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A conceptual framework for determining metaverse adoption in higher institutions of gulf area: An empirical study using hybrid SEM-ANN approach

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ABSTRACT

The metaverse is a kind of imagined world with immersive digital spaces that increase, allowing a more interactive environment in educational settings. The metaverse is an expansion of the synchronous communication that embraces an effective number of users to share different experiences. The study aims to investigate the students' perceptions towards metaverse system for educational purposes in the Gulf area. The conceptual model comprises the adoption properties, namely trialability, observability, compatibility, and complexity, users' satisfaction, personal innovativeness, and Technology Acceptance Model (TAM) constructs. The novelty of the paper lies in its conceptual model that correlates both personal-based characteristics and technology-based features. In addition, the novel approach of hybrid analysis will be used in the current study to perform deep-learning-based analysis of structural equation modelling (SEM) and artificial neural network (ANN). Moreover, the importance-performance map analysis (IPMA) is used in the current study to evaluate the involved factors for their importance and performance. The study identified Perceived Usefulness (PU) to be an essential predictor of the factor of Users' Intention to Use the Metaverse System (MS). The fact was discovered during ANN and IPMA analysis. Furthermore, this study is practically significant, as it helped the concerned authorities in educational sector in understanding the significance of each factor and allowed them to make efforts and plans according to the order of significance of factors. Another important implication of the study is methodological in nature. It validates that deep ANN architecture can offer deep insight into non-linear relationships shared by various factors of a theoretical model.

1. Introduction

Computer scientists and researchers intended to develop areas in virtual environments rapidly. The explosion of Internet and spread of social media applications provide cheap and ready access to hardware and software, to create better digital content that is represented by three-dimensional (3D) virtual environments (Collins, 2008; MacCallum & Parsons, 2019, pp. 21–28). The term metaverse was first used (Stephenson, 1992) in a science fiction novel to describe an immersive 3D virtual environment. The creation of metaverse facilitated day-to-day human communication and interaction over the Internet. Accordingly, metaverse can be defined as a world that has virtually enhanced physical reality and space. It is an infusion of real and physical universe that allows users to imagine multiple and myriad digital mirrors of the real world, both existent and non-existent, for a variety of purposes (Arcila, 2014; Collins, 2008; Díaz et al., 2020; Márquez, 2011).

Various universities and educational institutions conducted several studies with metaverse as their core. Researchers used metaverse in an educational environment, adopting a problem-based approach, where teachers and students can put forward the problem and find possible solutions in the imaginary world using 3D classes and avatar (Barry et al., 2009, p. 6066; Farjami et al., 2011; Kanematsu et al., 2012, 2013). Jeon and Jung (2021) agreed that metaverse platform is an essential tool for learners to increase their motivation and immersion. They can

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develop an interest for innovative learning styles and get self-directed learning experiences. Similarly, studies by Farjami et al. (2011); Han (2020), and Kanematsu et al. (2013) explored the importance of incorporating the metaverse system in invariant fields of study across the world, focusing on the development of real-life experiments where the metaverse system is used as a tool to solve the problem. Based on this, it is necessary to build a conceptual model that accounts for the influential role of metaverse system as seen from students' perspectives. The model also investigates the effectiveness of metaverse system by focusing on students' perception from a different perspective. The current study intends to build a model that reflects two crucial factors namely, students' satisfaction and personal innovativeness. The satisfaction element is accompanied by various factors including perceived trialability, observability, compatibility, and complexity. The higher the degree of perceived trialability, observability, compatibility, and complexity, the higher the satisfaction. Whereas, the lower the degree of perceived complexity, the higher the degree of satisfaction (Greenhalgh et al., 2004; Lee et al., 2011; Rogers, 2003, p. 551; Tobbin, 2010). The effectiveness of personal innovativeness is influenced by perceived ease of use and usefulness (Chang & Tung, 2008; Wu & Wang, 2005).

This study aims to investigate factors that influence the adoption of metaverse system in the Gulf area, determining the extent to which perceived usefulness and ease of use influence the adoption of metaverse system and impact personal innovativeness. The purpose is to establish a relation between users' level of satisfaction and adoption of metaverse system, focusing on attributes of perceived trialability, observability, compatibility, and complexity. The present study, hence, sought to fill this gap by developing a conceptual model that targets crucial elements of students' perceptions of metaverse system.

2. Literature review

2.1. Metaverse: scope and characteristics

The term metaverse was first used to fulfil fictional purposes where users appear as avatars or pseudonyms to imitate their interactions with other users in endless everyday situations. Metaverse is an immersive, 3D, virtual world where users, regardless of their location, engage in social and economic interactions, which are computational (Arcila, 2014; Díaz et al., 2020; Márquez, 2011; Vázquez-Cano & Sevillano--García, 2017). Metaverse has influential characteristics that set it apart from other tools in an educational environment including "Interactivity, Corporeity, and Persistence". Users can interact with each other through a virtual learning platform within the virtual world. The interactivity feature, which makes this world more dynamic, sets an innovative educational scenario of autonomous and collaborative learning, enabling access to all available resources. The metaverse system functions without the users having to move in the real world, and yet maintains a continuous connection with the virtual world with no time limitation. Similarly, the corporeity feature brings in the avatar, which is limitless in the virtual world, leading to a more realistically defined environment, as the shape of avatars is at par with or superior to 3D games. The persistence feature is crucial, as it helps save conversations, data, and objects even after the users depart from virtual world (Ando et al., 2013; Castronova, 2001; Díaz et al., 2020; Tarouco et al., 2013).

From an educational perspective, both the industry and business require an educated workplace that meets the new challenges in metaverse environment, which, in turn, requires new types of management and organisational leadership models (Ahmad et al., 2021). In addition, these environments explain and examine the human behaviour in an educational context to determine how it differs from behaviour in the real world (Salloum et al., 2021). Similarly, higher education institutions can take advantage of various techniques by providing a platform for faculty, staff, and students to communicate in a completely flexible environment where classrooms have no constraints instead of traditional classes. Students can communicate with professors in a digital environment with the click of a button. In this sense, the metaverse has the function of embracing a real university and institution by changing it to a virtual world where teachers, students, and learning models can interact in hybrid and collaborative classes (Ando et al., 2013; Tarouco et al., 2013).

Earlier research employed the methodology of single-stage linear data analysis (Sohaib et al., 2019), where Structural Equation Modeling (SEM) approach was used to perform single-stage analysis. The main drawback of this methodology was that it failed to detect non-linear relationships among model factors and only highlighted linear relations between them. Single-stage analysis with SEM failed to support advanced levels of decision-making (Sim et al., 2014). However, using two approaches simultaneously helps overcome this flaw: using SEM in the first stage of analysis, followed by Artificial Neural Network (ANN) approach in the second stage (Al-Emran et al., 2021; Khan & Ali, 2018; Leong et al., 2013). But, the commonly used ANN is shallow and merely comprises a single hidden layer (W. Huang & Stokes, 2016). The model accuracy can be increased, using deep ANN architecture that has several hidden layers for non-linear models in particular (Wang et al., 2017). Hence, this research applies deep learning-based ANN architecture while using hybrid SEM-ANN approach for better model accuracy. Moreover, TAM model, which served as the basic conceptual model in earlier works, has been replaced by a hybrid conceptual model in this study on the adoption of Metaverse system.

Metaverse system is closely related to the artificial intelligence technologies and collaborative learning systems that are used to enhance educational methodologies and learning styles. Recent studies have focused on various topics such as variations in students' attitudes in different countries all over the world, gender-differences. These studies focus on the blended –type of learning where the role of social media is crucial to assess the process of teaching. To successfully implement all these technologies, studies have shown that there is a need for extra tools that trace the development of learners' skills and performance, hence, they make use of eye-tracking techniques to assess how learners processed texts and graphics during the process of reading. The focus on virtual reality is an indicator that the metaverse system will have a remarkable effect in the near future. Virtual reality has been widely used by recent studies for educational purposes, describing its possible positive and negative effects (Chen et al., 2020, 2022).

