IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received March 16, 2022, accepted April 18, 2022, date of publication April 21, 2022, date of current version April 28, 2022.

Digital Object Identifier 10.1109/ACCESS.2022.3169285

Prediction of User's Intention to Use Metaverse System in Medical Education: A Hybrid SEM-ML Learning Approach

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ABSTRACT Metaverse (MS) is a digital universe accessible through a virtual environment. It is established through the merging of virtually improved physical and digital reality. Metaverse (MS) offers enhanced immersive experiences and a more interactive learning experience for students in learning and educational settings. It is an expanded and synchronous communication setting that allows different users to share their experiences. The present study aims to evaluate students' perception of the application of MS in the United Arab Emirates (UAE) for medical-educational purposes. In this study, 1858 university students were surveyed to examine this model. The study's conceptual framework consisted of adoption constructs including Technology Acceptance Model (TAM), Personal innovativeness (PI), Perceived Compatibility (PCO), User Satisfaction (US), Perceived Triability (PTR), and Perceived Observability (POB). The study was unique because the model correlated technology-based features and individual-based features. The study also used hybrid analyses such as Machine Learning (ML) algorithms and Structural Equation Modelling (SEM). The present study also employs the Importance Performance Map Analysis (IPMA) to assess the importance and performance factors. The study finds US as an essential determinant of users' intention to use the metaverse (UMS). The present study's finding is useful for stakeholders in the educational sector in understanding the importance of each factor and in making plans based on the order of significance of each factor. The study also methodologically contributes to Information Systems (IS) literature because it is one of the few studies that have used a complementary multi-analytical approach such as ML algorithms to investigate the UMS metaverse systems.

INDEX TERMS Personal innovativeness, satisfaction, triability, compatibility, users' satisfaction Metaverse, observability.

I. INTRODUCTION

The unprecedented rate of technology adoption among consumers and increased connectivity has motivated researchers and computer scientists to develop virtual environments rapidly. Collins [1] and MacCallum and Parsons [2] reasons that increased internet use and the development of social networking programs have provided an avenue for creating 3D virtual reality (VR) content. In his 1992 dystopic, cyberpunk novel, Snow Crash, Stephenson invented Metaverse. Stephenson [3] described a metaverse as a 3D virtual reality (VR) space accessible through personal terminals and virtual reality (VR) goggles in the novel. Since the term was coined, there has been increased human interaction and communication daily. Metaverse system (MS) is a digital space accessible through a virtual environment that allows people to enjoy immersive experiences and interactions [1]. It can be described as an interoperable and massively scaled network of real-time rendered 3D virtual worlds that can be synchronously accessed by an unlimited number of people with a personal sense of presence [1], [4]–[6]. Metaverse system (MS) is established by a convergence of virtually improved physical and digital reality [7]. Virtual Reality (VR) has all the characteristics of completely synthetic sights [1]. Commercial VR headsets include common methods of user interaction, such as head tracking or tangible controllers [2].

The associate editor coordinating the review of this manuscript and approving it for publication was Antonio J. R. Neves.

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As a result, users are immersed in completely virtual settings, interacting with virtual items via user interaction methods. Furthermore, VR is referred to as ''the farthest extent from reality on the Reality-Virtuality Continuum'' [3]. Such that, users of VR headsets must give their complete focus to the virtual environments, so separating themselves from physical reality [4]. Users in the MS will develop content in the digital twins, as previously stated. Users can now generate content in commercial virtual environments, such as VR painting. User interaction with virtual objects in a virtual world, such as changing the structure of a virtual object or making new art pieces, can be used to investigate user affordance. In these kinds of virtual settings, multiple users can work together in real-time. This corresponds to the sufficiently outlined prerequisites of virtual worlds: a shared sense of space, a shared sense of presence, a shared sense of time (real-time engagement), a method to interact (via gestures, text, voice, and other means), and a manner of sharing information and modify objects [5]. It is worth noting that numerous users in a virtual world, or a part of the MS, should view the same information as other users. Users can however interact continuously and in real-time with one another. To put it another way, how users perceive virtual objects and multiuser communication in virtual shared space will be crucial elements. Users in a virtual shared space like MS must collaborate synchronously with any changes or interactions from the physical equivalent, like augmented reality (AR), mixed reality (MR). The basis of creating the MS is to blend the contemporaneous behaviors of all the objects, avatars symbolizing their users, and their interactions, such as object-avatars, object-object, and avatar-avatar, by combining multiple virtual shared spaces. Every virtual environment operation should be synchronized and represent the variability of the virtual spaces [6]. Yet, maintaining and coordinating dynamic states/events at scalability is a big problem, particularly when we assume that infinite parallel users are interacting on virtual objects and interacting with one other without sensible latency, which can adversely influence user experiences [1].

Several academic institutions have carried out studies on MS [8], [9]. These studies have used a problem-based approach to explore the application of MS in an academic setting [10]. In such an approach, learners and tutors use 3D classes and avatars to solve problems virtually [11]. According to Jeon and Jung [12], MS creates an enhanced immersive experience that offers learning opportunities and increases learners' motivation. Jeon and Jung argue that MS allows students to be innovative and learn independently. Farjami *et al.* [7], Kanematsu *et al.* [13], and Hun [14] investigated the importance of MS in various fields such as a problem-based learning technique (PBL) as an educational framework and visual culture in the ''immersive metaverse'' through the visual cognition lens. The studies examined the importance of MS using real-life situations where MS was used to solve problems. The increasing role of a metaverse in learnings institutions calls for an investigation of the predictors of technological adoption in learning and educational settings. The present study investigates the impact of personal innovativeness (PI) and user satisfaction (US) on the user intention to use the Metaverse system (UMS) in learning and education settings. The US is dependent on Perceived Compatibility (PCO), Perceived Triability (PTR), and Perceived observability (POB) [15]. Specifically, a high POB, PTR, and PCO level are linked to the increased US. However, PI is dependent on Perceived ease of use (PEOU) [16] and Perceived usefulness (PU) of the technological innovation.

The primary objective of the present study was to examine predictors of UMS in the UAE. Specifically, the study aimed to investigate the impact of PU and PEOU on UMS in the UAE. The present study also intended to assess the effect of PEOU and PU on PI. Still, it intended to evaluate the impact of PCO, POB, PTR on US. Hence, the present study conceptual model was designed to the predictive value of PEOU and PU on UMS and predictors of PU and PEOU.

