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Unlocking the Potential of ChatGPT in Medical Education and Practice

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Abstract

Background: ChatGPT is an innovative application of advanced artificial intelligence technology in the field of medical education and practice. This technology leverages the capabilities of large language models, such as OpenAI's GPT-3, to provide users with natural language processing and generation capabilities. In the context of medical education and practice, ChatGPT can be used to enhance learning and decision-making by providing students, healthcare providers, and patients with access to instant, accurate information and guidance. With its ability to understand and respond to complex medical inquiries, ChatGPT has the potential to revolutionize the way medical knowledge is acquired and applied, making medical education and care more efficient and effective. By integrating this technology into medical education and practice, healthcare professionals can stay up-to-date with the latest developments, improve patient outcomes, and drive innovation in the field.

Objective: The objective of this study is to examine the student's views regarding the utilization of ChatGPT for educational purposes in the United Arab Emirates.

Methods: The theoretical framework involves the adoption properties, including the trialability, observability, compatibility, users' satisfaction, personal innovativeness, and Technology Acceptance Model (TAM) constructs. The uniqueness of this paper lies in its theoretical model which connects both individual-based characteristics and technology-based aspects. The originality of the study lies in its theoretical framework which combines both individual-based characteristics and technological features. Furthermore, a unique hybrid analysis method will be applied, combining deep learning-based structural equation modeling (SEM) and artificial neural network (ANN) analysis. Additionally, the study employs the Importance-Performance Map Analysis (IPMA) to assess the impact and performance of the various factors.

Results: The results of the ANN and IPMA analysis indicated that Perceived Usefulness (PU) is a critical predictor of Users' Intention to Use the ChatGPT.

Conclusions: This finding is significant as it helps decision-makers in the educational sector to prioritize their efforts and plans based on the relative significance of each factor. The study also has important methodological implications, demonstrating the potential of deep artificial neural network (ANN) architecture to provide a deeper understanding of the complex relationships among the factors in a theoretical model. Clinical Trial: n/a

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Original Paper

Unlocking the Potential of ChatGPT in Medical Education and Practice

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KEYWORDS

ChatGPT, structural equation modeling (SEM), artificial neural network (ANN), technology acceptance model, trialability, observability, compatibility, users' satisfaction, personal innovativeness.

1. Introduction

The rapid progress in artificial intelligence (AI) has heralded innovative applications in various domains, with medical education and practice being noteworthy beneficiaries. At the forefront of these AI-driven innovations is ChatGPT, a manifestation of the advanced capabilities of large language models, primarily built upon OpenAI's GPT-3 technology [1]. Its prowess in natural language processing and generation equips users—ranging from medical students to seasoned healthcare practitioners—with the ability to access instantaneous, precise information and guidance [2].

In the realm of medical education, the implications of ChatGPT are profound. It not only offers an avenue for enhanced learning but also augments decision-making processes. Given its capacity to decipher and aptly respond to intricate medical queries, ChatGPT is posited to reshape the methodologies by which medical knowledge is disseminated and harnessed. Such integration can catalyze the evolution of medical education and patient care (See Figure 1), optimizing efficiency and fortifying efficacy [3].

Figure 1. ChatGPT's impact on advancing medical education and decision-making

This paper endeavors to shed light on the perceptions of students in the United Arab Emirates concerning the educational incorporation of ChatGPT. At its core, the study hinges on a theoretical framework that intricately weaves adoption properties, including trialability, observability, compatibility, user satisfaction, personal innovativeness, and pivotal constructs of the Technology Acceptance Model (TAM) [4]. A distinguishing feature of this work is its synthesis of individual-centric attributes with technological nuances.

Our research approach is characterized by a novel hybrid analysis methodology, amalgamating the merits of deep learning-infused structural equation modeling (SEM) and the versatility of artificial neural network (ANN) analysis [5]. We further harness the Importance-Performance Map Analysis (IPMA) to discern the influence and performance trajectory of assorted factors [6].

Our preliminary findings, derived from ANN and IPMA analyses, underscore the preeminence of Perceived Usefulness (PU) as a decisive determinant steering Users' Intention to Adopt ChatGPT. This insight holds substantial value for educational strategists, enabling them to align their endeavors in resonance with the relative gravitas of influential factors. Furthermore, our methodological paradigm underscores the untapped potential of deep ANN structures in elucidating the labyrinthine interplay of factors within a theoretical model.

2. Literature Review

Artificial Intelligence (AI) has garnered significant attention in recent years, transforming several domains of human endeavor, including healthcare and education. Particularly in medical education, AI tools have been employed to provide adaptive learning experiences, assist in clinical decision-making, and facilitate patient simulations [7]. Early research in the 1990s and 2000s primarily focused on utilizing AI for diagnostic purposes. For instance, [8] investigation into computer-based diagnostic systems showcased the potential for AI to enhance clinical diagnosis. Concurrently, there was growing interest in integrating such systems into medical curricula to better prepare students for real-world scenarios [9].

Recent advancements have witnessed AI's integration into adaptive learning platforms. These systems, powered by AI algorithms, analyze student interactions and adjust content to suit individual learning preferences [10]. Miedany & Miedany, 2019 [10] discovered that students utilizing AI-driven adaptive learning platforms demonstrated improved knowledge retention and better clinical decision-making skills compared to traditional learning methods. Patient simulation tools, equipped with AI capabilities, have emerged as effective mediums for medical training. Such tools provide students with a quasi-real-world environment, allowing for hands-on experience without risks. Studies by (Bohr & Memarzadeh, 2020 [11] highlighted the effectiveness of AI-powered patient simulators in enhancing diagnostic accuracy and refining clinical skills.

With the emergence of sophisticated language models like GPT-3, there's a surge in the integration of chatbots in medical education. These chatbots can answer queries, simulate patient interactions, and provide instant feedback. A preliminary study by Kapoor et al. (2020) [12] revealed that medical students found chatbots like ChatGPT beneficial, particularly in case-based learning and revision sessions. While AI holds promise, its integration in medical education isn't devoid of challenges. Data privacy, potential biases in algorithms, and over-reliance on AI tools are pressing concerns [13]. Additionally, the ethical implications of AI decisions, especially in patient simulations, need rigorous scrutiny.

While substantial research exists on AI's applications in medical education, there's a noticeable paucity in studies specifically addressing:

- Long-term implications of AI-driven education on clinical practice.
- Comparative efficiency of different AI tools in medical education.
- Integration challenges in varied cultural and educational settings, like the United Arab Emirates.
- The actual impact of chatbots, especially in terms of enhancing student engagement and comprehension.

This literature review emphasizes the evolving role of AI in medical education, underscoring the need for comprehensive, long-term studies assessing AI's impact on medical practice. It's imperative to understand the diverse challenges that educators face while integrating AI tools, especially in culturally distinct regions. The identified research gap also accentuates the need for focused studies on the efficiency and impact of chatbots in medical education. The impending era promises a confluence of AI and medical education, potentially reshaping the teaching methodologies, enriching student experiences, and refining clinical practices. Embracing this synergy and critically examining its repercussions will be pivotal in steering the future of medical education.

3. Conceptual model and hypotheses

3.1 Users’ Satisfaction

These attributes serve as tools to gauge the acceptance of groundbreaking technology. Before their implementation, anticipations about users' perspectives on an innovation's characteristics often shape their inclination towards adopting the technology. The initiation of the adoption process generally suggests that the majority of these anticipatory attributes lean positively. Engaging with the innovative technology can either validate or contradict these positive expectations. Confirmed expectations often lead to the sustained adoption of the technology, while contradictions may halt the adoption process (Parthasarathy & Forlani, 2010; Rogers, 2003). Such validations often enhance satisfaction levels and foster continuity in tech usage. The swifter the satisfaction achieved, the faster the adoption rate. User satisfaction can be split into two categories: transaction-specific and cumulative satisfaction. Transaction-specific satisfaction arises from positive feedback during specific interactions with the technology. Cumulative satisfaction, on the other hand, stems from the overarching contentment with the technology, with the former believed to be a precursor to the latter satisfaction (Jones & Suh, 2000; Olsen & Johnson, 2003).