2.2. Previous studies and metaverse system

The educational environment will be ineffective if learning objectives are not met (Al-Maroof, Alhumaid, et al., 2021). One way to achieve these expectations is to implement appropriate teaching approaches such as metaverse. In this sense, the problem of achieving learning goals can be solved with the lack of time and space limitation in the metaverse system. Accordingly, learning in the immersive metaverse becomes as concrete as in the physical world, and can be strongly accompanied by the problem-based approach. The problem-based approach is considered a powerful tool that leads to a successful learning environment where virtual rooms and avatars replace physical learning environments (Farjami et al., 2011; Han, 2020; Kanematsu et al., 2013).

Problem-based learning approach has been effectively used in education to achieve various learning objectives such as engineering, technology, and materials science (AlQudah et al., 2021). This approach is integrated in the metaverse environment where students face problems and have to provide solutions for them. The students are in a space where avatars do everything on their behalf, thus, the students need to apply their knowledge in the virtual situation. In the metaverse system, teachers face their students with ill-structured problems similar to the ones in real life. The students as avatars examine the problem to find suitable solutions. Their work is usually evaluated by an offline questionnaire or through student-teacher discussions to view the effectiveness of the given solution. Learning environments where teachers ask students to propose the problem require preparation. After a clear direction and full understanding, students can deal with the problem through chat-based discussions in the metaverse. The preparation stage may lead to a clear and precise understanding and an increased interest to solve the problem. Results show that the problem-based approach in the metaverse is affected by the students' readiness and comprehension of the metaverse system. The use of metaverse system in educational learning has proven to have fruitful results in different countries such as Malaysia, Japan, and Germany (Barry et al., 2009, p. 6066; Farjami et al., 2011; Kanematsu et al., 2012, 2013).

Previous research concentrated on the importance of metaverse system in an educational environment, focusing on enormous experiences. The importance of AR was the core intention of the study by MacCallum and Parsons (2019, pp. 21–28). The educators were asked to use AR in the classroom to create mobile AR experiences using the metaverse AR tool. The results showed that the teachers were interested in the content rather than the AR tool itself. This questions whether the role of AR as part of metaverse was well-presented to teachers and students to enable them to comprehend the importance of metaverse in their daily classrooms. Another study by Díaz et al. (2020) have investigated the implementation of a virtual or metaverse system in an educational environment, focusing on the flexibility of access to synchronous and asynchronous information. The study paves the way for real teaching experiences where students and teachers can communicate by using library resources, visiting a museum, holding a meeting, etc. They implemented a quasi-experiment research design for a group of students. The tool was a questionnaire that was distributed to investigate the degree of students' satisfaction with the virtual world. Though the research focused on developing pedagogical strategies through emerging technologies, the study was limited to the teaching of mathematics at the University of Cundinamarca. In this sense, other types of theoretically based courses may reflect variant students' perceptions. In fact, students' perceptions and degrees of satisfaction may differ among courses depending on the nature of the course.

The effectiveness of metaverse lies in its interactive features and personalised user experience. Therefore, researchers take advantage of these two factors in the teaching and learning environments (Gaafar, n. d.; Ng et al., 2021). Ng et al. (2021) proposed a case study of virtual education to address the problem of unified resources allocation scheme. The results show that virtual world can minimise the difficulty and cost, which leads to better understanding and solutions to the user's problem of uncertainty (Ng et al., 2021). Hence, the metaverse educational environment can provide varied benefits in different educational fields including aeroplane teaching and training, mathematics and engineering, and STEM education. Aircraft training and maintenance have massive opportunities for interaction with virtual aeroplanes that deliver a near-real experience metaverse, improving the educational and training opportunities, which enhances the interaction with virtual objects in mixed reality. On the other hand, STEM education implements metaverse by exploiting the connectivity, which increases the means to present applications more appropriately (Kabát, 2016; Kefalis & Drigas, 2019). The effectiveness of metaverse in different fields has led to a mutual conception that metaverse has a close relation with motivation. Both students' and teamers' motivation is affected positively when they experience metaverse platform. In fact, it is a highly preferred style of interaction that meets the expectations of both sides (Jeon & Jung, 2021).

The recent studies have highlighted the importance of context collaborative learning which can support the metaverse system shortly. The studies consider the importance of context-awareness in the field of technology and education which is a tool to improve learning outcomes. A study by Fu et al. (2019) examined how a productive learning atmosphere can be fruitful in a technology-based environment. The study has concluded that strategies of cooperation within a group of learners and competitions among groups of learners create a better learning environment and a higher level of knowledge-development (Chen et al., 2020, 2022; Fu et al., 2009).

3. Towards conceptual model and hypotheses

3.1. Users' satisfaction and perceived trialability, observability, compatibility, and complexity

These properties are used as a measurement tool to assess the adoption of innovational technology, prior to which, expectations are often formed regarding users' perceptions of an innovation's properties, which can impact their preference for the innovational technology adoption. The first stage in the adoption process itself implies that majority of these pre-adoption attributes are positive. Upon interaction with innovational technology, the positive expectations may either be confirmed or unconfirmed. When expectations are confirmed, it results in continued adoption of the innovation. And when unconfirmed, it may result in discontinuation of the adoption process (Parthasarathy & Forlani, 2010; Rogers, 2003, p. 551). The confirmation, hence, may lead to a high level of satisfaction and continuity in using technology, such that the higher the level of satisfaction, the quicker the adoption. Users' satisfaction can be categorised as transaction-specific and cumulative satisfaction. Transaction-specific or encounter satisfaction is the positive evaluation from experiencing technology. Whereas cumulative or interchangeable satisfaction is the positive evaluation that comes from overall satisfaction of the technology, with transaction-specific satisfaction proposed as an antecedent to overall satisfaction (Jones & Suh, 2000; Olsen & Johnson, 2003).

Perceived trialability is closely related to the intention to use technology. The term trialability has been addressed and confirmed by various studies as positively impacting the adoption of the system. Trialability refers to the ease of dealing with innovation. It embraces other concepts such as level of effort needed and risk involved in experimenting with innovational technology, including undoing and recovering of operations easily (Chin, 1998; Lee et al., 2011; Lee, 2007; Sonnenwald et al., 2001). Perceived observability refers to the level at which innovativeness of technology is seen as remarkable and noticeable by others. The feedback provided by the group of classmates and neighbours may affect the adoption of technology. The idea of visibility stimulates peer discussion among classmates and other users.

Perceived compatibility involves the learner's indication of technology being compatible with their background, standards, and previous involvements. In other words, compatibility refers to the learners' perspectives on the benefits they attain by adopting technology (Greenhalgh et al., 2004). define compatibility as the degree to which an innovational technology will be more readily adopted if it matches users' preferences. This assumption is in agreement with (Rogers (2003, p. 551) conception of compatibility as people's readiness to accept new innovational technology when it's compatible with their well-known practices and predictions.

Previous literature proves that if learners feel as though the technology is in line with their values, needs, and experiences, the level of compatibility tends to be high, which shows positive relation of technology on the perceived usefulness (Agarwal & Prasad, 1999; Gefen, 2004; Moore & Benbasat, 1991).