In most cases, technology acceptance research employs the structural equation modelling (SEM) method to assess theories [17]. Therefore, the present research employed the Technology Acceptance Model (TAM) to assess predictors of UMS. It also intended to use machine learning (ML) algorithms and Partial Least Squares (PLS)-SEM to authenticate the research model.

II. LITERATURE REVIEW

A. CHARACTERISTICS AND SCOPE OF METAVERSE

The term 'metaverse' is often associated with the 1992 cyberpunk and dystopic novel Snow Crash by Neal Stephenson. A more recent inspiration of the term is in the Ready Player one written by Earnest Cline. However, the MS is far from science fiction. According to Díaz *et al.* [4], Arcila [5], Márquez [6], and Vázquez-Cano and Sevillano-García [18] defines metaverse as an immersibe 3D and virtual space that enables interaction among users, irrespective of place or time. It is a unique tool in the educational setting because of its key features of persistence, interactivity, and corporeity [19]. Through the interactivity characteristics, Metaverse ensures users' virtual platform interactions. Interactivity ensures real-time, interoperable, and synchronous learning. The MS allows users to interact and have continuous connections with the virtual world without leaving the real world [20]. Metaverse also allows unlimited users to experience a real-time rendered 3D virtual world with an individual sense of presence through the corporeity feature [21]. The metaverse persistence feature is equally important because it ensures continuity of data, such as communication, payments, identity, history, objects, and entitlements. Thus, persistence allows data to be saved even after the users have departed from the virtual world.

The metaverse environment will require an educated workforce to meet the challenges arising from its use in learning settings. Specifically, there will be a need for new leadership and management models. There will also be a need to examine how educational contexts' behaviours differ from the real settings. Learning institutions, especially universities,

can provide an unconstrained communication environment or platforms for staff, faculty, and students rather than physical settings [20]. Such platforms allow students to communicate with their teachers digitally [21]. Thus, Metaverse can change learning settings from physical classrooms to virtual environments enabling collaboration between students and teachers.

The present research uses two techniques to assess theoretical models; PLS-SEM and ML algorithm. According to Ringle *et al.* [22], PLS-SEM offers simultaneous measurement and structural model analysis. Barclay *et al.* [23] reason that PLS-SEM simultaneous analysis results are precious findings. The present research also employs a deep ANN algorithm via SPSS [24] to determine the association between factors in the research model. In the ML algorithm, the present study applied decision trees, Bayesian networks, and neural networks to predict the association between variables in the model [25]. The study used Weka to assess the model based on such classifiers as OneR, Logistic, LWL, J48, and BayesNet.

Existing research has focused on the linear relationship between variables in the models. One-stage linear data analysis [26], particularly through the SEM, has been used in most studies to predict the association between variables. However, Sim *et al.* [27] argues that linear association between variables may not predict the process of decision making. Scholars [28]–[30] have proposed the Artificial Neural Network (ANN) analysis as second -stage analysis to remedy the limitations associated with single-stage of SEM in data analysis. Nevertheless, Huang and Stokes [31] argue that, in most cases, the shallow type ANN involving only one hidden layer is applied in the analysis. The use of ANN with more than one layer or deep ANN is proposed in the literature [32] to improve non-linear models accuracy. The present study uses deep ANN, a hybrid SEM-ANN approach to analyse the data based on the recommendations. Such an approach deviates from the TAM model used in the existing literature.

B. PREVIOUS RESEARCH ON METAVERSE SYSTEM

The effectiveness of education is dependent on the achievement of learning goals. Implementing suitable learning and training approaches, especially MS, is necessary to achieve these goals [7]. MS implementation in the learning environment would help solve the constraints present in physical learning settings, such as limited space and insufficient time for teaching and learning. The MS, through virtual, creates a concrete educational environment similar to a real one. According to Farjami *et al.* [7], MS in a learning environment also employs an issue-based approach, an effective instrument in educational settings because it allows virtual rooms and avatars to replace real-life.

The issue-based strategy is integrated into the MS training and teaching settings and allows learners to identify issues and solve them. The MS also exposes learners to virtual spaces. These spaces will enable them to apply their knowledge to find a solution to problems. The Metaverse will also allow tutors to present complex tasks for their students. These complicated problems are the same as those in a physical learning environment. Once presented with a problem, the learners act as avatars and attempt to determine an appropriate solution to the ill-structured problems. Teachers evaluate student performance on complex problems issues using online questionnaires. Teachers can also discuss with learners to assess how they solved the tasks presented to them through the virtual space. In some instances, instructors prepare students to handle the task virtually by offering brief explanations on the proposed problem. The teacher's instructions and guidelines help students handle the tasks by chatting with other studies in the MS. Such a strategy of guiding students before the virtual classroom is necessary because it enables learners to understand the problem at hand clearly. It also motivates students to solve the proposed problem. The student's understanding of MS is vital in implementing the problem-based approach in MS. The MS has been a successful learning tool in many countries [7], including Germany, Malaysia, and Japan [7], [8], [10], [11].

Existing studies have investigated the usefulness of MS in education by using reported MS applications in educational settings. MacCallum and Parsons [2] researched the significance of augmented reality (AR). The research focused on using MS tools and especially AR among educators to create a mobile augmented reality experience in a learning environment. Based on the study, students showed greater interest in teaching and learning tasks than AR tools. MacCallum and Parsons questioned whether the learners were well knowledgeable about augmented reality tools to enjoy the benefit of MS in the learning environment. Díaz, Saldaña, and Avila [4] also investigated the application of MS in educational settings. Díaz *et al.* investigated whether students were satisfied with MS using a quasi-experiment study design in the learning environment. Even though Diaz *et al.*'s study focused on creating an educational strategy using technological innovations, it only focused on teaching mathematics at the University of Cundinamarca. Thus, the study was limited because it failed to cover other courses and may not be generalised to other areas. The perception of technological satisfaction can vary from one student to another based on a student's course.

Personalised experiences and interactions are the main features that make Metaverse effective [33]. Thus, studies examining the impact of a metaverse in the educational environment [34] should consider the effects of Metaverse on interaction and personalised experiences. Lim and others developed virtual education cases to solve unified resource distributions [33]. The research found that virtual education reduces the costs of teaching and learning. Virtual learning can also improve learning and solve user uncertainty issues [33]. Thus, Metaverse can be applied in different educational environments, including aircraft training, engineering, STEM education, and mathematics. In aircraft training, Metaverse can allow students to interact with virtual airplanes. The virtual interaction offers near-real experience and

improves aircraft learning and training. Metaverse can also be applied in STEM education to present applications appropriately [35], [36]. The impact of a metaverse in different fields has led to a conception that Metaverse is closely linked to motivations. Jeon and Jung [12] show that Metaverse is a highly preferred means of interaction because it positively impacts learners and students.