3.2 Perceived Trialability

Perceived trialability plays a pivotal role in shaping one's intent to harness technology. The concept of trialability underscores the facility with which users can navigate and experiment with a novel technological system. Various studies have spotlighted and endorsed its positive influence on the assimilation of new systems. At its core, trialability is about gauging the ease with which users can grapple with fresh innovations. The notion expands to encompass a range of related ideas. For instance, it delves into the amount of effort users must exert when familiarizing themselves with the technology, as well as the potential risks they might encounter. Furthermore, an essential facet of trialability is the system's ability to allow users to effortlessly backtrack or rectify actions. This flexibility is paramount, especially when users are in the exploratory phase of a new technological interface. A system that offers a high degree of trialability ensures that users can experiment without apprehension, knowing they can swiftly recover or amend operations when needed [14]–[17]. Such attributes often make innovative technology more approachable and user-friendly, boosting its chances of widespread acceptance.

3.3 Perceived Observability

Perceived observability hinges on the extent to which a technological innovation stands out and captures the attention of its audience. It's about how conspicuously an innovation manifests its benefits and advantages in a way that is discernible by others. When peers, classmates, or neighbors notice and discuss the distinctiveness of a technology, it can significantly influence its rate of adoption. This concept underscores the collective impact of social recognition and feedback. As individuals observe their peers using and benefiting from a particular technology, they often become more inclined to explore and adopt it themselves. In educational or communal settings, this dynamic is especially potent. The feedback and experiences shared by classmates, for instance, can either bolster enthusiasm for the innovation or raise concerns.

Furthermore, when a technology's merits are visibly demonstrable, it fosters organic conversations and debates among users and potential adopters. Such peer discussions, stimulated by the apparent benefits and features of the innovation, can lead to a cascading effect, amplifying interest and engagement with the technology. This ripple effect underscores the importance of visibility in driving adoption rates, especially in interconnected communities or groups.

3.4 Perceived Compatibility

Perceived compatibility centers on the user's perception of how well a technological innovation aligns with their prior experiences, values, and existing standards. Essentially, it gauges how consistent the technology feels with what users are familiar with and expect. According to [18], an innovation is more likely to be embraced when it resonates with the users' predilections. Rogers (2003) [19] mirrors this sentiment, suggesting that individuals are more amenable to adopting new technologies that gel with their established habits and anticipations. Historical data suggests that when users perceive a technology as harmonizing with their values, requirements, and past experiences, they're more likely to view it as highly compatible. This perception in turn, positively impacts their perceived value of the technology [20]–[22].

Many prior studies have delved into how perceived trialability, observability, and compatibility influence a broad spectrum of technologies and their applications. These studies typically frame these attributes as key determinants of perceived enjoyment, ease of use, and overall utility [23]–[25]. Yet, there's a noticeable research gap when it comes to exploring the interplay between users' satisfaction and the three aforementioned attributes, especially concerning the adoption of the ChatGPT language model. This study aspires to bridge this knowledge gap by probing the influence of these attributes on user satisfaction and eventual adoption. In light of the above, the subsequent hypotheses are presented:

H1: Perceived traibility would predict the users' Satisfaction.

H2: Perceived observability would predict the users' Satisfaction.

H3: Users' compatibility would predict the users' Satisfaction.

3.5 Personal Innovativeness and TAM Constructs

Innovation theory typically categorizes tech users as forward-thinking innovators who actively pursue new ideas. Such users, distinct in their approach, embrace uncertainties and often foster positive inclinations toward technological adoption. Personal innovativeness, in essence, cultivates favorable perceptions about cutting-edge technologies. It's suggested that a person's perspective on information technology is most profoundly influenced by their innovative tendencies. This inclination towards innovation can be likened to a willingness to take risks when exploring novel technologies [19].

The Technology Acceptance Model (TAM) outlines how personal technological innovation is often swayed by two pivotal elements: the perceived ease of technology use and its perceived utility [4]. The former emphasizes a user's conviction that a particular technology will boost their efficacy in specific tasks. The latter focuses on a user's belief that employing a certain technology can simplify tasks. Research by [26], [27] validates the strong linkage between behavioral intentions and both perceived utility and ease of technology use. Given these findings, the conceptual model being proposed postulates that personal innovativeness significantly shapes perceptions about a technology's usefulness and user-friendliness. These perceptions, in turn, are integral to the decision to embrace systems like the metaverse [17], [28]. Based on this, the ensuing hypotheses have been crafted:

H4: Personal innovativeness would predict the perceived ease of use.

H5: Personal innovativeness would predict the perceived usefulness.

H6: Users' satisfaction would predict the intention to use ChatGPT.

H7: Perceived ease of use would predict the intention to use ChatGPT.

H8: Perceived usefulness would predict the intention to use ChatGPT.

3.6 The Conceptual Framework

The present research introduces a theoretical model to assess the incorporation of ChatGPT into medical education. This assessment focuses on two key factors: users' satisfaction and their individual innovative tendencies. These are evaluated in relation to distinct variables. Specifically, perceived trialability, observability, and compatibility determine users' contentment, while perceived ease of use and perceived usefulness gauge their inclination for personal innovation, as depicted in Figure 2.

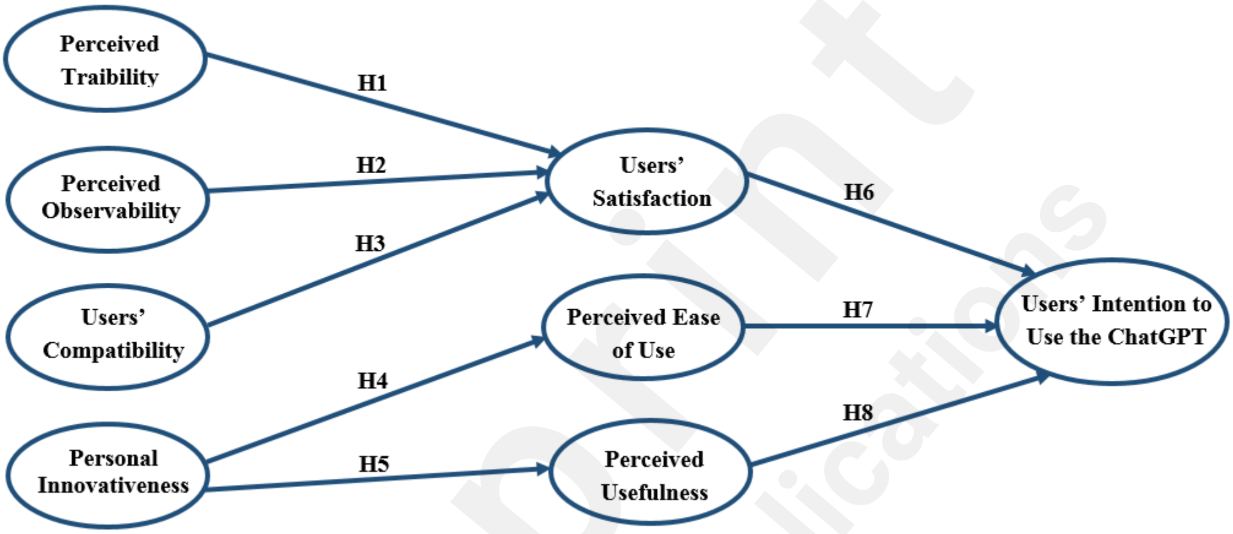

Figure 2. Research Model

4. Research Methodology

4.1 Data collection

The data collection spanned from September 20, 2023, to October 30, 2023. University students in the UAE received online surveys. An email was sent to participants detailing the study's objectives and a survey link. This link was also disseminated via social media channels, including university-specific Facebook pages and Whatsapp groups. Participation was entirely voluntary. Of the 800 surveys distributed, a 91.6% completion rate was achieved. Only the fully completed questionnaires were considered for evaluation, leading to the exclusion of 67 incomplete responses. While 733 is deemed an appropriate sample size for a population of 100,000 students, this study's 733 completed questionnaires exceeded the required sample size as per [29]. Consequently, Structural Equation Modeling (SEM) was deemed fit to test the study's hypotheses, given the sufficient sample size [30]. Although established theories informed the proposed hypotheses, adjustments were made to ensure their relevance to the Internet of Things (IoT) domain when necessary. For the assessment of the measurement model, this study utilized SEM, SmartPLS Version (3.2.7), and the concluding path model.

