highlights the robustness of the research methodology employed in this study.

The evaluation of the structural model primarily involves assessing the coefficient of determination (R^2 value) (Hair Jr et al., 2016). This coefficient is defined as the squared correlation between the actual and predicted values of a given endogenous construct, primarily used to gauge the model's predictive accuracy (Hair Jr et al., 2016; Senapathi & Srinivasan, 2014). It reflects the combined impact of exogenous latent variables on an endogenous latent variable. The coefficient, being the squared correlation between the actual and predicted values, further implies the extent of variance in the endogenous constructs. A high value is indicated by a coefficient exceeding 0.67, while values ranging from 0.33 to 0.67 are deemed moderate, and those between 0.19 to 0.33 are considered weak. Any value below 0.19 is regarded as unacceptable, as per (Chin, 1998). As evidenced in Table 5 and Figure 3, the model exhibited moderate predictive strength, accounting for approximately 56.7% of the variance in perceived usefulness and the adoption of Chatbot. The influences of Users' Satisfaction (UST), Perceived Usefulness (PU), Perceived Ease of Use (PEU), and Flow Experience (FLE) on Users' adoption of Chatbot (ADP) were significant, with respective beta values of 0.586 ($P<0.001$), 5.716 ($P<0.05$), 0.509 ($P<0.001$), and 0.762 ($P<0.001$). The results of the hypothesis testing are summarized in Table 6.

Table 5. R^2 of the endogenous latent variables.

Construct	R^2	Results
ADP	0.567	Moderate

Table 6. Hypotheses-testing of the research model (significant at p** < = 0.01, p* < 0.05).

H	Relationship	Path	t-value	p-value	Direction	Decision
H1	UST -> ADP	0.586	14.851	0.000	Positive	Supported**
H2	PU -> ADP	0.257	5.716	0.004	Positive	Supported*
H3	PEU -> ADP	0.509	16.036	0.000	Positive	Supported**
H4	FLE -> ADP	0.762	13.821	0.001	Positive	Supported**

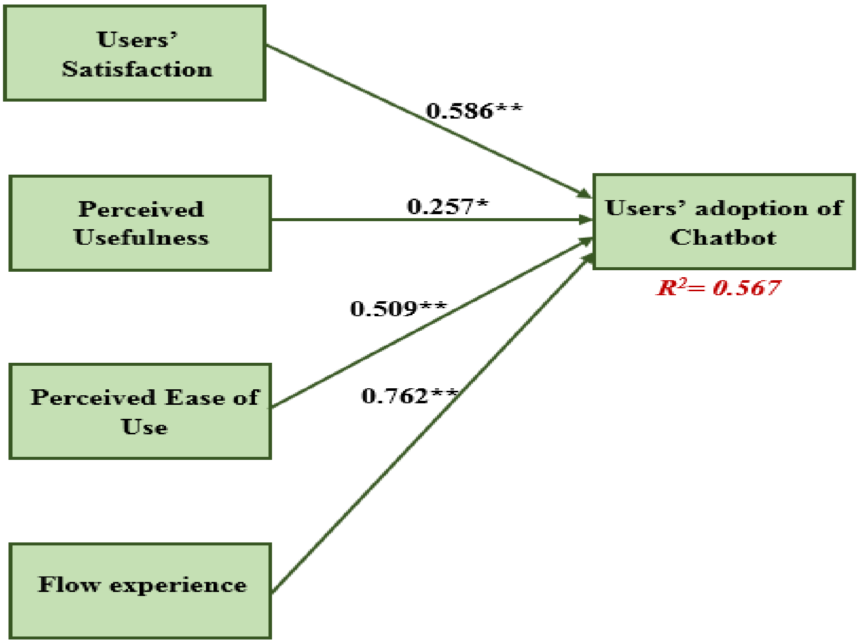

Fig 3. Model's path coefficient (noteworthy at p** ≤ 0.01, p* < 0.05).

4.3 Hypotheses testing using ANN

The study utilizes SPSS to conduct Artificial Neural Network (ANN) analysis, focusing exclusively on the significant predictors identified through Partial Least Squares Structural Equation Modeling (PLS-SEM). This involves considering factors like UST, FLE, PEU, and PU. The ANN model, as illustrated in Figure 4, includes one output neuron (representing Users' adoption of Chatbot) and multiple input neurons (such as UST, FLE, PEU, and PU). A two-layer deep ANN structure was used to enhance deep learning for each output neuron node (V.-H. Lee et al., 2020). The sigmoid function is the chosen activation function for both the hidden and output neurons in this research. Additionally, the values for input and output neurons are normalized within the range of [0, 1] to improve the performance of the proposed model (Liébana-Cabanillas et al., 2018). To prevent overfitting in the ANN models, a tenfold cross-validation technique with a 70:30 split for training and testing data was implemented (Sharma & Sharma, 2019). The model's accuracy is evaluated using the root mean square error (RMSE), with the ANN model showing RMSE values of 0.1276 and 0.1395 for training and testing data, respectively. Given the small differences in RMSE values and the standard deviations for both datasets (0.0048 and 0.0096), the model demonstrates high accuracy in applying ANN.