III. CONCEPTUAL MODEL AND HYPOTHESES

A. THE PERSONAL INNOVATIVENESS AND TAM CONSTRUCTS

The innovative model classifies technology consumers as innovators and information-seeking people. Users of technology can adapt well when there is high uncertainty and be more positive toward adopting and using technology. Thus, PI encourages individuals to behave positively toward technological innovations. PI considerably affects the individual cognitive interpretation of IT. According to Rogers [37], PI is the propensity to take technological risks arising and is influenced by PU and PEOU. Based on Davis [17], TAM influences PI in technology PI, and PU and PEOU are the most critical factors in the TAM. PU refers to the level of belief a technology user has that it would be useful, while PEOU is the users' belief that a given technological innovation will require limited effort to operate. Wu and Wang [15] and Chang and Tang [16] indicate a significant association between behavioural intention and PEOU and PU. The present study's conceptual model suggests that PI significantly influences PU and PEOU. Based on Lee *et al.* [38] and Gor [39], PU and PEOU are primary predictors of MS adoption. Thus, the present study is based on the following hypotheses;

H1: Personal Innovativeness (PI) would predict the Perceived Usefulness (PU).

H2: Personal Innovativeness (PI) would predict the Perceived Ease of Use (PEOU).

B. THE USERS' SATISFACTION AND THE PERCEIVED TRIALABILITY, OBSERVABILITY, AND COMPATIBILITY

The US, PTR, POB, and PCO are essential in evaluating technological adoption. User perception of the usefulness of a given technological innovation is a crucial predictor of technological adoption. Specifically, user satisfaction, triability, compatibility, and observability can predict the level of technology acceptance and use. The initial phase of technological adoption requires users to have positive US, PTR, POB, and PCO. Technology users can confirm or disconfirm their views on a given technological innovation upon using it. Users can indicate that technology has a positive effect on them. In such cases, technological acceptance and use continue [37]. However, users can also suggest that technology is not useful. In such cases, there the adoption of technological innovation ends. Thus, users' favourable view of technology may indicate that the innovative technology has positive PTR, POB, and PCO. Technological adoption is faster when US is high. US takes two forms; cumulative and transaction-specific satisfaction. Users report transaction-specific when they have positive experiences or encounters with technological innovation. However, cumulative satisfaction arises when users report overall contentment with technological innovation. Thus, transaction-specific satisfaction is an antecedent to cumulative satisfaction [37], [40].

The PTR is closely linked to technological innovations adoption. Research shows that triability or dealing with technological innovations positively affects the adoption of technological innovations. Triability also encompasses users' effort when using technology and the risk involved in adopting technological innovations. The risk may involve recuperating adoption costs [42]. However, POB refers to how users consider technological innovation outstanding and extraordinary. The feedback provided by technology users can measure POB. Such feedback can influence technological adoption. PCO is the level at which users consider technology to be matching their standard, task, and needs [38], [41]–[43].

Greenhalgh *et al.* [44] define compatibility as how technology matches users' preferences. Thus, compatibility influences the adoption of technological innovations. Rogers [37] supports the assumption that technology is compatible when it matches users' preferences indicating that technology is compatible when users perceive it to fit recognisable practices and predictions. Existing research shows that PCO levels increase when technological innovation meets users' needs, experiences, and values [45]–[47]. The positive impact of PCO on technology adoption shows a positive association between PU and technological adoption. Many existing studies have assessed the effects of PTR, POB, and PCO on the adoption of technological innovation [48], [49]. These studies have shown that PTR, POB, and PCO significantly influence PU and PEOU [50].

Nevertheless, limited studies have shown the association between US and PTR, POB and PCO in using technology, particularly the MS. The present study aims to fill the research gaps by assessing the effect of PTR, POB, and PCO on US and the adoption of technological innovations, particularly MS. Thus, the following hypotheses are established:

H3: Perceived Observability (POB) would predict the Users' Satisfaction (US).

H4: Users' Compatibility (PCO) would predict the Users' Satisfaction (US).

H5: Perceived Traibility (PTR) would predict the Users' Satisfaction (US).

H6: Perceived Usefulness (PU) would predict Users' Intention to Use the Metaverse System (UMS).

H7: Perceived Ease of Use (PEOU) would predict Users' Intention to Use the Metaverse System (UMS).

H8: Users' Satisfaction (US) would predict Users' Intention to Use the Metaverse System (UMS).

C. THE CONCEPTUAL FRAMEWORK

The conceptual framework of the present study aims to assess the UMS by investigating two main aspects of UMS;

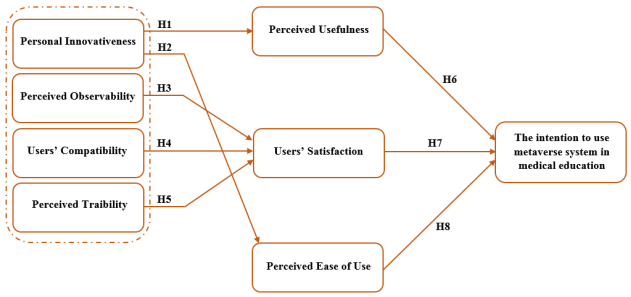

FIGURE 1. Research model.

US and PI. The two elements are joined by other predictors, including PTR, POB, PCO, PEOU, and PU. The US is assessed by PTR, POB, PCO, while PI is assessed using PEOU and PU, as shown in Fig.1. The theoretical model first takes the form of SEM and is then evaluated using the ML algorithm.

IV. RESEARCH METHODOLOGY

A. DATA COLLECTION

Data were collected through online questionnaires distributed to students studying in the universities within UAE. The questionnaire links were emailed to targeted learners to respond online. The questionnaires were also posted to the appropriate social media accounts in various UAE universities, such as WhatsApp and Facebook, to enhance the response rate. The data collection took place during the winter of 2021/2022. Specifically, the data collection took one month between January 15, 2022, and February 10, 2022. Target institutions granted the ethical clearance for the present study. Participation in the online survey was elective or non-compulsory. The department randomly distributed two thousand questionnaires. Respondents replied to 1858 online surveys out of the initial 2000 questionnaires distributed. The completed questions represent a response rate of 93%. Nevertheless, 142 online surveys were excluded from further analysis due to the absence of values. Thus, respondents completed only 1858 online surveys.