4.2 Personal/Demographic Information

Figure 3 presents the demographic details of the study participants. Of the respondents, 56% were male and 44% were female. Age-wise, 72% fell between 18 and 29 years, while 52% were aged above 29. A significant proportion of the participants were well-educated: 68% had completed a bachelor's degree, 18% held a master's degree, and 4% had earned doctoral degrees. Additionally, 5% had either a diploma or an advanced diploma. The educational backgrounds underscore a broad academic context among the participants. As per [31], this research employed a "purposive sampling approach" owing to the voluntary nature of participant involvement. The study's sample was notably diverse, encompassing students from various colleges, a range of ages, and a variety of academic programs. The demographic data in Figure 3 was analyzed using IBM SPSS Statistics 23.

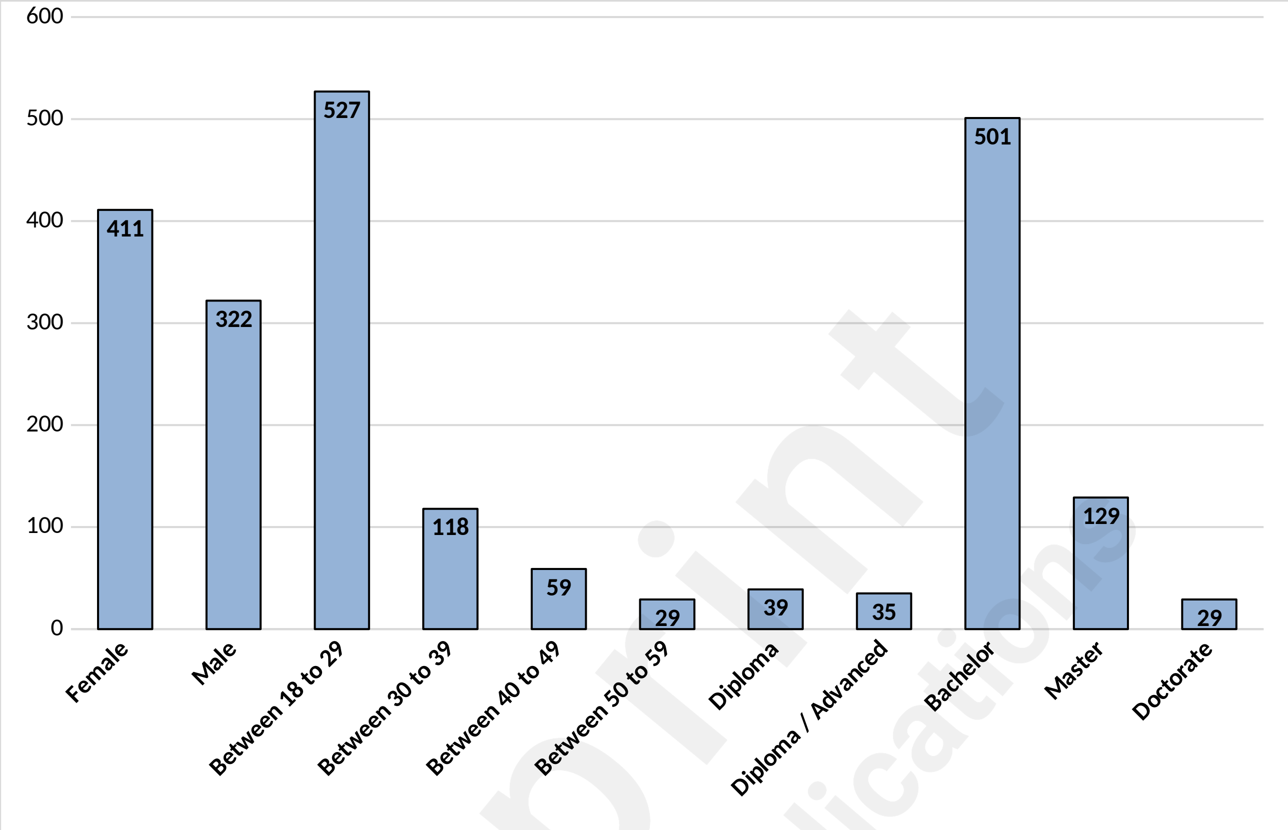

Figure 3. Demographic data of the respondents (*n=733*).

4.3 Study Instrument

A 23-item survey was employed to validate the hypothesis. This instrument assessed the 8 constructs presented in the questionnaire, with their origins detailed in Table 1. Questions from prior research were adapted to fit this study's requirements, ensuring more relevant findings.

Table 1: Measurement Items

Constructs	Items	Instrument	Sources
Perceived Trialability	TRI1	I would like to experiment with ChatGPT prior to actual medical lectures.	[32]–[34]
	TRI2	It takes time to become accustomed to using ChatGPT in a medical education environment.	
	TRI3	I found ChatGPT beneficial after my trial in the medical education setting.	
Perceived Observability	OBS1	I believe ChatGPT can be integrated into my regular medical lectures.	[32], [35]
	OBS2	I believe ChatGPT offers significant value in the context of medical education	
	OBS3	My experience with ChatGPT is relevant to all facets of medical education.	
Perceived Compatibility	COM1	I believe ChatGPT aligns well with my medical study objectives.	[27]
	COM2	I intend to use ChatGPT because it meets my expectations for medical learning.	
	COM3	I'm confident that ChatGPT will align with the cultural norms of my medical community.	
Personal Innovativeness	INN1	I believe I will use ChatGPT in my medical studies.	[36]
	INN2	I feel prepared to engage with emerging technologies like ChatGPT in my medical education.	
	INN3	I anticipate incorporating ChatGPT into my medical education.	
Users' Satisfaction	SAT1	I'm convinced that ChatGPT offers substantial value within the realm of medical education.	[37]
	SAT2	I feel that ChatGPT brings numerous benefits to my daily medical lectures.	
	SAT3	I believe ChatGPT is a valuable tool for medical learning.	
Perceived Ease of Use	PEU1	I find ChatGPT to be user-friendly in the medical education context.	[38]
	PEU2	I believe I can leverage ChatGPT for various medical education objectives, given its user-friendliness.	
	PEU3	I anticipate challenges in utilizing ChatGPT under specific conditions in the medical education realm.	
Perceived Usefulness	PUS1	I believe ChatGPT offers value for real-time medical lectures and discussions.	[38]
	PUS2	I feel that ChatGPT brings numerous benefits to my medical studies.	
	PUS3	I'm convinced that ChatGPT is beneficial for live medical lectures and dialogues.	
Users' Intention to use ChatGPT	INT1	I am certainly inclined to integrate ChatGPT into my medical studies.	[39], [40]
	INT2	I intend to utilize ChatGPT for specific medical education objectives.	

4.4 Pilot study of questionnaire

This research conducted a preliminary study to ensure the reliability of the questionnaire items. From the available pool of 800 students, a random sample of 80 students, representing 10% of the population (as per research norms), participated in this pilot phase. Subsequently, the SPSS software was used to execute the Cronbach's alpha test, determining the internal consistency of the measurement items. The results revealed a reliability coefficient of 0.70, considered satisfactory in the realm of social science [41]. Table 2 presents the Cronbach's alpha values for the five measurement scales.

Table 2: Cronbach's alpha values for the pilot study (Cronbach's alpha ≥ .70)

Constructs	Cronbach's Alpha
TRI	0.881
OBS	0.857
COM	0.775
INN	0.871
SAT	0.729
PEU	0.888
PUS	0.754
INT	0.843

4.5 Common Method Bias (CMB)

The research utilized Harman's single-factor test on eight variables to assess the data for potential Common Method Bias (CMB) as per [42]. Subsequently, 10 factors were integrated into a singular factor. The analysis highlighted that the principal factor accounts for 23.67% of the variance, whereas a significant variance threshold stands at 50% ([42]. This suggests the data is suitably devoid of CMB.