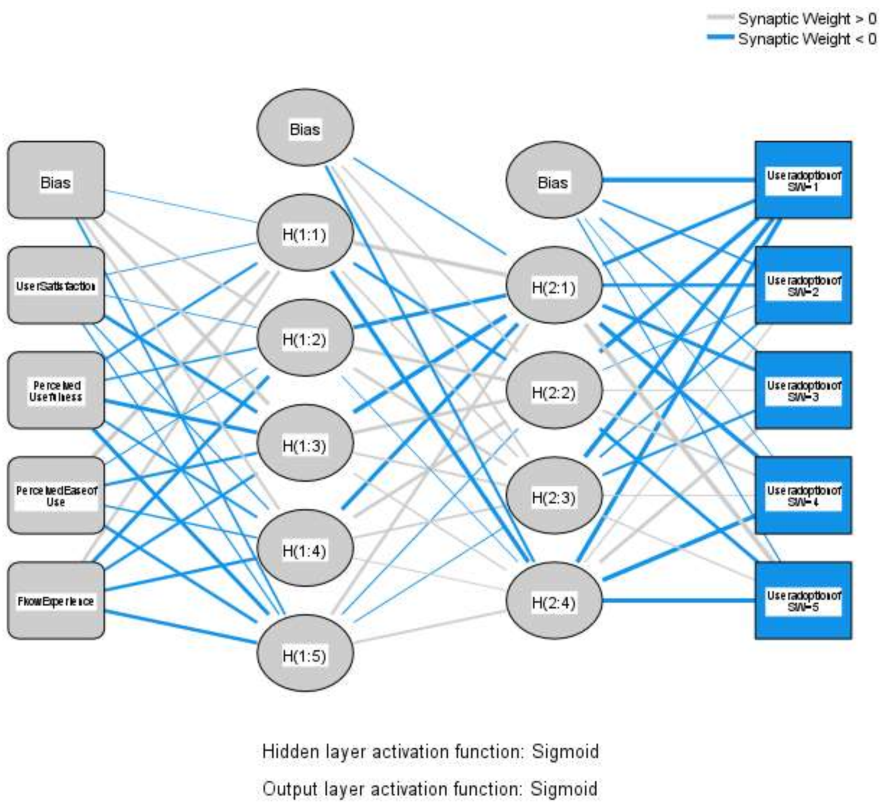

Fig 4. ANN model.

4.4 Sensitivity Analysis

To determine the relative importance of each predictor in the ANN model, the study calculates the normalized importance by comparing the mean value of each predictor with the highest mean value, expressed as a percentage. This is detailed in Table 7, which presents both the mean and normalized importance for all predictors used in ANN modeling. The sensitivity analysis results, as shown in Table 10, highlight that PEU is the most significant predictor for the Adoption of Chatbot Watch, followed in importance by PU, UST and FLE. To further verify and confirm the accuracy and effectiveness of the ANN application, the study recommends assessing the goodness of fit, analogous to the R^2 value in PLS-SEM analysis. The findings demonstrate that the ANN analysis's predictive capability (with an R^2 value of 89.3%) significantly surpasses that of the PLS-SEM (which has an R^2 of 56.7%). This suggests that the ANN method more effectively explains the endogenous constructs than the PLS-SEM approach. Additionally, the difference in variances could be attributed to the advanced ability of the deep learning ANN method to discern non-linear relationships among the constructs.

Table 7. Independent Variable Importance

	Importance	Normalized Importance
FLE	0.101	39.3%
PEU	0.396	100.0%
PU	0.268	83.6%
UST	0.195	65.8%

4.5 Importance-Performance Map Analysis

In our study, we employed the Importance-Performance Map Analysis (IPMA) as a sophisticated technique within Partial Least Squares Structural Equation Modeling (PLS-SEM), focusing on the adoption of Chatbot as the primary variable. (Ringle & Sarstedt, 2016) have highlighted that IPMA enhances the comprehension of PLS-SEM analysis outcomes. IPMA goes beyond merely evaluating path coefficients (the importance aspect) and incorporates the mean values of latent constructs and their indicators (the performance aspect). IPMA helps identify how influential the precursor factors are in shaping the target factor (Users' adoption of Chatbot), while the performance is gauged by the average values of these latent constructs. Figure 5 depicts the IPMA findings, wherein the importance and performance of seven factors (UST, FLE, PEU, and PU) were assessed. The results indicate that PEU ranks highest in terms of both importance and performance. PU is observed to have the second highest values in these measures. Furthermore, while FLE ranks third in importance, it records the lowest in performance. Conversely, UST has the least impact in terms of importance.