The present study only used students as respondents to the questionnaires because it considerably impacted them. University students would likely substitute less effective technology with more effective ones. Thus, it was necessary to use students to assess factors that influence their technological adoptions. Students can know about existing technological innovation from peers but may not implement the technology due to resource constraints.

The cumulative sample of 1858 constitutes a good sample size [51] since the estimated sample for a population consisting of 1500 is 306. The present study sample of 1858 significantly exceeded the Krejcie and Morgan 306 criteria. The sample size was also appropriate for the SEM model [52] used to test the hypothesis. The present study hypotheses were derived from existing theoretical models but were adjusted to fit the adoption of MS in learning settings. The measurement model was evaluated using the SEM and SmartPLS version 3.2.7. The path model was used for further evaluation of the model.

TABLE 1. Demographic statistics for 1858 respondents.

Criterion	Factor	Frequency	Percentage
Gender	Female	1015	55%
	Male	843	45%
Age	Between 18 to 29	919	49%
	Between 30 to 39	855	46%
	Between 40 to 49	51	3%
	Between 50 to 59	33	2%
Education qualification	Bachelor	1023	55%
	Master	682	37%
	Doctorate	153	8%

B. PERSONAL DEMOGRAPHIC INFORMATION

The respondent's personal statistics are shown in Table 1. As shown in Table 1, 55% of the respondents were males, while 45% were female. Table 1 also indicates that respondents aged 18 and 29 constituted 49% of the sample, while those above 29 comprised 51%. The education backgrounds were as follows; 55% of the respondents had bachelor's degrees, 37% had master's degrees, and 8% had doctoral degrees. The majority of the participants were undertaking their bachelor's degrees. The present study also employed purposive sampling in data collection. According to Emran and Salloum [53], purposive sampling is used when it is easy to access the respondents and the respondents are willing to be involved in the research. The respondents (students) were from various universities in UAE, had different ages, and were at different educational levels (see Table 1). However, they were easily accessible and were willing to participate in the present study. The IBM SPSS version 23 was used to measure the respondent demographics. Table 1 shows students' demographic statistics.

C. STUDY INSTRUMENT

The study employed a 21-item questionnaire to validate the research model and hypotheses because it evaluated the nine survey constructs. The sources of the nine constructs are shown in Table 2. The questions used in the present study questionnaires were derived from existing studies but were modified to fit the study objectives. Specifically, the adjustment was necessary to tailor the question based on the present study's needs and improve the generalisation of the study findings.

D. A PILOT STUDY OF THE QUESTIONNAIRE

The present study uses a pilot study to determine the reliability of the questionnaire. The pilot study involves approximately two-hundred participants from the desired population. The 200 participants represented 10 % of the sampled respondents. Cronbach's alpha (CA) test was employed to assess the pilot study findings. Specifically, the CA through SPSS was used to evaluate the study's internal reliability.

TABLE 2. Measurement items.

Constructs	Items	Definition	Instrument	Sources
Perceived Trialability	PTR1	Trialability " has to do with how easily users of technology can deal with innovation in technology" [54]–[56].	"I would like to try the MS before the actual classes".	[54]–[56]
	PTR2		"It take time to get used to MS".	
	PTR3		"I find the MS useful after my trail".	
Perceived Observability	POB1	Observability "is defined as how the technology can be described, seen, and imagined. It is considered a crucial factor in the adoption of technology in the educational environment" [54], [57].	"I think the MS can be used in my daily classes".	[54], [57]
	POB2		"I think the MS has a good value".	
	POB3		"My experience with the MS can be applicable to all educational settings".	
Perceived Compatibility	PCO1	Compatibility "is the extent to which innovation is considered as compatible with the end-users current beliefs, expectations, and requirements. Compatibility can affect people intention to adopt technology" [16].	"I think the MS is compatible with my studying purposes".	[16]
	PCO2		"I will use MS because it satisfies my expectations".	
	PCO3		"I believe that the MS will suit my culture".	
Personal Innovativeness	PI1	Personal innovativeness "is defined as the degree of willingness that users may have to accept technology. In other words, it refers to users' readiness to use and accept new technology. The concept of readiness is embedded within personal innovativeness as an external factor to measure users acceptance of technology" [58].	"I think I am will use MS in my study".	[58]
	PI2		"I believe that I am ready to deal with new technology such as the MS".	
User's Satisfaction	US1	Users' satisfaction "refers to the positive feeling that users develop due to the use of new technology. It stems from the fact that users' think that it suits his or her expectations and future usages" [59].	"I believe the MS has a great value in the educational setting".	[59]
	US2		"I believe the MS has many advantages in my daily lectures".	
	US3		"I think the MS is worth using".	
Perceived Ease of Use	PEOU1	It refers to" the degree the user thinks that the innovation is effortless" [60].	"I think the MS is effortless".	[60]
	PEOU2		"I think I can use the MS for different educational purpose because it is easy".	
	PEOU3		"I thin MS will be difficult to be used in certain circumstances".	
Perceived Usefulness	PU1	It refers to "the degree the user believes that the innovation has significant benefits" [60].	"I think the MS is useful for live lectures and forums".	[60]
	PU2		"I think the MS adds many advantages to my study".	
Users' Intention to Use the MS	UMS1	Intention to use technology" is defined as "users' preference to accept or reject technology by implementing certain techniques to ensure the continuous use of technology".	"I will definitely use the MS in my education.	[23], [61]
	UMS2		"I will use the MS to limited educational purposes".	

A CA coefficient of 0.70 is regarded as accepted [61]. The 0.7 criteria are based on patterns in social research. Table 7 shows constructs and their respective CA coefficient.

E. COMMON METHOD BIAS (CMB)

Harman's single-factor with the seven measurement scales [62] was used to test for CMB in the collected data. The test reveals that the newly created factor explained 29.43 % of the variation in the largest variance. However, 29.43 % falls below the 50 % limit. Thus, there were no CMB issues in the data.

F. SURVEY STRUCTURE

The survey presented to the respondents had three sections.

- Section 1: section one of the questionnaire survey covers the respondent demographic information
- Section 2: section two of the questionnaire focus on user intention to use MS (UMS)
- Section 3: section covers 19 items associated with PTR, POB, PCO PI, PEOU, PU, and the US

A five-point Likert Scale was used to assess the 21-item survey. The Likert Scale was a five-point scale starting from strongly disagree (1) to strongly agreed (5).

TABLE 3. Pilot study Cronbach's alpha coefficient.