5. Findings and Discussion

5.1 Data Analysis

This study stands apart from earlier empirical investigations by employing a dual-stage analysis, in contrast to the traditional single-stage SEM approach. The research incorporates a hybrid SEM-ANN technique grounded in deep learning to evaluate connections between theoretical model elements and to confirm research hypotheses. In the initial phase, the research employs partial least squares structural equation modelling (PLS-SEM) through SmartPLS for assessing the proposed research framework [43], [44]. Given the exploratory nature of this research model and the dearth of associated literature, PLS-SEM emerges as a fitting choice [45]. The application of PLS-SEM in this investigation aligns with established protocols for deploying PLS-SEM in information systems research. Consequently, the research model undergoes a bifurcated evaluation, emphasizing both the measurement and structural models, echoing the strategies proposed by [46]..

A distinctive feature of PLS-SEM is the importance-performance map analysis (IPMA), aiming to scrutinize the research model's constructs to deduce their significance and efficiency. This PLS-SEM evaluation further gains credibility, assessment, and validation through the integration of ANN alongside IPMA. ANN excels at examining intricate or non-linear associations between determinants, functioning as a tool for approximating functions. Key components of ANN entail its network configuration, the learning directive, and the transfer mechanism [46]. and can be further broken down into radial basis, feed-forward multilayer perceptron (MLP) framework, and recurrent network [47]. Globally, the MLP neural network approach under ANN finds favor among practitioners. Structurally, MLP is comprised of multiple input and output strata, interspersed with intermediary hidden nodes. At its base layer, it houses neurons or determinants acting as raw data receivers. This data transitions via synaptic weights towards the hidden layers, producing an output contingent on the selected activation function. Notably, the sigmoidal function is a popular choice for activation [48], [49]. To summarize, this study harnesses the MLP neural network within the ANN framework for both its training and validation processes.

5.2 Convergent validity

As recommended by [50], evaluating construct reliability (encompassing composite reliability (CR), Dijkstra-Henseler's rho (pA), and Cronbach's alpha (CA)) in tandem with validity (both convergent and discriminant) serves as an effective method for analyzing the measurement model. Table 3 displays Cronbach's alpha (CA) values for construct reliability that fall between 0.708 and 0.901. These values exceed the established benchmark of 0.7 [51]. Additionally, Table 3 showcases that the composite reliability (CR) has values spanning from 0.800 to 0.925, surpassing the standard 0.7 value [52]. An alternative approach suggested for researchers is to utilize Dijkstra-Henseler's rho (ρA) as the reliability coefficient when examining construct reliability [53]. Similar to CA and CR, the ρA coefficient should be equal to or greater than 0.70 for preliminary studies, and should exceed 0.8 or 0.9 in more refined stages of research [51], [54], [55]. Table 3 confirms that the ρA coefficient for each measurement construct comfortably exceeds 0.70. Based on these outcomes, the study solidly establishes construct reliability. Ultimately, the analysis assumes that the constructs are largely devoid of errors.

For the assessment of convergent validity, factor loading and average variance extracted (AVE) tests are implemented, following guidelines from [50]. The data in Table 3 reveals that all factor loading values surpassed the advised benchmark of 0.7. Also, the AVE values presented in Table 3 exceed the standard value of 0.5, ranging between 0.705 and 0.836. Given these results, convergent validity for each construct can be confidently established.

5.3 Discriminant validity

To gauge discriminant validity, both the Fornell-Larker criterion and the Heterotrait-Monotrait ratio (HTMT) were evaluated [50]. The data in Table 4 reveals that the AVE values and their respective square roots surpass their correlations with other constructs. This confirms their consistency with the Fornell-Larker standard [56]. Table 5 showcases the results for the HTMT ratio. As observed, every construct displayed a value beneath the benchmark of 0.85 [57], signifying compliance with the HTMT ratio standards. Based on these observations, discriminant validity has been verified. The assessment of the measurement model yielded no discernible issues pertaining to validity and reliability. Thus, the compiled data is deemed fit for the evaluation and dissection of the structural model.

Table 3: Convergent validity results with acceptable values (Factor loading, CA, and CR ≥ 0.70 & AVE > 0.5).

Constructs	Items	Factor Loading	CA	CR	pA	AVE
Perceived Trialability	TRI1	0.840	0.791	0.800	0.877	0.705
	TRI2	0.804				
	TRI3	0.873				
Perceived Observability	OBS1	0.910	0.892	0.925	0.931	0.819
	OBS2	0.880				
	OBS3	0.925				
Perceived Compatibility	COM1	0.915	0.896	0.898	0.935	0.828
	COM2	0.900				
	COM3	0.915				
Personal Innovativeness	INN1	0.921	0.880	0.886	0.926	0.807
	INN2	0.871				
	INN3	0.901				
Perceived Ease of Use	PEU1	0.922	0.881	0.887	0.926	0.801
	PEU2	0.865				
	PEU3	0.908				

Perceived Usefulness	PUS1	0.883	0.901	0.904	0.938	0.836
	PUS2	0.918				
	PUS3	0.883				
Users’ Satisfaction	SAT1	0.896	0.857	0.859	0.913	0.778
	SAT2	0.861				
	SAT3	0.889				
Users’ Intention to Use ChatGPT	INT1	0.943	0.889	0.906	0.931	0.819
	INT2	0.844				

Table 4: Fornell-Larcker Scale

	TRI	OBS	COM	INN	PEU	PUS	SAT	INT
TRI	**0.899**							
OBS	0.680	**0.839**						
COM	0.741	0.688	**0.914**					
INN	0.710	0.687	0.809	**0.905**				
PEU	0.626	0.499	0.730	0.703	**0.898**			
PUS	0.659	0.635	0.613	0.581	0.465	**0.910**		
SAT	0.604	0.503	0.744	0.682	0.692	0.485	**0.905**	
INT	0.702	0.694	0.698	0.663	0.536	0.652	0.546	**0.882**

Table 5: Heterotrait-Monotrait Ratio (HTMT)

	TRI	OBS	COM	INN	PEU	PUS	SAT	INT
TRI								
OBS	0.813							
COM	0.832	0.815						
INN	0.787	0.796	0.800					
PEU	0.706	0.591	0.817	0.805				
PUS	0.740	0.748	0.681	0.627	0.520			
SAT	0.680	0.596	0.825	0.769	0.777	0.538		
INT	0.805	0.839	0.793	0.739	0.615	0.742	0.619	

5.4 Hypotheses Testing using PLS-SEM

To gauge the interconnectedness of various theoretical elements within the structural model, we employed the structural equation model via Smart PLS. This model utilized the maximum likelihood estimation method, as cited by [58]. This approach allowed us to test the proposed hypotheses. [14] has previously highlighted the model's robust predictive capabilities. Our analysis revealed that the model could account for variances of approximately 59% in User Satisfaction, 39% in Perceived Ease of Use, 53% in Perceived Usefulness, and 56% in Users' Intention to Use ChatGPT. Detailed outcomes can be found in Table 6 and Figure 4. We derived our conclusions using the PLS-SEM method, leading to the confirmation of several hypotheses. Table 7 provides an overview of beta (β) values, t-values, and p-values associated with these hypotheses. Most hypotheses, specifically H1 through H6 and H9, gained empirical support. However, hypotheses H7 and H8 were exceptions, not receiving unanimous agreement from the researchers.

In our study, significant relationships were observed between Users' Satisfaction (SAT) and Perceived Trialability (TRI) (β =.324), Perceived Observability (OBS) (β =.275), and Perceived Compatibility (COM) (β =.287), supporting hypotheses H1, H2, and H3 respectively. Additionally, Personal Innovativeness (INN) showed strong correlations with Perceived Ease of Use (PEU) (β =.626) and Perceived Usefulness (PUS) (β =.730), reinforcing hypotheses H5 and H6. However, the associations between Users' Intention to Use ChatGPT (INT) with both SAT (β =.012) and PEU (β =.113) were not statistically significant, challenging hypotheses H5 and H6. Conversely, a strong positive relationship was identified between INT and PUS (β =.652), validating hypothesis H9.