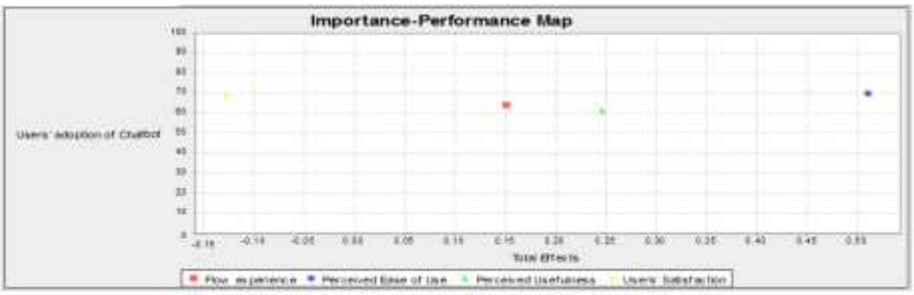

Fig 5. IPMA results

5. Discussion and Conclusion

This research rigorously investigates the impact of Chatbot implementation in healthcare. It utilizes a comprehensive model that merges Technology Acceptance Model (TAM) elements with additional external factors, including elements of flow theory and user satisfaction. The study finds that the TAM factors - perceived ease of use and perceived usefulness - directly and notably influence Chatbot adoption. It posits that technologies perceived as effortless or beneficial are likely to see widespread adoption across various sectors, both academic and non-academic (Alfadda & Mahdi, n.d.; Ozkan-Yildirim & Pancar, 2021). In the educational sector, this aligns with previous studies suggesting that ease of use and usefulness encourage adoption among teachers, administrators, and students (Khudhair, H. Y., & Hamid, A. B. A., 2015).

Flow theory, another external factor in this study, also shows a significant impact on technology adoption. The research indicates that a user's level of engagement can either positively or negatively influence their willingness to adopt technology. In this context, Chatbots have been found to notably increase user engagement, thereby positively affecting adoption. This is supported by other studies (Ma et al., 2021; Wang et al., 2021) that link flow experience to influencing user behavioral intentions.

User satisfaction is also found to be influenced by ease of use and perceived usefulness. Users who find the Chatbot easy to use and beneficial demonstrate greater satisfaction in adopting this technology. This finding echoes other research (Najjar et al., 2021; Saeed Al-Maroof et al., 2020), which asserts that when users perceive high value in technology, their satisfaction levels increase, positively impacting their behavioral intentions. Similarly, technologies regarded as effortless are associated with heightened user satisfaction.

5.1 Practical implication in the educational field

This research offers significant insights for developers of educational Chatbots, guiding them to create Chatbots that effectively meet the specific needs of the educational sector. Our findings suggest that any development in educational Chatbots should align closely with the unique requirements of both students and educators. It is crucial for developers to understand how these Chatbots can fulfill the needs of educators, incorporating features that increase their likelihood to use and rely on this technology.

Developers must also consider the timeliness and functionality of certain features in these Chatbots. The study underscores the importance of delivering accurate information promptly, which could encourage more frequent reliance on Chatbots by educators and students. The effectiveness of users in the educational domain improves when Chatbot features are regularly updated and tailored to their evolving needs. When the functionalities provided by educational Chatbots are well-suited to the needs of the education sector, managers of these technologies can better understand and cater to individual requirements. Adapting Chatbot features to more effectively align with users' needs enhances the compatibility between the Chatbots and their users, ultimately supporting the long-term objective of integrating this technology into the educational framework.

5.2 Theoretical implication in the educational field

From a methodological standpoint, this study distinguishes itself from prior empirical research, which predominantly depended on Structural Equation Modeling (SEM), by adopting a novel hybrid SEM-Artificial Neural Network (ANN) approach utilizing deep learning techniques. This approach is particularly relevant in the context of mobile learning (m-learning). The forecasting accuracy of the ANN model used in this research significantly surpasses that of traditional PLS-SEM methods. This enhanced predictive capability is believed to originate from the deep ANN architecture's proficiency in identifying and processing non-linear relationships between various elements in the theoretical framework.

5.3 Limitations of the Study

In this research on educational Chatbots, certain limitations were encountered which should be addressed in future studies. The research was confined to a specific educational context, which may affect the generalizability of the findings. Expanding future research to include a wider range of educational settings, beyond the scope of this study, would be beneficial. Additionally, due to time and budget constraints, the data was collected solely from one type of educational institution, potentially reflecting a unique educational culture. This specificity means the results may not be fully applicable to other educational environments. Moreover, this study's cross-sectional design and brief data collection period using surveys might not fully capture the evolving impact of educational technologies over time. Future research could benefit from a longitudinal approach and more extended observation periods to gain clearer insights. This study also relied primarily on survey responses from educators and students, suggesting that future studies might employ varied data collection methods, like interviews and observations, for a more comprehensive understanding. This study focused on specific external variables relevant to educational Chatbots. Future research could explore different external variables, adapting to the evolving features and uses of Chatbots in education. While this study integrated the Technology Acceptance Model (TAM) with flow theory, subsequent research might consider other models that address specific social and psychological factors. Additionally, our research was limited to the educational field, but other studies could explore the application of Chatbots in both academic and non-academic settings. Lastly, this study did not emphasize gender differences in Chatbot usage, presenting an opportunity for future research to delve into this aspect and uncover significant gender-related variations in Chatbot adoption and use in education.

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