Constructs	Cronbach's Alpha.
PTR	0.890
POB	0.813
PCO	0.815
PCM	0.888
PI	0.890
PEOU	0.749
PU	0.856
US	0.895
UMS	0.872

V. FINDINGS AND DISCUSSION

A. DATA ANALYSIS

Prior empirical research used ML algorithms through different methods such as neural networks, Bayesian networks [24], and decisions to determine the relationship in the research model. However, the present study uses Weka (ver. 3.8.3) to assess the research models based on various classifiers [25] such as OneR, BayesNet, J48, and Logistics. Also, unlike previous research that has employed a one-stage analysis of SEM, the present study uses the hybrid SEM-ANN method to validate the research hypotheses. The hybrid SEM-ANN model is a two-phase model. The first phases involve using PLS-SEM [22] to assess the research model. The approach is suitable because the theoretical model is exploratory, and there is no related literature [63]. The study also applies PLS-SEM in IS general guidelines. The analysis of the research models involved two approaches; structural model analysis and measurement model analysis [64]. The present study assesses the performance and importance of the variables in the study model using Importance Performance Map Analysis (IPMA) through SmartPLS. IPMA is an advanced PLS-SEM approach. The second phase is validating the PLS-SEM analysis using the deep ANN.

The deep ANN is also used to ascertain the efficacy of the predictor and predicted factors in the research model. Deep ANN is a suitable analysis tool for a non-linear and complex input and output association. ANN technique usually involves three critical approaches [64]; learning rule, transfer function, and network architecture. These three mechanisms are further split into the multilayer perceptron (MLP) network, radian basis, and recurrent network. The MLP is a widely used technique and consists of output and input layers linked via hidden nodes [27]. The input layer has predictors (neurons) which carry data to the hidden layers [65]. The data are transmitted in synaptic weight form. The selected activation function determines each hidden layer output [66]. The most widely used activation function is the sigmoidal function. Thus, the present study employs a neural network of MLP to assess the conceptual model.

B. CONVERGENT VALIDITY

Construct reliability (composite and constructs), [67] and validity (discriminate and convergent) should be considered to evaluate the measurement model. CA coefficient in Table 4 is used to assess the construct reliability of the measurement model [68]. As shown in Table 4, CA coefficients range from 0.719 to 0.918. These coefficients are significantly higher. The composite reliability coefficients in Table 4 also range between 0.770 and 0.966. These coefficients also considerably exceed the 0.7 thresholds [69]. Studies [70] can also use Dijkstra-Henseler's rho (pA) reliability coefficient to assess the construct reliability. The pA coefficient equals or exceeds 0.7 for exploratory studies [71] and 0.8 and 0.90 for advanced research phases [68]. Table 4 shows that pA for each measurement construct exceeds 0.70. Thus, the results in Table 4 confirm the presence of construct reliability.

The convergent validity of each measurement was assessed using factor loading and average variance extracted (AVE) [67]. The AVE value in Table 4 falls between 0.639 and 0.883. These values exceed 0.5 thresholds. The factor loading values exceed the 0.7 thresholds. These results also confirm the presence of convergent validity.

C. DISCRIMINANT VALIDITY

Heterotrait-Monotrait ratio (HTMT) and Fornell-Larker criterion [67] were used to assess discriminant validity. The Fornell-Larker condition is met since the AVEs values, and their square root exceeds its correlation with other variables (see Table 5) [72]. Also, the HTMT ratios are confirmed in Table 6 because the values exceed 0.85 thresholds [73]. Thus, the HTMT ratio and Fornell-Larker condition indicate a presence of discriminant validity. The measurement model assessment shows that there are no validity and reliability-related issues. Therefore, the SEM model is applicable in evaluating the collected data.

D. MODEL FIT

The model fit can be assessed using SmartPLS, with various fit measures. Based on Trial [74], the standard root means square residual (SRMR) is the first fit measure under SamrtPLS. Hair *et al.* [75] indicate that SRMR shows how the correlation of the observed model differs from the implied correlation matrix. In SRMR, coefficients that do not exceed 0.08 suggest that a model is a good fit [76]. The second fit measure under Smart PLS is NFI. The NFI is a ratio of the proposed model chi-square value and chi-square value of the benchmark model [77]. A model is regarded as a good fit when its NFI value exceeds 0.90 [78]. However, NFI is not a preferred measure of model fit because its value increases with parameter values [75]. The third measure of model fit under SmartPLS is RMS-theta. RMS-theta assesses the residuals correlation of the outer model. A PLS-SEM model is a good fit when its RMS-theta value nears zero. Specifically, theta values that do not exceed 0.12 indicate that a model is a good fit [79]. The other two measures of goodness of fit under SmartPLS are the geodesic distance (d_ULS) and squared Euclidian distance (d_G). These two approaches indicate the difference between the empirical and composite factor covariance matrices [70], [75]. A model is regarded as saturated if it assesses the correlation between all constructs, while a model

TABLE 4. Measuring the construct reliability and convergent validity.

Constructs	Items	Factor Loading	Cronbach's Alpha	CR	PA	AVE
Perceived Trialability	PTR1	0.904	0.867	0.924	0.910	0.725
	PTR2	0.873				
	PTR2	0.825				
Perceived Observability	POB1	0.800	0.826	0.826	0.825	0.741
	POB2	0.844				
	POB3	0.745				
Perceived Compatibility	PCO1	0.786	0.737	0.770	0.777	0.639
	PCO2	0.745				
	PCO3	0.825				
Personal Innovativeness	PI1	0.866	0.918	0.964	0.930	0.883
	PI2	0.773				
Perceived Ease of Use	PEOU1	0.786	0.916	0.966	0.951	0.845
	PEOU2	0.845				
	PEOU3	0.743				
Perceived Usefulness	PU1	0.793	0.834	0.929	0.914	0.828
	PU2	0.886				
User's Satisfaction	US1	0.752	0.793	0.910	0.909	0.829
	US2	0.811				
	US3	0.873				
Users' Intention to Use the MS	UMS1	0.819	0.719	0.774	0.775	0.732
	UMS2	0.886				

TABLE 5. Fornell-Larcker scale.

	PTR	POB	PCO	PI	PEOU	PU	US	UMS
PTR	**0.803**							
POB	0.269	**0.852**						
PCO	0.362	0.633	**0.802**					
PI	0.532	0.548	0.668	**0.806**				
PEOU	0.537	0.568	0.330	0.544	**0.807**			
PU	0.557	0.590	0.217	0.576	0.542	**0.857**		
US	0.629	0.565	0.607	0.643	0.648	0.629	**0.865**	
UMS	0.656	0.561	0.598	0.584	0.618	0.656	0.561	**0.898**

TABLE 6. Heterotrait-Monotrait ratio (HTMT).