Table 6: R^2 of the endogenous latent variables

Constructs	R^2	Results
INT	.560	Moderate
PEU	.392	Moderate
PUS	.533	Moderate
SAT	.594	Moderate

Table 7: Summary of hypotheses tests at p**=<.01, p* <.05 Significant at p**=<.01, p* <0.05

H	Relationship	Path	*t*-value	*p*-value	Direction	Decision
H1	TRI -> SAT	.324	5.138	.000	Positive	Supported**
H2	OBS -> SAT	.275	3.767	.000	Positive	Supported**
H3	COM -> SAT	.287	4.521	.000	Positive	Supported**
H5	INN -> PEU	.626	12.956	.000	Positive	Supported**
H6	INN -> PUS	.730	16.727	.000	Positive	Supported**
H7	SAT -> INT	.012	0.182	.855	Positive	Not supported
H8	PEU -> INT	.113	1.656	.098	Positive	Not supported
H9	PUS -> INT	.652	8.749	.000	Positive	Supported**

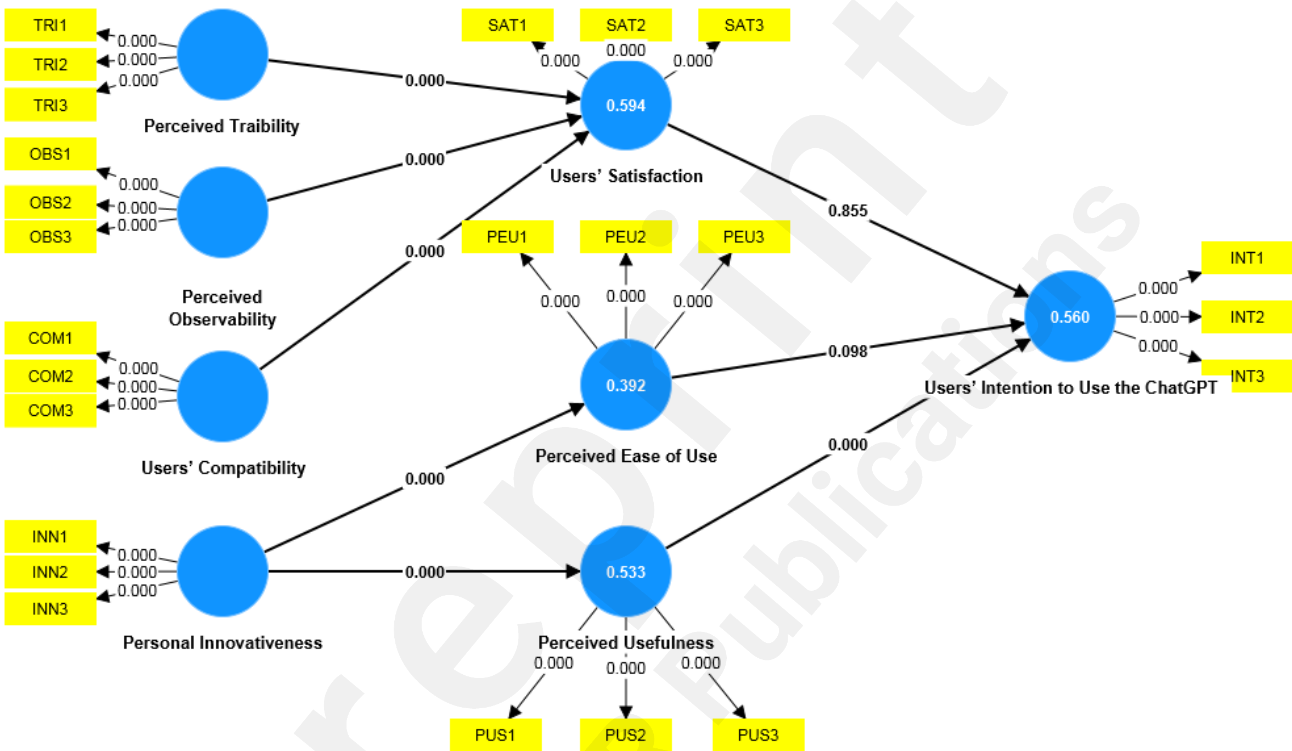

Figure 4. Hypotheses testing results (significant at p** < =.01, p* <.05).

5.5 ANN Results

The study utilized SPSS for an ANN evaluation based on insights from [59], focusing solely on variables identified by PLS-SEM as highlighted by [60]. Specifically, the investigation centered on factors like TRI, OBS, COM, INN, SAT, PEU, and PUS. The configuration of this ANN setup is illustrated in Figures 5 through 8. This setup integrates a unique output neuron (Users' Intention to Use ChatGPT (INT)) with multiple input counterparts (TRI, OBS, COM, INN, SAT, PEU, and PUS). To ensure comprehensive learning at every output point, a dual hidden layer ANN architecture, as discussed by [61], was adopted. We incorporated the sigmoid function for activation in both hidden and output nodes. By adjusting the input and output neurons to fit within a [0, 1] spectrum, based on recommendations from [62], the model's performance was optimized. We allocated 80% of the data for training and 20% for testing, incorporating the ten-fold cross-validation strategy, a method endorsed by [48], to curb potential ANN model overfitting. We gauged the neural model's precision using the RMSE, obtaining values of 0.1307 for training and 0.1456 for testing. The negligible variance between SD and RMSE for training (0.0051) and testing (0.0076) underscores the ANN's role in boosting the precision of our research framework.