Complexity is used to indicate the degree of difficulty in understanding innovations of newly used technology. Considering this definition, the present study uses these terms to refer to the extent of learners' perceived difficulty, which may affect their learning performance. Previous studies have shown that when the end-users perceive technology as being complex, they show low intention to use the system. In fact, complexity has a negative impact on the use of technology (Hardgrave et al., 2003; Shih, 2007; Tobbin, 2010). Technology acceptance requires low complexity to enable users to use the technology with simplicity and user-friendly. The best way to encourage technology adoption is through simplicity. When innovational technology is perceived as difficult, people are less likely to adopt it. Interestingly, the features and characteristics of this innovational technology need to be easily accessible for the technology to be treated as simple and adopted rapidly (Greenhalgh et al., 2004; Rogers, 2003, p. 551).

Though several previous studies examined the effectiveness of perceived trialability, observability, compatibility, and complexity on enormous technology and applications, they examined these properties as having a significant impact on perceived enjoyment, perceived ease of use, and usefulness (Al-Rahmi et al., 2019; Chew et al., 2004; Hayes et al., 2015). However, this area lacks in research in terms of examining the relation between users' satisfaction and perceived trialability, observability, compatibility, and complexity to use the technology, particularly the metaverse system. This study intends to fill this gap by investigating the impact of these properties on the users' satisfaction and adoption. Accordingly, the following hypotheses are formed:

H1. The more positive users' trialability is, the higher the users' satisfaction.

H2. The more positive perceived observability is, the higher the users' satisfaction.

H3. The more positive perceived compatibility is, the higher the users' satisfaction.

H4. The more positive perceived complexity is, the lower the intention to use MS.

3.2. Personal innovativeness and TAM constructs

Innovation theory generally classifies users of technology as highly innovative individuals who are active seekers of innovational ideas. They are a specific type of user who copes with high levels of uncertainty and develops positive intentions towards acceptance. In this sense, personal innovativeness aims to develop positive beliefs on innovational technology. It is argued that the highest impact on an individual's cognitive interpretations of information technology relate to factors of personal innovativeness, which can be seen as an instance of risk-taking propensity that appears as a consequence of using new technology (Rogers, 2003, p. 551).

The technology acceptance model, TAM, shapes technological personal innovation, which is usually affected by the crucial and influential fronts in this model, perceived ease of use and perceived usefulness of technology (Davis, 1989). The former indicates the degree to which any user believes that a specific technology would enhance their performance for particular purposes. The latter concerns the degree to which a user believes that using a particular technology reduces effort. Studies by Chang and Tung (2008) and Wu and Wang (2005) confirm a significant relationship between behavioural intention and perceived usefulness and ease of use. Thus, the proposed conceptual model suggests that personal innovativeness has a significant impact on perceived usefulness and ease of use, which form the primary relevance for adoption of metaverse system (Gor, 2015; Lee et al., 2011). Accordingly, the following hypotheses are formed:

H5. The more positive personal innovativeness is, the higher the perceived ease of use.

H6. The more positive personal innovativeness is, the higher the perceived usefulness.

H7. The more positive users' satisfaction is, the higher the intention to use metaverse system.

H8. The more positive perceived ease of use is, the higher the intention to use metaverse system.

H9. The more positive perceived usefulness is, the higher the intention to use metaverse system.

3.3. The conceptual framework

The current study proposed a conceptual framework that measures the adoption of metaverse system, by examining two main attributes namely, users' satisfaction and personal innovativeness as coined with other independent variables of perceived trialability, observability, compatibility, and complexity on one hand, and perceived ease of use and usefulness on the other hand. In other words, the users' satisfaction is measured by perceived trialability, observability, compatibility, and complexity, whereas their personal innovation is measured by perceived ease of use and usefulness as illustrated below.

Table 1
Demographic data of the respondents.

Criterion	Factor	Frequency	Percentage
Gender	Female	520	60%
	Male	342	40%
Age	Between 18 and 29	416	48%
	Between 30 and 39	375	44%
	Between 40 and 49	46	5%
	Between 50 and 59	25	3%
Educational qualification	Bachelors	535	62%
	Masters	274	32%
	Doctorate	53	6%

4. Research methodology

4.1. Data collection

Data collection process was between October 10, 2021 and December 20, 2021. Participating students from the universities in the UAE, KSA, and Oman were provided with online surveys. Concerned universities granted ethical clearance to the research team. The aim of the research and survey link, which the research team shared on social media platforms including the universities' respective Facebook pages and Whatsapp groups as well, were shared with participants through an e-mail. Participation in the study was on voluntary basis. 1000 questionnaires were randomly distributed to students and the research team recorded a response rate of 86% (862/1000 were completed). Completed questionnaires were authorised to be included in the evaluation process and incomplete ones (138/1000) were excluded. Primary reasons for the inclusion of student population in the study are their relevance to study topic and due to them being the main end-users of technology. Students can request their teachers and institutional heads a replacement of a technology that isn't beneficial to their learning. At times, students are unfamiliar with the practical use of technology, as they only possess theoretical knowledge from different social media platforms.

Moreover, students can seek the help and support of teachers when they face difficulty to use technology, as teachers are proficient in technology use compared to students. Since 306 is assessed to be the appropriate sample size for a given population of 1500 students, 862 filled questionnaires were approved by Krejcie and Morgan (1970) as the suitable sample size for this study despite being quite higher than the required sample size. Hence, SEM can be applied to test hypotheses in this study, which has an apt sample size (Chuan & Penyelidikan, 2006). Although recognised theories were used as a basis for the proposed hypotheses, the hypotheses could be modified to become relevant to the domain of Internet of Things (IoT) when required. This research used SEM, SmartPLS Version (3.2.7), and the final path model to assess the measurement model.

4.2. Personal/demographic information

Table 1 records the demographic or personal data of participants collected for this study. Accordingly, 40% of respondents were males and 60% were females; 48% of respondents were students between the ages 18 and 29 and 52% were aged above 29. The data indicated a strong educational context of respondents, with majority of them holding

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" (Jon et al., 2001; Martins et al., 2004; Rogers, 1995).	I would like to try using MS before actual classes.	Jon et al. (2001); Martins et al. (2004); Rogers (1995)
	PTR2		It take time to get used to MS.	
	PTR3		I found 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" (Bennett & Bennett, 2003; Martins et al., 2004).	I think MS can be used in my daily classes.	Bennett and Bennett (2003); Martins et al. (2004)
	POB2		I think MS has a good value.	
	POB3		My experience with MS is 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" (Chang & Tung, 2008).	I think MS is compatible with my study purposes.	Chang and Tung (2008)
	PCO2		I will use MS, as it satisfies my expectations.	
	PCO3		I believe that MS will suit my culture.	
Perceived Complexity	PCM1	Complexity "is the degree to which the technology is difficult to understand or use" (Bennett & Bennett, 2003).	I think MS is very difficult to be used.	Bennett and Bennett (2003)
	PCM2		I believe it is hard to sue MS on a daily basis.	
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 user's acceptance of technology" (Agarwal & Prasad, 1998).	I think I am will use MS in my study.	Agarwal and Prasad (1998)
	PI2		I believe I am ready to deal with new technology such as the MS.	
Users' 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" (Simanjuntak & Purba, 2020).	I believe that MS has great value in educational settings.	Simanjuntak and Purba (2020)
	US2		I believe that MS has many advantages in my daily lectures.	
	US3		I think MS is worth using.	
Perceived Ease of Use	PEOU1	It refers to "the degree the user thinks that the innovation is effortless" (Doll et al., 1998).	I think MS is effortless.	Doll et al. (1998)
	PEOU2		I think I can use MS for different educational purposes since it's easy.	
	PEOU3		I think MS will be difficult to use in certain circumstances.	
Perceived Usefulness	PU1	It refers to "the degree the user believes that the innovation has significant benefits" (Doll et al., 1998).	I think MS is useful for live lectures and forums.	Doll et al. (1998)
	PU2		I think MS adds many advantages to my study.	
Users' Intention to use 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 MW in my education.	Barclay et al. (1995); Teo et al. (2008)
	UMS2		I will use MW for limited educational purposes.	

important qualifications and university degrees. 62% of respondents had completed their bachelor's program, 32% had completed their master's program, and 6% had received doctoral degree. In line with Al-Emran and Salloum (2017), this study applied "purposive sampling approach" due to the voluntary participation of study respondents. The sample of the study was rich in diversity, as it included students from several colleges; moreover, the ages of respondents were diversified with diverse degrees and programs being pursued by them. IBM SPSS Statistics 23 was used to analyse the demographic data recorded in Table 1.