	PTR	POB	PCO	PI	PEOU	PU	US	UMS
PTR								
POB	0.648							
PCO	0.460	0.730						
PI	0.791	0.716	0.576					
PEOU	0.566	0.500	0.743	0.565				
PU	0.362	0.497	0.584	0.561	0.598			
US	0.263	0.225	0.526	0.660	0.622	0.626		
UMS	0.213	0.2287	0.688	0.414	0.525	0.783	0.513	

is estimated when it considers the total effect and model structure [75]. The global PLS-SEM model fit threshold is 0.082. As per Table 8, the value of RMS_theta was equal to 0.052, which reveals the appropriateness of the goodness-of-fit for the PLS-SEM model to demonstrate the global PLS model validity. As shown in Table 7, the PLS-SEM model fits well because the RMS-theta of 0.085 is less than the 0.082 thresholds.

E. HYPOTHESES TESTING USING PLS-SEM

SEM with SmartPLS was employed to evaluate the interdependence of the structural model theoretical constructs [74], [75]. Specifically, SEM with SmartPLS was used to assess the study hypotheses. The model had high predictive power [41], with a % age of variance within PEOU, PU, UMS, and US,

TABLE 7. Model fit indicators.

	Complete Model	
	Saturated Model	Estimated Mod
SRMR	0.051	0.050
d_ULS	0.644	1.537
d_G	0.648	0.648
Chi-Square	448.401	448.401
NFI	0.884	0.884
Rms Theta		0.065

approximately 52%, 53%, 59%, and 61%, respectively (see Table 8 and Fig.2).

The p-values and *t*-values of the PLS-SEM model are shown in Table 9. The p-values are less than 0.01 and 0.05, indicating that the empirical data supported the research hypotheses. Specifically, the result shows that the empirical data support all the hypotheses from one to eight. The first and second hypotheses (H1and H2) were met because PI was significantly associated with PU and PEOU (see Table 9). The third, fourth, and fifth hypotheses were also supported because there was a significant relationship between POB and US, PCO and US, PTR and US (see Table 9). The empirical data supported the sixth, seventh, and eighth hypotheses because there was a statistically significant relationship between PU and UMS, PEOU and UMS, and US and UMS (see Table 9).

F. HYPOTHESES TESTING USING CLASSICAL ML

Various methods, including the Bayesian network, neural network, and decision tree, were employed under the ML algorithm to test the research hypotheses. These approaches were used to predict the association within the theoretical model [23]. Weka (ver. 3.8.3), based on such classifiers as J48, OneR, and BayesNet [24], [82], were used to test the predictive model (see Table 10). Based on Table 10, J48 reported the highest performance in assessing PU. It reported the highest performance because it predicted PU with 77.48% accuracy for ten-fold cross-validation. J48 also reported the highest improved performance as shown by .774 TP-squared rate, .795 recall, and .798 precision. These results (see Table 10) support the first hypothesis of the study (H1).

J48 also reported the highest performance in predicting PEOU. It predicted PEOU with an accuracy level of 69.93% (see Table 11). Thus, the result also supports the study's second hypothesis (H2).

The highest improved performance in predicting US using POB, PCO, and PTR attributes was also depicted in J48. It predicted US with an accuracy level of 79.35% (see Table 12). Thus, the third, fourth and fifth (H3, H4, and H5) hypotheses were also supported.

Table 13 shows that J48 and OneR had a better prediction of UMS using PU, PEOU, and US attributes than other classifiers. J48 and one R predicted UMS with 73.65% and 72.32% levels of accuracy. Therefore, the result supported the sixth, seventh and eighth (H6, H7, and H8) hypotheses.

TABLE 8. R^2 of the endogenous latent variables.

Constructs	R^2	Results
UMS	0.588	Moderate
PEOU	0.518	Moderate
PU	0.533	Moderate
US	0.610	Moderate

TABLE 9. Hypotheses-testing of the research model (significant at p** <= 0.01, p* < 0.05).

H	Relationship	Path	*t*-value	*p*-value	Direction	Decision
H1	PI -> PU	0.681	16.865	0.000	Positive	Supported**
H2	PI -> PEOU	0.579	14.389	0.000	Positive	Supported**
H3	POB -> US	0.383	5.586	0.018	Positive	Supported*
H4	PCO -> US	0.429	8.534	0.005	Positive	Supported**
H5	PTR -> US	0.291	5.865	0.003	Positive	Supported**
H6	PU -> UMS	0.447	14.420	0.000	Positive	Supported**
H7	PEOU -> UMS	0.856	9.233	0.000	Positive	Supported**
H8	US -> UMS	0.758	19.601	0.000	Positive	Supported**

G. HYPOTHESES TESTING USING DEEP ANN

The ANN analysis was carried out using SPSS and relied on PLS-SEM significant predictors. Thus, ANN analysis only considered PU, PCO, PEOU, POB, PTR, PI, and US predictors. Fig. 3, 4, 5, and 6 indicate that the deep ANN model comprises one output neuron and several input neurons [83]. The output neuron in the ANN model is the UMS in medical education, and the input neurons include PU, PCO, PEOU, POB, PTR, PI, and US. The deep learning for the output neuron node was established using a two-hidden layer ANN architecture. Still, the sigmoid function was used as an output and hidden neurons [84]. The study also standardised output and input range between 0 and 1 to enhance the proposed model performance. A ten-fold cross-validation was used in the study to avoid overfitting ANN models. Cross-validation was used in training and testing data in the ratio of 70 to 30 [65]. The root means square of error (RMSE) was also used to improve neural network model accuracy. The deep ANN model reported 0.1285 RSME for training and 0.1316 RMSE for testing (see Fig. 3, 4, 5, and 6). As per the. The standard deviation of 0.0038 for training and 0.0089 for testing data under RMSE shows that the models have high precision with deep ANN.

H. SENSITIVITY ANALYSIS

The average of each independent is used against the highest mean percentage value to calculate the normalised importance. Table 14 shows that the most vital predictor of behavioural intention is US. The PEOU and PCO come second and third as the most crucial predictors of behavioural intentions. The goodness of fit (similar to R-squared in PLS-SEM) was used to validate the performance and accuracy of deep ANN analysis [76]. The result shows that deep ANN reported higher predictive power (R2 = 92.4%) than PLS-SEM (R2 = 58.8%) and ML algorithm (R2 = 79.35%). The result shows that deep ANN is better in explaining the endogenous constructs than PLS-SEM and ML algorithms. Still, deep learning is superior to PLS-SEM and ML algorithms in predicting non-linear association between constructs.