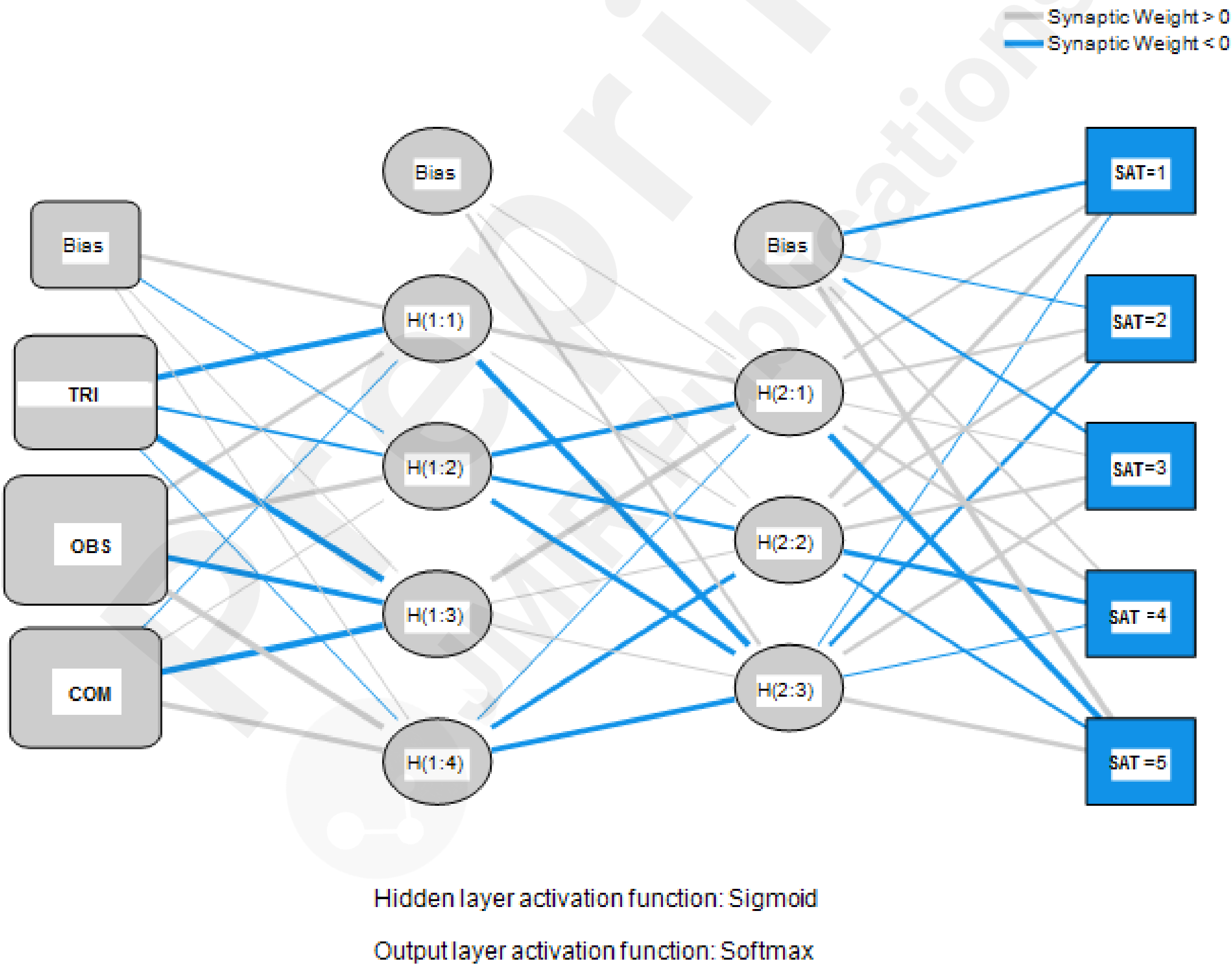

Figure 5. ANN model.