4.3. Study instrument

A survey consisting of 23+ items was used as an instrument for hypothesis validation. It helped evaluate the 9 constructs included in the questionnaire, the sources of which are accounted for in Table 2. The questions used in previous studies were modified and tailored to the needs of this study to enhance result applicability.

4.4. Pilot study of questionnaire

This study performed a pilot study to check for adequate reliability of questionnaire items. The pilot study participants were chosen at random from the given population of 500 students. Since the total population for this analysis is 500, applying a sample size of 10% (according to research standards) gives 50; thus 50 students took part in the pilot study. The next phase of pilot study employed SPSS software to perform Cronbach's alpha test to check for internal reliability of measurement items; the outcomes indicated a reliability coefficient of 0.70, which is an acceptable value since this study belongs to the domain of social science (Nunnally & Bernstein, 1978). Table 3 depicts the values of Cronbach's alpha calculated for 7 measurement scales.

Table 3
Cronbach's alpha values for pilot study (Cronbach's Alpha $\geq$0.70).

Constructs	Cronbach's Alpha
PTR	0.830
POB	0.859
PCO	0.794
PCM	0.865
PI	0.798
PEOU	0.799
PU	0.775
US	0.870
UMS	0.772

Table 4
Convergent validity results with acceptable values (Factor loading, CA, and CR ≥ 0.70 & AVE >0.5).

Constructs	Items	Factor Loading	Cronbach's Alpha	CR	pA	AVE
Perceived Trialability	PTR1	0.770	0.856	0.912	0.873	0.776
	PTR2	0.772				
	PTR2	0.922				
Perceived Observability	POB1	0.891	0.815	0.890	0.821	0.730
	POB2	0.755				
	POB3	0.774				
Perceived Compatibility	PCO1	0.883	0.725	0.769	0.776	0.628
	PCO2	0.762				
	PCO3	0.745				
Perceived Complexity	PCM1	0.883	0.746	0.784	0.724	0.550
	PCM2	0.910				
Personal Innovativeness	PI1	0.900	0.926	0.953	0.927	0.872
	PI2	0.856				
Perceived Ease of Use	PEOU1	0.891	0.905	0.955	0.906	0.914
	PEOU2	0.788				
	PEOU3	0.926				
Perceived Usefulness	PU1	0.852	0.822	0.918	0.823	0.849
	PU2	0.922				
Users' Satisfaction	US1	0.775	0.782	0.900	0.831	0.818
	US2	0.833				
	US3	0.749				
Users' Intention to Use MS	UMS1	0.795	0.708	0.763	0.799	0.721
	UMS2	0.721				

4.5. Common method Bias (CMB)

The study conducted a Harman's single-factor test on 7 factors to check the collected data for presence of CMB (Podsakoff et al., 2003). Following which, 10 factors were used to load multiple factors into a single one. As revealed in analysis, the highest value of variance represented by the designed factor is 25.49% while the threshold value of variance is at least 50% (Podsakoff et al., 2003), which indicates that the collected data is appropriately free of CMB.

4.6. Survey structure

The questionnaire survey, which was handed out to the participating students, is based on the following 3 sections (Al-Emran & Salloum, 2017):

- The first contained questions regarding participants' personal data.
- The second contained two items to inquire Users' Intention to Use MS.
- The third was based on 21 items related to "Perceived Trialability, Perceived Observability, Perceived Compatibility, Personal Innovativeness, Perceived Ease of Use, Perceived Usefulness, and Users' Satisfaction".
  After filling the questionnaires, they (23 items) were assessed using a five-point Likert Scale, which evaluated the questionnaires on the basis of 5 points of strongly disagree (1), disagree (2), neutral (3), agree (4), and strongly agreed (5).

5. Findings and discussion

5.1. Data analysis

This research is superior to previous empirical research, as it applies 2 stages of analysis instead of single-stage SEM analysis. The 2-step deep-learning-based technique of hybrid SEM-ANN is applied to test the relationships among theoretical model factors and validation of research hypotheses. In the first stage, partial least squares structural equation modelling (PLS-SEM) is applied with the help of SmartPLS to test the proposed research model (MOUZAEK et al., 2021; Ringle et al., 2015). PLS-SEM is appropriate for the exploratory theoretical model of this research, which lacks relevant literature (Makki et al., 2020). The use of PLS-SEM in this study is guided by general guidelines specified for applying PLS-SEM to research studies relevant to information systems (Al-Emran et al., 2018). Hence, the research model for this study was analysed in a couple of steps (involving the analysis of measurement model and structural model) as emphasised in the recommendations of the research by Simpson (1990).

PLS-SEM offers a novel technique: importance-performance map analysis (IPMA). The main aim of this technique is to assess research model constructs to evaluate their importance and performance. Moreover, PLS-SEM analysis is supported, assessed, and validated by applying ANN with IPMA. ANN assesses the dependent and independent variables, and it works best for investigating non-linear or complex relationships among input and output constructs. It serves as a function approximation instrument. Important ANN mechanisms include network design, learning rule, and transfer function (Simpson, 1990), subsequently categorised as radian basis, feed-forward multilayer perceptron (MLP) network, and recurrent network (Sim et al., 2014). The ANN technique of MLP neural network is preferred by ANN users around the world. MLP is designed with multiple input and output layers with hidden nodes in between for interlinking. MLP has a number of neurons or independent variables on the input layer that act as receptors of raw data. This data is moved as synaptic weights to hidden layers, yielding an output depending on the activation function used. The activation function of sigmoidal function is extensively used (Asadi et al., 2019; Sharma & Sharma, 2019). In short, MLP neural network has been applied to the research model as an ANN technique for its training and testing.

5.2. Convergent validity

As suggested by Hair et al. (2017), construct reliability (including composite reliability (CR), Dijkstra-Henseler's rho (pA), and Cronbach's alpha (CA)) and validity (including convergent and discriminant validity) are good tools to evaluate the measurement model. As listed in Table 4, the Cronbach's alpha (CA) values for construct reliability range between 0.708 and 0.926, which are greater than the threshold value of 0.7 (Nunnally & Bernstein, 1994). Further, Table 4 indicates composite reliability (CR) to show values ranging between 0.763 and 0.955, which is also higher than the threshold value of 0.7 (Kline, 2015). As an alternative, investigators need to use Dijkstra-Henseler's rho (ρA) reliability coefficient to assess construct reliability (Dijkstra & Henseler,

Table 5
Fornell-larcker scale.

	PTR	POB	PCO	PCM	PI	PEOU	PU	US	UMS
PTR	**0.881**								
POB	0.440	**0.855**							
PCO	0.555	0.663	**0.793**						
PCM	0.444	0.425	0.488	**0.742**					
PI	0.454	0.480	0.669	0.513	**0.934**				
PEOU	0.299	0.506	0.520	0.179	0.585	**0.956**			
PU	0.370	0.676	0.624	0.640	0.723	0.560	**0.921**		
US	0.455	0.571	0.634	0.415	0.669	0.526	0.677	**0.904**	
UMS	0.555	0.570	0.637	0.634	0.672	0.672	0.560	0.440	**0.949**

Table 6
Heterotrait-monotrait ratio (HTMT).