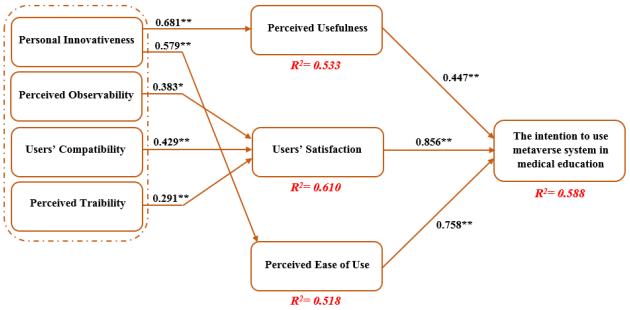

FIGURE 2. Path coefficient of the model (significant at p** < = 0.01, p* < 0.05).

TABLE 10. Impact of PI on PU.

Classifier	CCI[1] (%)	TP[2] Rate	FP[3] Rate	Precision	Recall	F-Measure
BayesNet	73.36	.733	.149	.745	.749	.744
Logistic	73.35	.732	.216	.755	.758	.753
LWL	67.28	.672	.200	.598	.600	.600
AdaBoostM1	71.20	.712	.299	.709	.721	.720
OneR	72.18	.721	.310	.715	.723	.722
J48	77.48	.774	.598	.777	.795	.798

[1]CCI: Correctly Classified Instances, [2]TP: True Positive, [3]FP: False Positive.

I. IMPORTANCE-PERFORMANCE MAP ANALYSIS

The present study employs IPMA, with the target variable being behavioural intention. IPMA is important because it enhances the understanding of PLS-SEM analysis [77]. In addition to testing importance measures or path coefficients, IPMA also tests the values of performance measures. The total effect under IPMA shows that importance measures influence behavioural intentions (target factors) while the average value of the latent construct represents their performance. Fig.7 shows the importance and performance of PU, PCO, PEOU, POB, PTR, PI, and US based on IPMA. Based on Fig.7, US reported the highest importance and performance values followed by PEOU. PTR reported the third-highest importance measure value and lowest performance measure value. PU reported the lowest importance measure value.

TABLE 11. Impact of PI on PEOU.

Classifier	CCI1 (%)	TP[2] Rate	FP[3] Rate	Precision	Recall	F-Measure
BayesNet	65.25	.653	.314	.659	.660	.663
Logistic	65.14	.651	.258	.655	.658	.659
LWL	64.18	.641	.331	.643	.644	.648
AdaBoostM1	63.35	.633	.348	.635	.636	.637
OneR	64.64	.646	.349	.647	.648	.649
J48	69.93	.700	.375	.701	.700	.703

TABLE 12. Impact of POB, PCO, and PTR on US.

Classifier	CCI1 (%)	TP[2] Rate	FP[3] Rate	Precision	Recall	F-Measure
BayesNet	70.30	.703	.558	.712	.720	.713
Logistic	72.37	.724	.322	.730	.729	.734
LWL	72.69	.727	.285	.715	.708	.716
AdaBoostM1	71.15	.711	.325	.734	.740	.735
OneR	71.31	.713	.326	.733	.735	.738
J48	79.35	.793	.758	.779	.777	.770

TABLE 13. Impact of PU, PEOU, and US on UMS.

Classifier	CCI1 (%)	TP[2] Rate	FP[3] Rate	Precision	Recall	F-Measure
BayesNet	71.36	.713	.329	.714	.715	.711
Logistic	73.35	.733	.360	.742	.734	.735
LWL	73.69	.735	.344	.745	.736	.734
AdaBoostM1	72.18	.722	.459	.732	.723	.724
OneR	72.32	.724	.485	.730	.725	.727
J48	73.65	.733	.658	.748	.738	.739

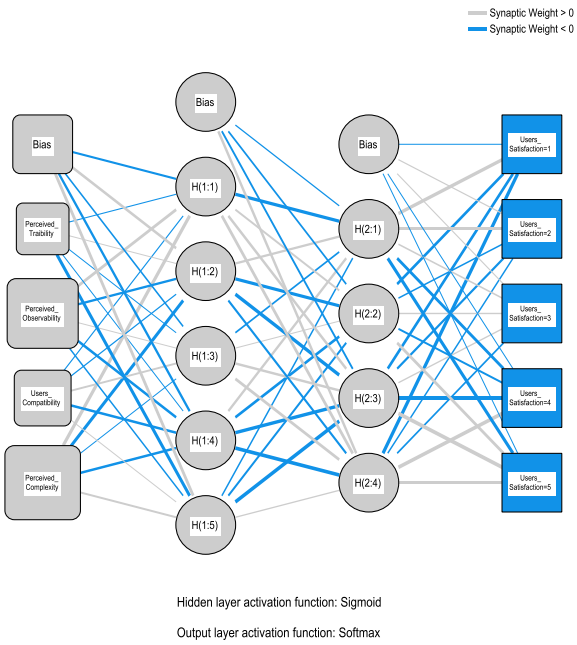

FIGURE 3. ANN model.

VI. DISCUSSION

The present study used a hybrid approach involving PLS-SEM, ML algorithm, and deep ANN to test the hypotheses. The result showed that deep ANN strongly supports UMS. The ANN model had higher predictive power than the ML algorithm and PLS-SEM. The study also found a significant correlation between PU and PEOU. The findings show that personal and technology-based characteristics influenced respondents' perception of MS. Higher PU and PEOU lead to higher MS adoption. The study focused on the adoption properties and established an association between the properties and US. Specifically, the study found that PTR, POB, and PCO properties increase MS adoption. Thus, enhancing these properties is necessary for improved MS students' adoption. The present study's finding supports prior findings showing that PTR, POB, and PCO positively impact the adoption of technological innovations. Thus, the current research has shown that students consider PTR, POB, and PCO significant MS adoption predictors. Prior research arrives at similar findings that PTR, POB, and PCO significantly influence student tests and choices in educational settings [15], [48], [78]. The study findings also reveal that students will prefer technological innovation when it meets their needs, matches their culture, and is deemed outstanding by other users [79]–[81]. Thus, students who view PTR, POB, and PCO as significant are likely to be highly satisfied with MS and have most likely to have a positive attitude toward its adoption.