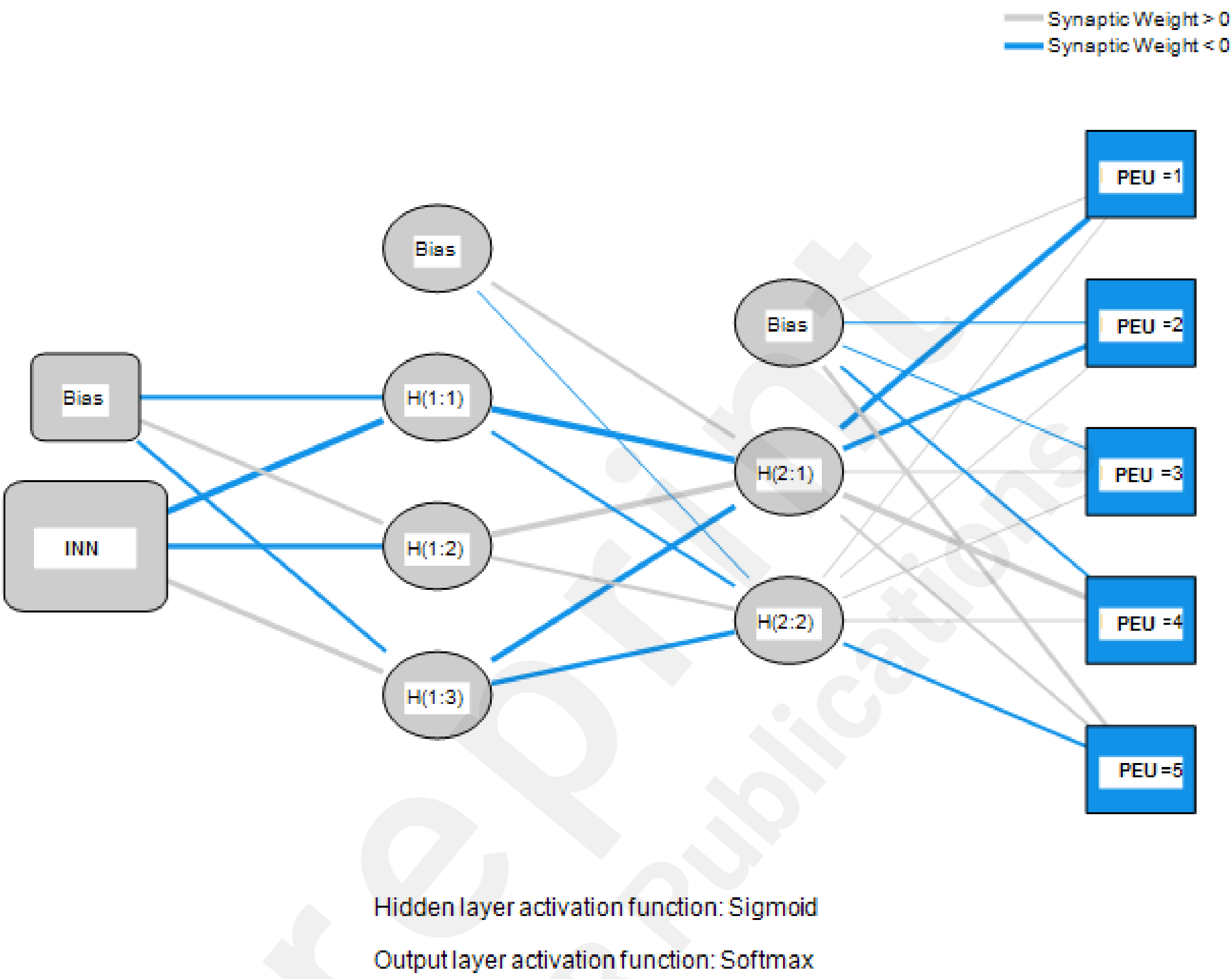

Figure 6. ANN model

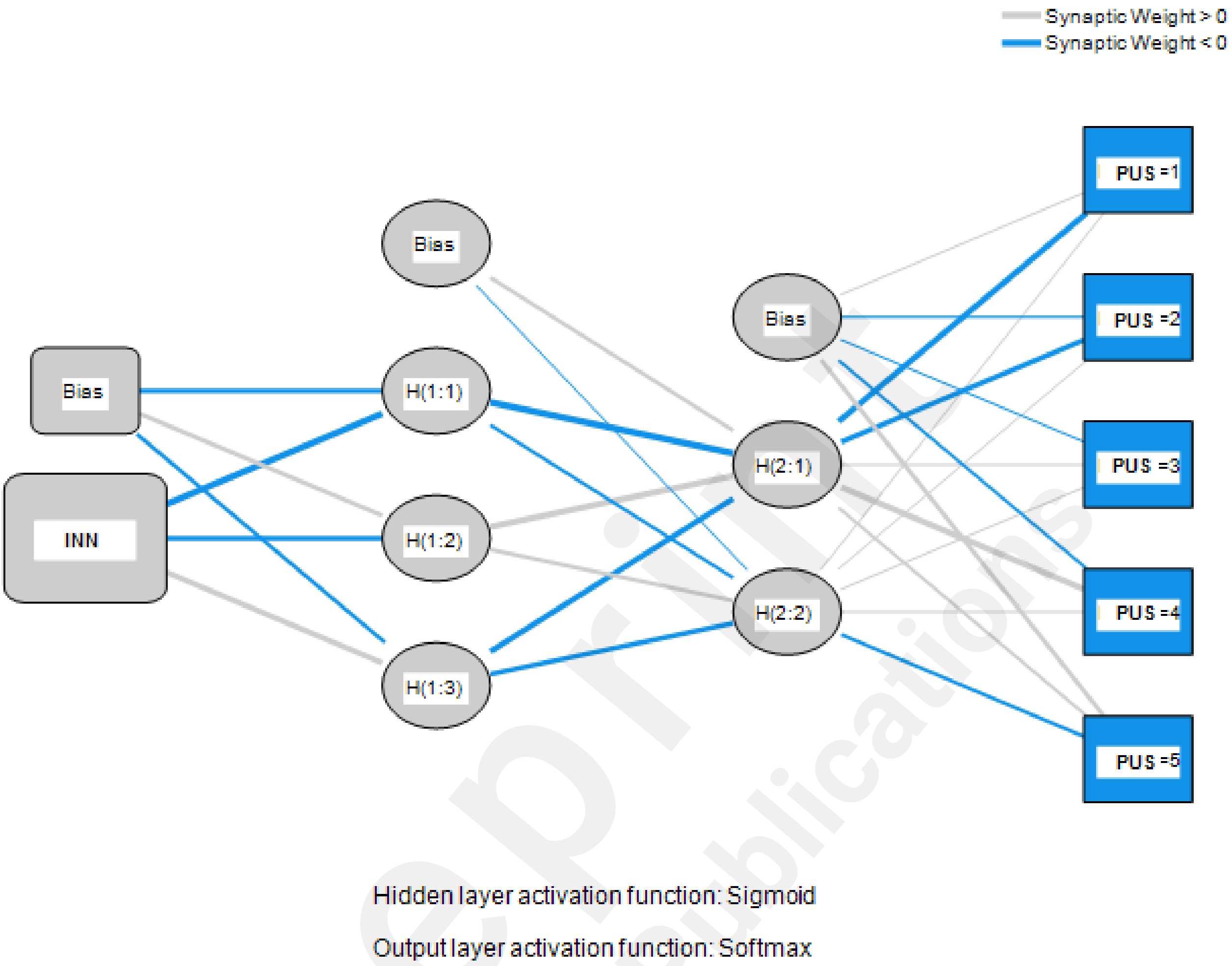

Figure 7. ANN model

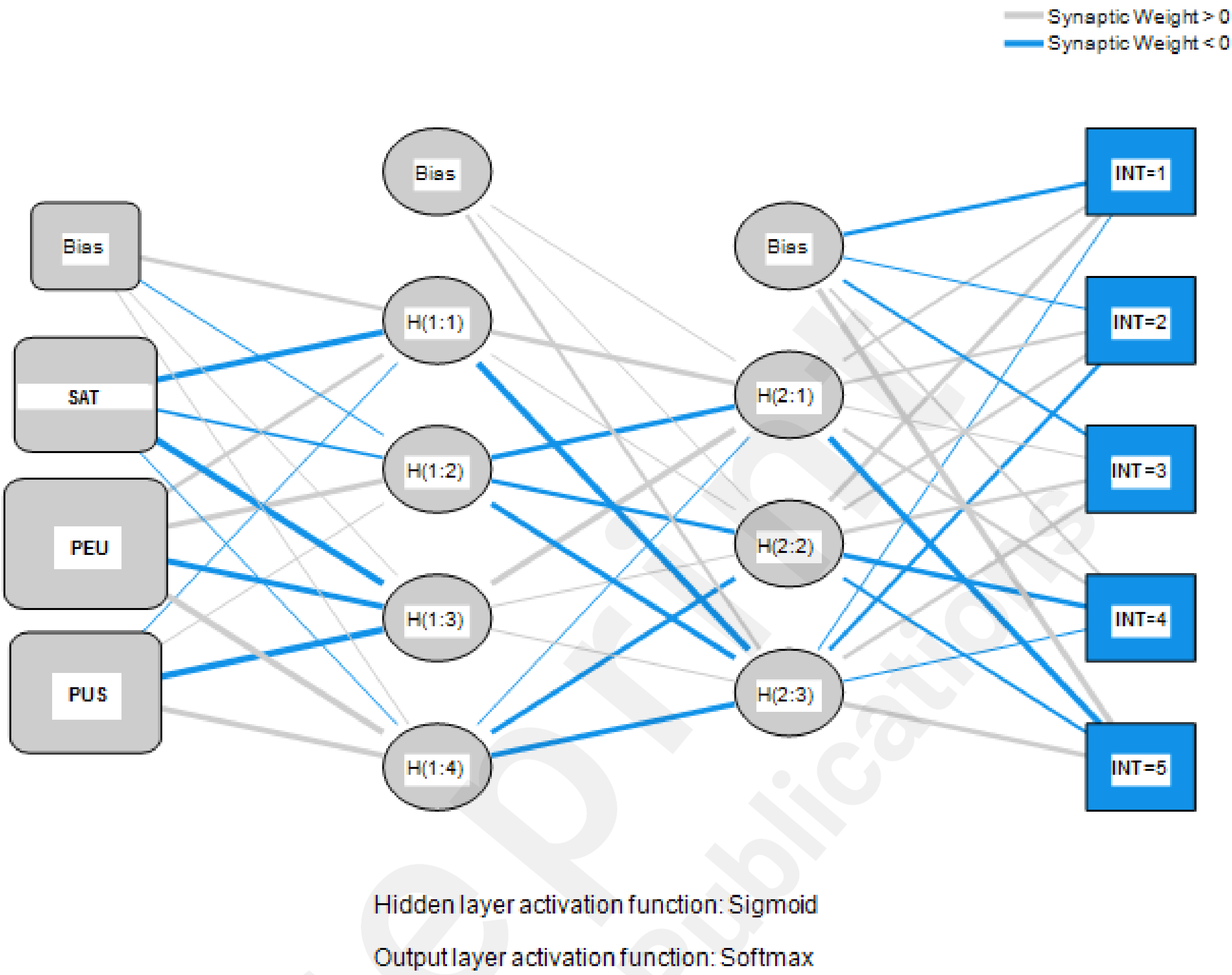

Figure 8. ANN model

5.6 Sensitivity Analysis

The relative significance of each predictor is determined by comparing its average importance value to the peak mean importance value, expressed as a percentage. Each factor in the ANN model underwent an assessment for both average and normalized significance values, with the outcomes noted in Table 8. This table also highlights the hierarchical relevance of three factors among PTR, POB, PCO, PCM, PI, PEOU, PU, and US that influence users' willingness to adopt MS, with PU emerging as the primary factor. Another metric, known as the goodness-of-fit, is employed to ascertain the efficacy of the ANN method and corroborate its precision, a validation that other metrics also support. This metric serves a parallel role in ANN as R^2 does in PLS-SEM, as pointed out by [63]. Yet, the ANN approach provides a more comprehensive understanding of internal constructs, boasting a higher predictive strength (R^2 = 89%) than PLS-SEM (R^2 = 57.2%). Since the deep-learning ANN method more adeptly captures the intricate dynamics among the model's components, there exists a slight variation in variance values.

Table 8: Independent Variable Importance

	Importance	**Normalised Importance**
TRI	.126	21.2%
OBS	.138	24.5%
COM	.244	68.6%
INN	.395	89.5%
SAT	.203	53.2%
PEU	.288	75.4%
PUS	.598	100.0%

5.7 Importance-Performance Map Analysis

The use of the Improved Performance Measurement Analysis (IPMA) augments the clarity and comprehension of results generated by Partial Least Squares Structural Equation Modeling (PLS-SEM), as endorsed by prior studies [64]. Within this study, 'behavioural intention' stood out as the chief construct evaluated using IPMA. This method allows for a comparative review of performance values and the relevance of path coefficients. By capturing the combined effects, IPMA clarifies how certain factors influence the behavioural intentions, our focal construct. The mean values of underlying variables depict the performance levels of these constructs. As presented in Figure 9, IPMA provides insights into the performance and relevance of constructs like TRI, OBS, COM, INN, SAT, PEU, and PUS. Notably, PUS scored highest in both importance and performance dimensions, with INN trailing closely behind. In contrast, PEU showed the least impressive performance figures but secured a middle position in terms of significance. When it came to importance, TRI, OBS, and COM garnered the lowest scores.