	PTR	POB	PCO	PCM	PI	PEOU	PU	US	UMS
PTR									
POB	0.512								
PCO	0.268	0.080							
PCM	0.690	0.503	0.587						
PI	0.502	0.589	0.004	0.209					
PEOU	0.332	0.778	0.783	0.639	0.120				
PU	0.429	0.711	0.654	0.529	0.778	0.539			
US	0.554	0.525	0.449	0.554	0.783	0.356	0.433		
UMS	0.369	0.580	0.658	0.369	0.639	0.679	0.770	0.762	

2015). Like CA and CR, reliability coefficient ρA need to have values greater than or equal to 0.70 in exploratory investigations, and values greater than 0.8 or 0.9 for advanced stages of studies (Hair et al., 2011; Henseler et al., 2009; Nunnally & Bernstein, 1994). The table clearly indicates a reliability coefficient ρA with values higher than 0.70 for all individual measurement constructs. These findings substantiate construct reliability. In the final assessment, the constructs were assumed to be error-free in an acceptable way.

For measuring convergent validity, tests for average variance extracted (AVE) and factor loading are conducted (Hair et al., 2017). Based on the results in Table 4, values of all factor loadings were greater than the recommended value of 0.7. Furthermore, the results in Table 1 indicate generated AVE values to be greater than the threshold value of '0.5', as they ranged between 0.550 and 0.914. Considering these findings, it is possible to attain convergent validity for all constructs.

5.3. Discriminant validity

For measuring discriminant validity, Fornell-Larker criterion and Heterotrait-Monotrait ratio (HTMT) were measured (Hair et al., 2017). The results in Table 5 indicate that values of AVEs and their square roots are higher compared to their correlations with other constructs, confirming an alignment of the requirements with the Fornell-Larker condition (Fornell & Larcker, 1981).

Table 6 presents the findings of HTMT ratio. As shown, all constructs had a value lower than that of the threshold value, 0.85 (Henseler et al., 2015), which indicates conformity with HTMT ratio. Based on the findings, discriminant validity is established. No problems linked to validity and reliability surfaced in the analysis findings of assessment of the measurement model. Hence, the collected data can be used to assess and analyse the structural model.

5.4. Model fit

The use of SmartPLS in this study involves various fit measures including exact fit criteria, standard root mean square residual (SRMR), NFI, RMS_theta, d_G, d_ULS, and Chi^2, which show the PLS-SEM model fit (Trial, n.d.). SRMR is the fit measure that shows the disparity between observed correlations and correlation matrix concluded from the model (Hair et al., 2016). While a good model fit measure requires SRMR values lower than 0.08 (Hu & Bentler, 1998), it requires NFI values higher than 0.90 (Bentler & Bonett, 1980). Value of NFI is obtained from the ratio between Chi^2 values of the proposed and null model (or benchmark model) (Lohmöller, 1989). However, NFI fails to efficiently determine the fitness of the model in every instance, as it changes with dimensions of parameters (Hair et al., 2016). The significance of squared Eucledian distance, d_ULS, and geodesic distance, d_G, cannot be denied, as these fit measures indicate the difference between two covariance matrices (empirical covariance matrix and a matrix inferred from composite factor model) (Dijkstra & Henseler, 2015; Hair et al., 2016). The fit measure of RMS_theta is used to evaluate the degree of outer model residuals correlation, and can be applied only for reflective models (Lohmöller, 1989). The PLS-SEM model is considered more competent as the value of RMS_theta approaches zero; specifically, values below 0.12 indicate a good fit of the model (Henseler et al., 2014). Hair et al. (2016) emphasised that unlike the estimated model, which focuses on model structure and overall factor effects, the saturated model focuses on how each construct correlates to other constructs in the model.

Table 7
Model fit indicators.

	Complete Model	
	Saturated Model	Estimated Model
SRMR	0.049	0.049
d_ULS	0.753	1.426
d_G	0.537	0.537
Chi-Square	423.289	432.728
NFI	0.773	0.773
Rms_Theta	0.063	

The calculated value of RMS_theta was 0.063, which indicates adequate goodness-of-fit for PLS-SEM model; thus, confirming global PLS model validity. The value has been tabulated in Table 7 (see Fig. 1).

5.5. Hypotheses testing using PLS-SEM

To assess interdependence of the different theoretical constructs of the structural model, the structural equation model was used with Smart PLS (Al-Maroof, Alhumaid, et al., 2021), with maximum likelihood

Table 8
R^2 of the endogenous latent variables.

Constructs	R^2	Results
Users' Intention to Use MS	0.572	Moderate
Perceived Ease of Use	0.492	Moderate
Perceived Usefulness	0.524	Moderate
Users' Satisfaction	0.483	Moderate

estimation (Al-Emran et al., 2020; Salloum et al., 2019). The proposed hypotheses were evaluated through these tools. The model was reported to have a high predictive power (Chin, 1998), the percentage of variance within being 48% for Users' Satisfaction, 49% for Perceived Ease of Use, 52% for Perceived Usefulness, and 57% for Users' Intention to Use MS. These results are shown in Table 8 and Fig. 2 as well.

The estimations and findings were made, employing PLS-SEM technique, which led to the establishment of hypotheses. The beta (β) values, *t*-values, and *p*-values of these hypotheses are provided in Table 9. Undoubtedly, all these hypotheses were supported by all the researchers. Data analysis shows that the empirical data supported hypotheses H1, H2, H3, H4, H5, H6, H7, H8, and H9. The relationships between Users' Satisfaction (US) and Perceived Trialability (PTR) ($\beta = 0.244$, $P < 0.05$), Perceived Observability (POB) ($\beta = 0.378$, $P < 0.05$), Perceived Compatibility (PCO) ($\beta = 0.246$, $P < 0.05$), and Perceived Complexity (PCM) ($\beta = 0.498$, $P < 0.05$) support hypotheses H1, H2, H3, and H4. The relationships between Personal Innovativeness (PI) and Perceived Ease of Use (PEOU) ($\beta = 0.661$, $P < 0.001$) and Perceived Usefulness (PU) ($\beta = 0.559$, $P < 0.001$) were statistically significant, thus, supporting hypotheses H5 and H6. Finally, the relationships between Users' Intention to Use MS (UMS) and Users' Satisfaction (US) ($\beta = 0.640$, $P < 0.001$), Perceived Ease of Use (PEOU) ($\beta = 0.760$, $P < 0.001$), and Perceived Usefulness (PU) ($\beta = 0.292$, $P < 0.001$) support hypotheses H7, H8, and H9.

5.6. ANN results

The research involves the use of SPSS to conduct ANN analysis (Alhashmi et al., 2019), using only the predictors obtained from PLS-SEM (Alshurideh et al., 2020), i.e., the analysis only accounts for factors of PTR, POB, PCO, PCM, PI, PEOU, PU, and US. The structure of

Table 9
Hypotheses-testing of research model (significant at $p^{**} <= 0.01$, $p^{*} < 0.05$).