As a personal based-feature, PI has a significant influence on MS adoption. Specifically, students who are highly willing to adopt technological innovation would likely positively perceive MS adoption. Thus, students who prefer technological innovation tend to view uncertainty positively. Such positive perception motivates them to adopt new technology such as MS. The present study results support existing findings that students' technological perception is directly linked to their PU. Youth, particularly students, would be motivated to adopt technological innovation due to its uniqueness [82], [83]. Students also consider PU to influence the intentions to adopt new technology. Accordingly, the level of student PU may vary depending on technological innovational features and uncertainty level [84]–[86]. Based on the present research findings, PEOU influences student acceptance and adoption of MS. The positive association between PU and PEOU suggests that students readily adopt new technological innovations if familiar with them and consider that using them requires less effort [87], [88]. The present research findings support the previous results that showed that PEOU and PU significantly influence the adoption of technological innovations [89]. However, the adoption of new technology can also be affected by the culture within a given community. Research [90] shows no association between innovation and adoption of technological innovation in some instances

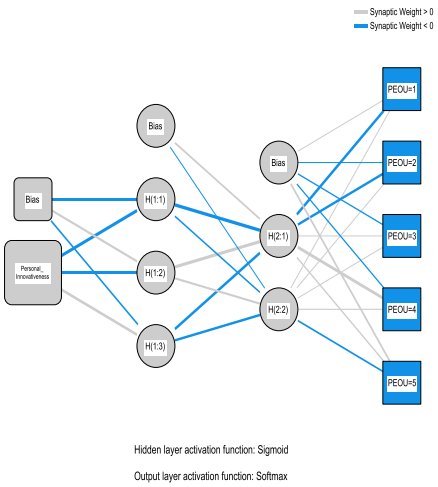

FIGURE 4. ANN model.

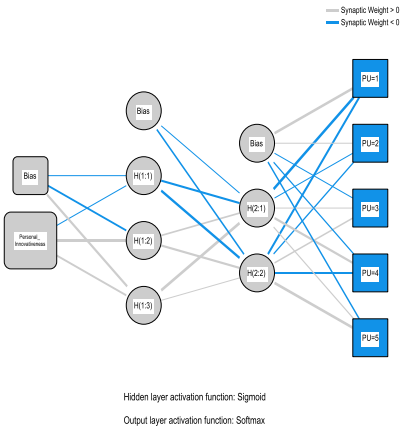

FIGURE 5. ANN model.

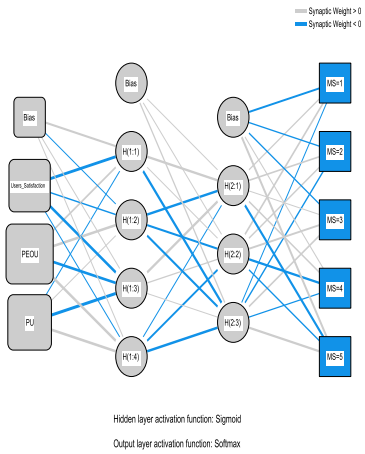

FIGURE 6. ANN model.

because of low-level value orientations, particularly collectivism. Thus, including the cultural aspects, previous findings tend to differ from the present research findings. For example, individuals living in the Gulf area tend to accept and adopt

TABLE 14. Independent variable importance.

	Importance	Normalized Importance
PTR	.156	22.4%
POB	.169	36.7%
PCO	.365	80.3%
PI	.223	52.6%
PEOU	.499	98.2%
PU	.294	55.5%
US	.558	99.6%

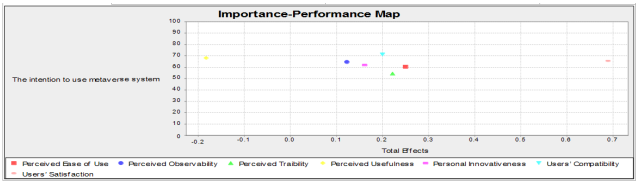

FIGURE 7. IPMA output.

new technological innovations because the culture prefers new technologies. Still, high adoption arises when innovative aspects of technological innovation are outstanding and valuable.

A. THEORETICAL AND PRACTICAL IMPLICATIONS

The present research used PLS-SEM and ML algorithms to test the research model. The hybrid method in the present study contributes to IS research because it is among the few studies to use ML algorithms to predict UMS. Research [63] has shown that PLS-SEM can predict dependent variables and validate the conceptual model. Similarly, Arpaci [24] indicates that ML can predict dependent variables based on predictor variables. The present study is also unique because it used various approaches with ML algorithms. These methodologies included neural networks, Bayesian networks, and decision trees. However, the decision tree or J48 had better performance than the other methodologies. As a non-parametric procedure, J48 was used to classify categorical and continuous variables. The classification was undertaken by dividing the sample into similar small samples based on significant predictors [24]. The PLS-SEM approach, a non-parametric approach, was used to assess the coefficients' significance. The ANN model had higher predictive power than the ML algorithm and PLS-SEM models. ANN's high predictive power can be attributed to the deep architecture that allows it to locate non-linear relationships between variables.

B. MANAGERIAL IMPLICATIONS

The present research findings have a significant impact on education. The study finds that PI (personal characteristics) significantly influence UMS. The study also found PEOU and PU (technology characteristics) to influence UMS among learners. Thus, teachers and technology developers should focus on personal and technology-based features that attract

students to MS. Such an approach can improve positive student perception and eagerness to adopt MS in learning. Future studies should focus on the impact of gender on the different student's views of MS use in education settings.

C. LIMITATIONS AND SUGGESTIONS FOR FUTURE STUDIES

The present research consists of various drawbacks despite its contribution to IS literature. The conceptual study model is limited because it is based only on PI and US. The present study also used only two TAM constructs; PEOU and PU. Even though the limit of two variables is vital in enhancing the measurement process, it failed to consider other constructs that could affect the model [36]. The distribution of the questionnaire through the internet could also result in a biased response [91]. The study findings may not be applicable in other settings since the focus was only on educational settings.

VII. CONCLUSION

The MS technology will continue to change the world in different spheres, from education to economics. Specifically, MS supported with other technologies will be vital in teaching and learning. The recent Facebook announcement that it is changing its name to Metaverse indicates a possible increase in technological innovation that will significantly change the world. The increased innovation and use of VR and AR in education settings will dramatically impact teaching and learning practices. Due to the impact of MS on teaching and learning, the present study intended to assess factors influencing students' adoption of MS in universities within the Gulf area. The study finds that PI closely influences the students' intentions to use MS. The PI was further affected by PEOU and PU. The study contributes to the existing literature on technological adoption by showing that adoption properties such as PTR, POB, and PCO influence technology adoption, particularly MS. These results are consistent with findings from existing studies.

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