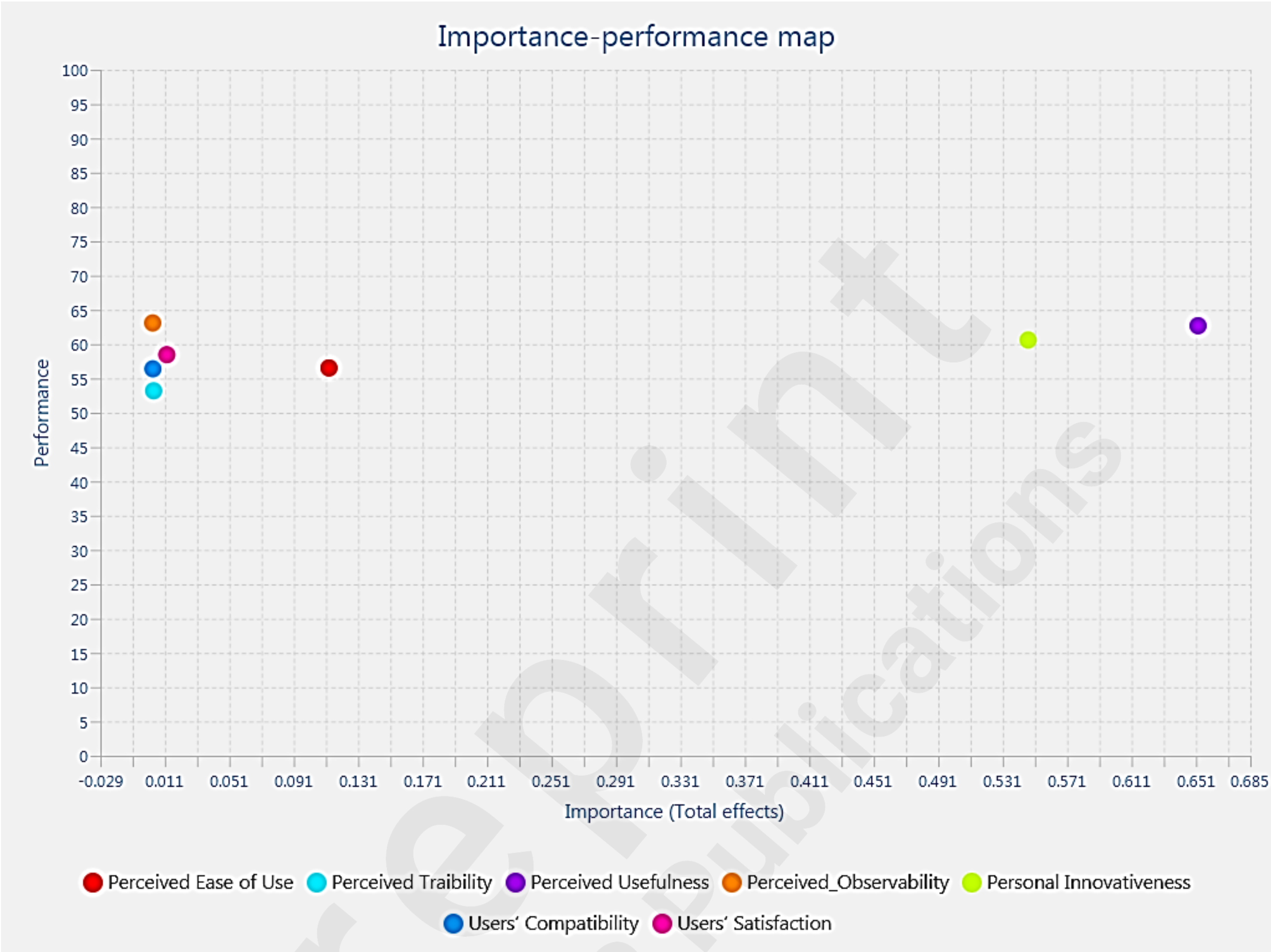

Figure 9. IPMA results

6. Discussion of Results

In the recent investigation, a hybrid model employing both PLSM and ANN analytical methodologies was utilized to delve into the factors affecting the adoption of ChatGPT in medical education. While both methodologies bolstered the significance of 'users' intention to use ChatGPT', the ANN analysis provided a more compelling predictive power with an R^2 value of 0.86%, outshining PLSM's R^2 at 0.56%. This elevated R^2 value from the ANN method highlights the profound influence of personal and technological characteristics on student's adoption choices. It suggests those embracing technological innovations and comfortable with uncertainties are more likely to adopt ChatGPT. The study underscored the essential role of adoption-centric properties, notably trialability, observability, and compatibility, in influencing the uptake of ChatGPT by medical students. Echoing findings from earlier studies like [23], [26], [65], the current research asserts that students weigh these properties significantly when considering the adoption of technological tools like ChatGPT. Positive perceptions arise when the technology aligns well with their cultural milieu and when it's deemed favorable by peers, enhancing the propensity to adopt.

Moreover, the influence of personal traits, especially personal innovativeness, was identified as a strong driver for ChatGPT adoption. Students displaying an affinity for innovative technology and comfortable with uncertainties exhibited a more favorable disposition towards ChatGPT. This aligns with prior research [66], [67], suggesting that a student's perception of usefulness and novelty often acts as a motivator for embracing new technology. Nevertheless, regional variations, like the high tech-acceptance observed in the Gulf region, and factors such as the playfulness of technology warrant further exploration.

6.1 Theoretical and Practical Implications

In terms of the methodological approach used in this study, it's clear that our methods surpass many other empirical investigations. Specifically, we've integrated a cutting-edge hybrid analysis that leans on deep-learning techniques instead of just relying on the traditional SEM analysis typically seen in such research. As a result, this study enriches the body of literature related to m-learning. Additionally, the ANN model presents a more potent predictive capability compared to the PLS-SEM model. This superiority stems from the enhanced benefits provided by the intricate architecture of deep ANN, which excels at pinpointing non-linear relationships among the factors of the theoretical model.

6.2 Managerial Implications

The results of this research offer contemporary insights for medical education utilizing ChatGPT. From the study, it is clear that medical students' willingness to use ChatGPT is considerably influenced by personal innovation, an intrinsic trait. Simultaneously, their inclination is shaped by perceived ease of use and perceived usefulness, characteristics intrinsic to the technology.

Given this, medical educators and IT facilitators should present opportunities that highlight the advantages of ChatGPT, emphasizing both individual-driven traits and technological attributes. By doing so, medical students' positive assessment of and readiness to utilize ChatGPT is likely to grow, resulting in enhanced medical training experiences. Upcoming studies should delve into individual variations and gender-specific preferences concerning teaching philosophies and values. These factors might influence the adoption of technology by medical professionals and their unique requirements.

6.3 Limitations and Future Research

The present research has a few limitations when applied to medical education using ChatGPT. Firstly, the theoretical model primarily revolves around just two key variables: personal innovativeness and user satisfaction, which might not encompass the entire spectrum of factors affecting ChatGPT adoption in medical education. Secondly, the Technology Acceptance Model (TAM) was restricted to its two core constructs: perceived ease of use (PEOU) and perceived usefulness (PU), to maintain focus on the significant attributes that influence personal innovativeness. Thirdly, the method of distributing the survey through online platforms and social media implies a potential bias, as medical students with better internet access might have responded more, possibly inflating the response rate. Lastly, while ChatGPT can be versatile in various settings, this study specifically narrows its applicability to medical education environments. It's worth noting that the dynamics of teaching and learning in medical education could be uniquely influenced by ChatGPT.

7. Conclusion

The introduction of ChatGPT in the realm of medical education signifies a transformative shift in how future healthcare professionals will be educated. As a tool backed by advanced technologies, ChatGPT holds immense promise in revolutionizing medical teaching methodologies. Given the rapid technological advancements, as evidenced by initiatives like the rebranding of Facebook to Meta and its foray into the metaverse, it's clear that we are on the cusp of a new era that melds reality with the virtual. ChatGPT, in this context, can be envisaged as a pioneering tool that could reshape internet-based learning, laying down a foundation for novel medical teaching and learning practices. This study delved into the perceptions of medical students regarding the adoption of ChatGPT in the Gulf region, aiming to understand the determinants of their adoption intent. Our findings revealed that the inclination of students to integrate ChatGPT into their learning was closely tied to their inherent innovativeness. This inclination was further bolstered by ChatGPT's perceived ease of use and perceived usefulness in the medical curriculum. These insights not only build upon the existing body of knowledge on technology integration in education but also underscore the importance of considering factors like trialability, observability, and compatibility in the adoption process. In essence, this study provides a glimpse into the future of medical education, highlighting the potential of innovative tools like ChatGPT.

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