H	Relationship	Path	*t*-value	*p*-value	Direction	Decision
H1	PTR -> US	0.244	3.329	0.025	Positive	Supported*
H2	POB -> US	0.378	3.120	0.036	Positive	Supported*
H3	PCO -> US	0.246	2.783	0.042	Positive	Supported*
H4	PCM -> US	0.498	3.246	0.032	Positive	Supported*
H5	PI -> PEOU	0.661	13.864	0.000	Positive	Supported**
H6	PI -> PU	0.559	15.696	0.000	Positive	Supported**
H7	US -> UMS	0.640	9.529	0.000	Positive	Supported**
H8	PEOU -> UMS	0.760	17.041	0.000	Positive	Supported**
H9	PU -> UMS	0.292	10.163	0.002	Positive	Supported**

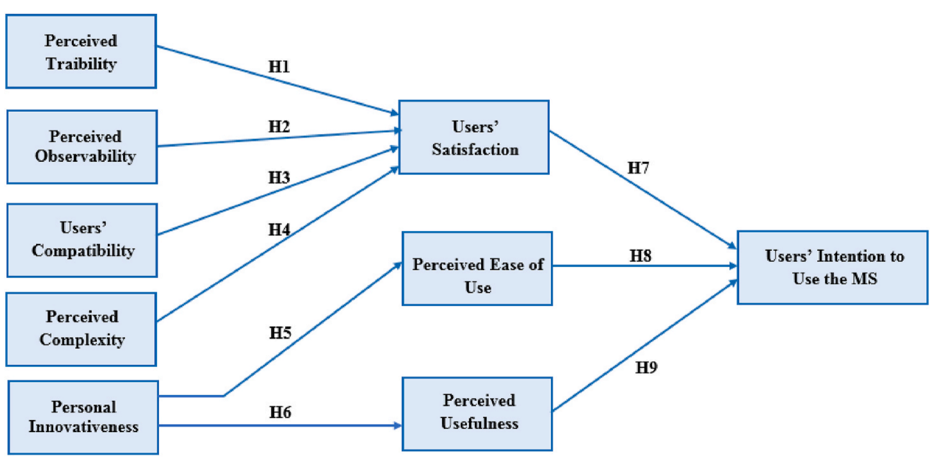

Fig. 1. Research model.

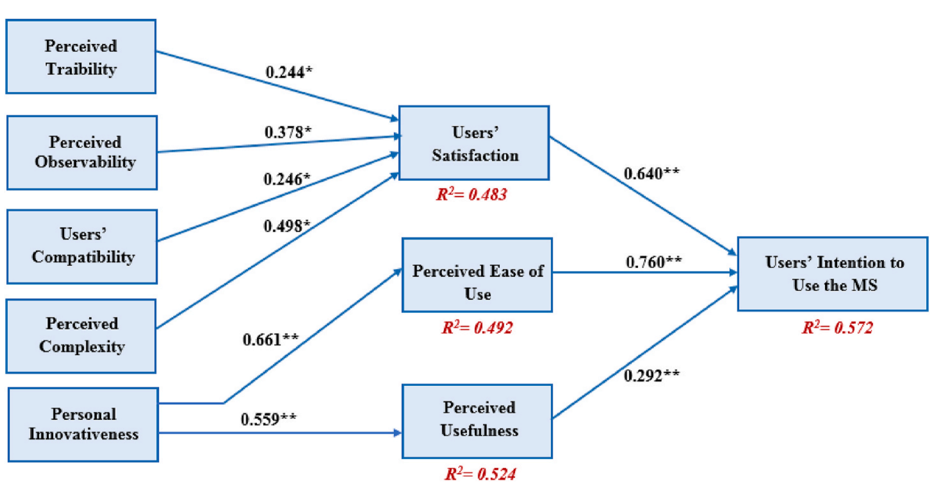

Fig. 2. Path coefficient of the model (significant at $p^{**} <= 0.01$, $p^{*} < 0.05$).

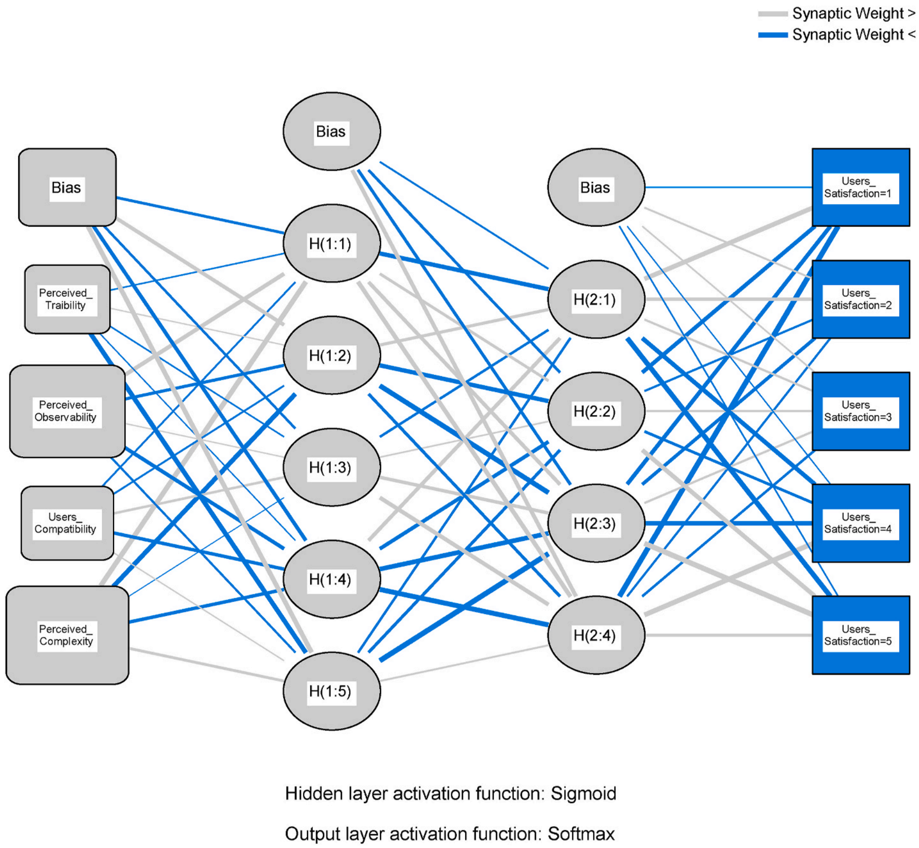

Fig. 3. ANN model.

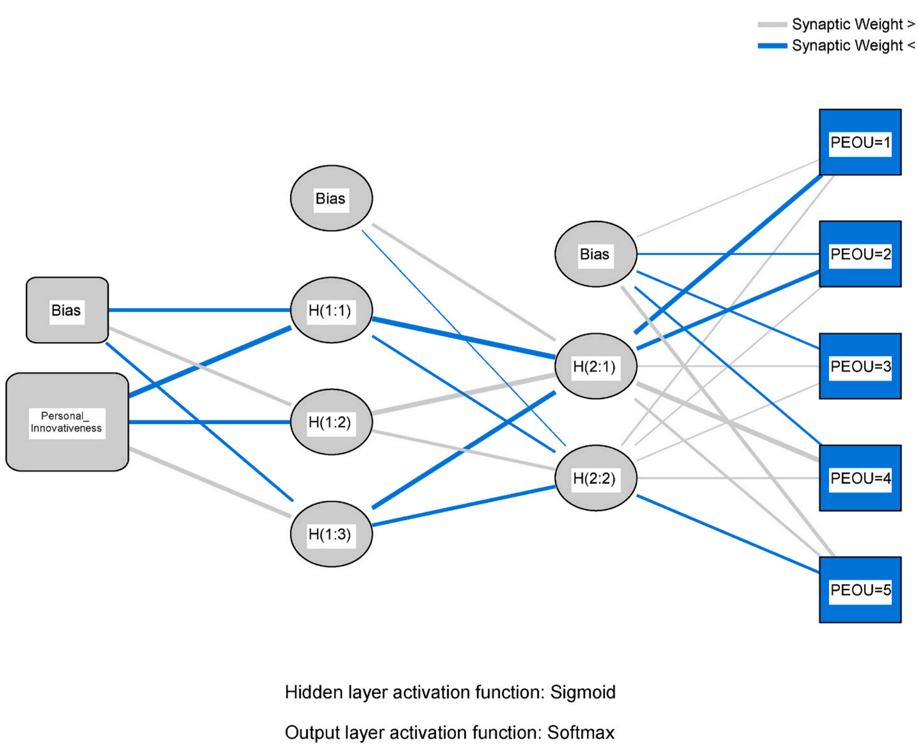

Fig. 4. ANN model.

the ANN model is given in Figs. 3–6; a single output neuron (users' intention to use MS), along with multiple input neurons (PTR, POB, PCO, PCM, PI, PEOU, PU, and US) constitute the ANN model. To facilitate deep-learning in every node of output neuron, a deep ANN structure with two-hidden layers was used in this study (Lee et al., 2020). The sigmoid function was also applied to hidden and output

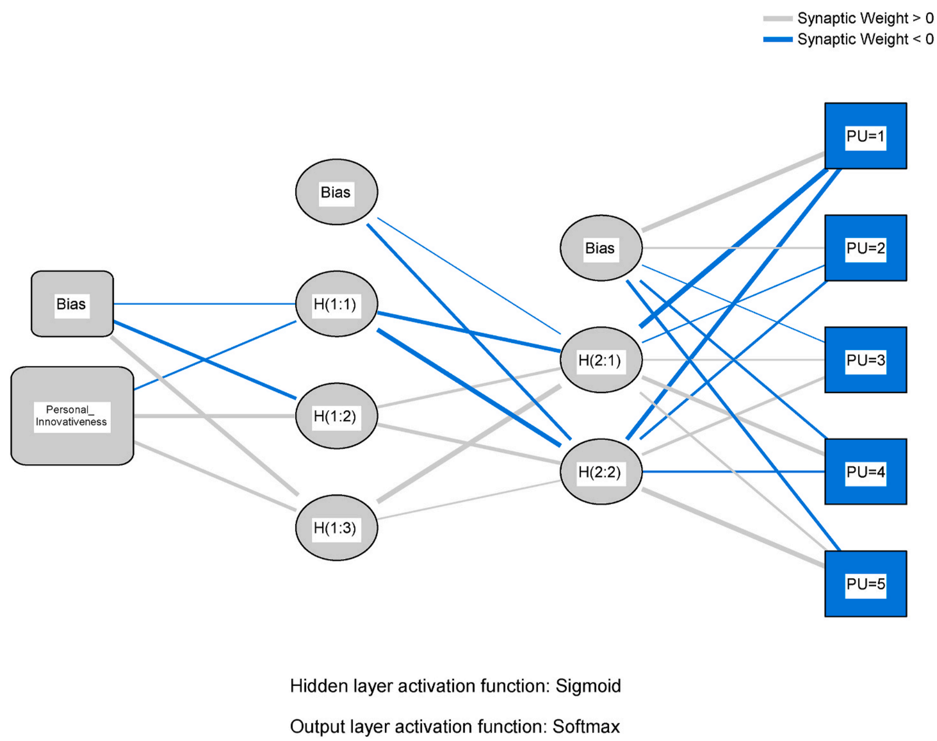

Fig. 5. ANN model.

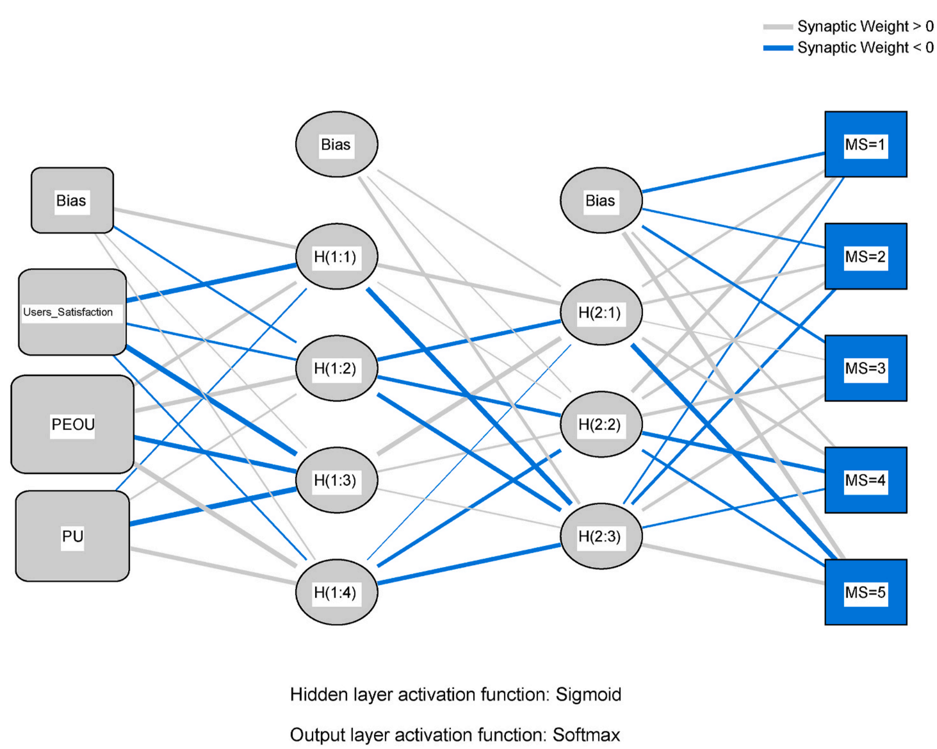

Fig. 6. ANN model.

neurons as an activation function. Additionally, the research model was made more proficient in terms of performance by standardising the input and output neurons in the range [0, 1] (Liébana-Cabanillas et al., 2018). The training and testing data were taken in the ratio 80:20 while applying the ten-fold cross-validation technique to prevent ANN models from over-fitting (Sharma & Sharma, 2019). The root mean square of error (RMSE) is evaluated to determine the accuracy of the neural network model. The RMSEs evaluated for training data was 0.1332 and for testing data was 0.1419. The ANN enhanced the accuracy of proposed research model as is evident from the insignificant disparity between values of SD (standard deviation) and RMSE evaluated for training data (equaling to 0.0053) and testing data (equaling to 0.0089).

Table 10
Independent variable importance.

	Importance	Normalised Importance
PTR	0.113	18.3%
POB	0.125	25.9%
PCO	0.353	79.4%
PCM	0.324	85.2%
PI	0.219	49.7%
PEOU	0.479	95.1%
PU	0.524	100.0%
US	0.303	51.5%

5.7. Sensitivity analysis

Normalised importance is evaluated for each predictor by obtaining the ratio between its average importance value and maximum mean value of importance, and is represented in percentage form (Alhumaid et al., 2021; Almarzouqi et al., 2022; Elnagar et al., 2021). Each predictor involved in ANN modelling was evaluated for mean importance value and normalised importance value. The resultant values were recorded in Table 10. Further, the sensitivity analysis outcomes stated in Table 10 suggest the order of significance of the three factors from among PTR, POB, PCO, PCM, PI, PEOU, PU, and US that predict users' intention to use MS. Accordingly, PU leads other factors. Another fit measure named goodness-of-fit is used to evaluate the ANN application and reinforce its accuracy and performance, which is already validated by other fit measures. Goodness-of-fit measure renders the same function in ANN application as R^2 in PLS-SEM analysis (Leong et al., 2019). However, ANN analysis offers better explanation of endogenous constructs, as its attributed with greater predictive power (R^2 = 89%) compared to PLS-SEM (R^2 = 57.2%). Additionally, since deep-learning ANN technique better explains the non-linear relationships between model constructs, there is some disparity in the values of variances.

5.8. Importance-performance map analysis

PLS-SEM offers the novel IPMA technique. In this research, behavioural intention served as the target variable during IPMA execution. According to Ringle and Sarstedt (2016), IPMA accounts the performance of each construct, providing a better understanding of the results obtained from PLS-SEM. IPMA not only helps estimate path coefficients or importance measures, but also helps analyse the average of latent constructs and associated performance measures or indicators (Ringle & Sarstedt, 2016). IPMA technique is based on the concept that a particular factor's framing impact on the target factor (behavioural intention in this case) and its significance is represented by the total effects, where factor performance is evaluated using the average of latent constructs. Fig. 7 shows the results from applying IPMA. PTR, POB, PCO, PCM, PI, PEOU, PU, and US are the 8 factors tested for importance and performance, and the performance of PU was found to be most superior. The performance of US was least impressive amongst PU and POB; but it was third with respect to importance. Similarly, PTR scored the least importance measure.

6. Discussion of results

The study adopted a hybrid model that attempts to produce results by applying two different methodologies namely, PLSM and ANN analyses. The significant results of the analyses revealed that the variable, 'users' intention to use metaverse system,' is strongly supported based on the PLSM methodology. The current results have been assisted by ANN analysis. It provides a better explanation for the predictive power indicating R^2 = 0.89% compared to PLSM, whose value is R^2 = 0.57%. The detailed results revealed an active and positive correlation between perceived usefulness (R^2 = 0.52%) and perceived ease of use (R^2 = 0.49%). This means that students were profoundly affected by personal-based characteristics and technology-based features. The result suggests that students with a higher acceptance of uncertain situations and innovational technology have a higher level of metaverse system adoption.

The current study focused on adoption-based properties and created a relation between these properties and users' satisfaction. The properties of trialability, observability, compatibility, and complexity heavily impact adoption of metaverse system. Therefore, these properties need to be emphasised and sustained to guarantee an increase in metaverse adoption by students. The current results agree with previous studies where trialability, observability, compatibility, and complexity can have a positive impact on technology adoption. In other words, the current conceptual model proves that students evaluate the importance of trialability, compatibility, observability, and complexity as positive and significant in adopting a metaverse system. This is consistent with previous studies, as these properties heavily impact the students' preferences, choices, and educational practices (Al-Rahmi et al., 2019; Huang, 2004; Wu & Wang, 2005). In addition, the results of these studies indicate positive perceptions of students towards the adoption of innovational technology when technology is perceived as satisfactory and compatible with their culture and evaluated as remarkable by others (Al-hawari & Mouakket, 2010; Ho et al., 2019; Wixom & Todd, 2005). Likewise, students who feel that properties of trialability, observability, compatibility, and complexity are significant and influential indicate a high level of satisfaction and probability of having positive attitudes towards metaverse system adoption.

The personal-based characteristics, which includes personal innovativeness, are influential factors with great impact on metaverse system adoption, and propose that students with high eagerness to use innovational technology show positive perception towards the adoption of metaverse system. Simply put, students who prefer to use an innovational technology have positive feelings towards uncertain situations and can develop more positive intentions toward it. The current results are in line with previous studies that confirms that students' perception is directly connected to perceived usefulness, considering the fact that the youth may enjoy the novelty of technology as an added motivational feature (Lai, 2017; Liu et al., 2009). Similarly, students' perceived usefulness is significantly effective, with a high impact on their behavioural intention to use the innovational technology. Other factors that can affect the adoption of technology such as playfulness aspect deserves

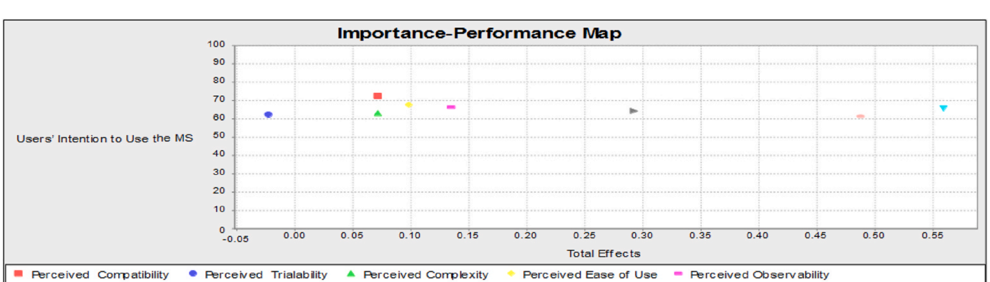

Fig. 7. IPMA results.

further study. Accordingly, students' perceptions might differ based on the uncertainty degree and innovational features of the technology (Lin & Yeh, 2019; Padilla-MeléNdez et al., 2013; Wang et al., 2021). In addition, the current study suggests that students' perceptions may be affected by PEOU. The significant correlation between personal innovativeness and PEOU helps establish the assumption that students will readily use innovational technology if it's effortless and they can get easily accustomed (Taylor & Todd, 1995; Venkatesh & Morris, 2000). The reasoning for this is that students of different ages prefer to have technology that is unique and developed with effortless features and functions. In line with previous studies, a study by Rienties et al. (2016) emphasised the significant effect of both PEOU and PU on technology adoption; it seems that the nature of the community affects the adoption of technology differently (Khlaisang et al., 2019). found no relation between innovation and technology adoption due to relatively lower level of collectivism value orientation. The previous results contrast with the current study, as the nature of the community is different. People in the Gulf area readily accept and use technology frequently. The level of adoption is higher when the innovational aspects are clearly manifested and properly used.

6.1. Theoretical and practical implications

With regard to the methodology employed in current study, evidently, this study is a step ahead of other empirical studies, as the former employs the novel approach of hybrid analysis, involving deep-learning analysis rather than the simple use of SEM analysis seen in other empirical studies. Therefore, this study contributes to the literature pertaining to m-learning. Moreover, ANN model is attributed with greater predictive power in comparison to PLS-SEM model mainly due to the additional advantages offered by deep ANN architecture in identifying of non-linear association of theoretical model factors.

6.2. Managerial implications

The findings of the current study provide up-to-date implications for teaching and learning. Based on the findings, the students' perceptions to use metaverse systems are significantly affected by personal innovation, which is a personal-based characteristic. Likewise, their perception is affected by perceived ease of use and perceived usefulness, which are technology-based features. Accordingly, teachers and technology supporters should provide students with opportunities that attract the metaverse system, focusing on personal-based characteristics and technology-based features. In this way, students' positive evaluation and their willingness to use the metaverse system will increase with time, leading to further improvement in the educational settings. Future research must consider individual differences and gender distinction with regard to preference towards teaching beliefs and values, and academic influence, which in turn may affect the academics' usage of technology and their needs.

6.3. Limitations of the study and future studies

The current study has several limitations. First, the conceptual model faces a significant limitation, as its limited to two crucial variables, personal innovativeness and users' satisfaction. Second, it was necessary to limit TAM construct to two constructs of PEOU and PU for measurement and to focus on two relevant attributes that affect personal innovativeness. Third, the survey was distributed on the Internet and social media; it is quite possible that the student's access will be easier and number of respondents will increase. Fourth, the metaverse can be used in different settings. This study restricts its scope to educational settings where the teaching and learning environments will be highly affected by the metaverse system (Kabát, 2016; Louro, 2009).

7. Conclusion

The metaverse system is a kind of technology that will change the world from different perspectives including economical, engineering, and educational. It is assisted by innovative technologies, which form a crucial part of educational practices. With the recent announcement of the Facebook founder who renamed Facebook as Metaverse or Meta World, all are expecting new technologies that will change the world. It is a new world of virtual reality that will replace the internet and pave the way for innovational teaching and learning practices. Considering the advantages the metaverse system can bring to teaching and learning, this study investigated university students' perceptions of a metaverse in the Gulf area, exploring the factors influencing their intentions to use this world. The results suggested that students' perceptions to use metaverse were significantly associated with their innovativeness, which is, in turn, influenced by perceived ease of use and perceived usefulness. The study results contribute to the existing studies on technology adoption theories, proposing a significant effect of the adoption properties trialability, observability, compatibility, and complexity. The findings are consistent with previous studies. It can also illustrate how students perceive the innovational technology used in education.

Declaration of competing interest

All authors declare that there is no conflict of interest.

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