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Exploring the Drivers for the Adoption of Metaverse Technology in Engineering Education using PLS-SEM and ANFIS

Attasit Wiangkham[1] · **Rattawut Vongvit**[1]

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Abstract
The rapid development of metaverse technology provides countless opportunities for social interaction, collaboration, communication, and knowledge-sharing that will significantly impact human life. To ensure widespread adoption and acceptance, however, issues concerning approval, accessibility, privacy, and user behavior must be resolved. Therefore, this study investigated the drivers of metaverse technology adoption for engineering education by utilizing an extended Unified Theory of Acceptance and Use of Technology (UTAUT) model that incorporates variables such as hedonic motivation, habit, trust in technology, and cyber security. The study collected data from 370 respondents and then carried out an analysis of the data using partial least squares structural equation modeling (PLS-SEM) and an adaptive neuro-fuzzy inference system (ANFIS). The findings indicated that cyber security, performance expectancy, social influence, and hedonic motivation have a significant impact on behavior intention to use metaverse technology for learning, with cyber security having the strongest effect. These results provide important insights for organizations seeking to enhance their cyber security practices and promote positive user behavior. Additionally, the study highlighted ways to improve the adoption and acceptance of metaverse technology in engineering education.

Keywords Metaverse technology · Behavior intention · UTAUT · Engineering education · ANFIS

✉ Rattawut Vongvit
rattawut@g.swu.ac.th

Attasit Wiangkham
attasitw@g.swu.ac.th

1 Department of Industrial Engineering, Faculty of Engineering, Srinakharinwirot University, Ongkharak, Nakhon Nayok 26120, Thailand

1 Introduction

Metaverse technology is rapidly gaining attention as the next frontier of virtual social interaction (Hennig-Thurau et al., 2022; Tayal et al., 2022). This technology allows users to immerse themselves in a virtual world. Metaverse technology can be fully or partially virtual, using virtual reality (VR) or augmented reality (AR) in real-world contexts (Allam et al., 2022; Rospigliosi, 2022). Users can engage in various activities and events in a virtual space that is limited only by their imagination. With the potential for lifelogging, the Metaverse offers endless possibilities for creating and recording experiences (Wu & Ho, 2023). As this technology continues to evolve, its impact on society is likely to be significant, and it will undoubtedly transform how people connect and interact with each other. The Metaverse offers several advantages over traditional modes of social interaction. It provides a more immersive and engaging experience (Buhalis et al., 2023), allowing users to participate fully in virtual environments and activities. It also opens new avenues for collaboration, communication, and knowledge sharing, regardless of users' locations (Hare & Tang, 2023; Lee et al., 2022; Lin et al., 2022).

Metaverse technology has numerous potential applications, including gaming, education (De Back et al., 2021), entertainment (Ampountolas et al., 2023), and social interaction (Rospigliosi, 2022) (Shen et al., 2021). In the gaming industry, metaverse technology can offer immersive and interactive experiences for players. Using metaverse technology in education can open new channels for remote collaboration and learning. With metaverse technology, users can experience live events virtually. Metaverse technology can help people connect and create virtual communities (Golf-Papez et al., 2022). It can be used to open new e-commerce, marketing, and advertising avenues (Sawiros et al., 2022). The potential applications of metaverse technology are numerous and varied, and it is anticipated that they will significantly impact many aspects of daily life (Wu & Ho, 2023).

Despite the aforementioned, the potential for lack of inclusivity and accessibility is one potential weakness related to user acceptance and the use of metaverse technology (Aburbeian et al., 2022; Toraman, 2022). A digital divide could result from some users lacking the equipment or technical know-how to access and engage in a virtual environment (Mystakidis, 2022). Additionally, users might be hesitant to share personal information or participate in activities in a virtual space due to privacy and security concerns (Christopoulos et al., 2021; Wang et al., 2023). Cultural and social barriers may also impact user adoption and acceptance of metaverse technology (Bibri, 2022). Finally, certain users may prefer traditional face-to-face interaction and have no interest in engaging with others in a virtual environment (Dwivedi et al., 2022). Metaverse developers and stakeholders must address these potential weaknesses to ensure the technology is inclusive, accessible, and appealing to a wide range of users.

One of the other challenges for developing metaverse technology is predicting how users will behave in the virtual world (Alfaisal et al., 2022). Because of this complexity, researchers have developed integrated models and theories to explain human behavior in online environments (Lee & Gu, 2022). Understanding how users interact with the virtual world and others within that space is critical for designing appealing and engaging metaverse applications (Venkatesh et al., 2012). Numerous studies have been conducted at universities and academic institutions to explore the Metaverse for educational applications. However, user acceptance poses significant limitations to its implementation (Alawadhi et al., 2022; Alfaisal et al., 2022; Hwang & Chien, 2022; Inceoglu & Ciloglugil, 2022). The findings regarding users' intention to use the Metaverse in medical education support demonstrate that perceived ease of use (PEOU) and perceived usefulness (PU) have a significant impact on the adoption of technological innovations. However, the conceptual study model is limited as it solely relies on the variables of perceived importance (PI) and user satisfaction (US), and thus, it is necessary to incorporate other factors for a more comprehensive understanding. The findings in higher institutions in the Gulf area suggest that students' perceptions of using metaverse technology are significantly correlated with their innovation, which is influenced by the ease of use and perceived benefit (Akour et al., 2022). The case study conducted in Oman regarding the intention to use metaverse technology in higher education reveals that inventiveness plays a significant role in determining the effectiveness of the metaverse system. At the same time, apparent ubiquity is less influential in promoting its use. Additionally, context awareness, complexity, and enjoyment substantially impact the adoption of the metaverse system in higher institutions (Salloum et al., 2023). The metaverse as a teaching platform for Lean masterclass offers significant benefits, such as hedonistic and immersive effects, while acknowledging challenges, such as tiredness and cybersickness, that can be mitigated through experience development, technology, and course organization (Hines & Netland, 2022). The studies on the metaverse platform for engineering education in South Korea identified factors influencing the essential elements for effective engineering education, such as practical and realistic interaction, meaningful feedback, high immersion experience, realistic practice-based education, and a student-centered approach (Won et al., 2021). The metaverse in education offers significant potential for productivity. However, its use raises concerns regarding personal data privacy breaches and security risks such as cybercrime, fraud, and cyberbullying, as users must share sensitive information to access the virtual world (De Felice et al., 2023).

Acknowledging these potential issues and implementing necessary measures to address them while exploring the metaverse's potential is crucial. Metaverse technology is gaining traction in education; however, there needs to be more research focused specifically on its application in engineering education. It is critical to address cyber security factors and foster trust in technology when considering integrating metaverse technology into engineering education. Therefore, this research investigates the factors influencing behavioral intention to use metaverse technology for learning in engineering education. The study uses an extended UTAUT model that incorporates variables such as hedonic motivation, habit, while also introducing trust in technology and cybersecurity as crucial factors specific to metaverse technology, thus creating a modified research model. The goal is to gain insights into the factors influencing users' intentions to use metaverse technology for learning as well as identify ways to enhance the adoption and acceptance of such technology in engineering education. Partial Least Squares Structural Equation Modeling (PLS-SEM) was utilized to assess the proposed research model, augmented by an adaptive neuro-fuzzy inference system (ANFIS) approach, to elucidate the nonlinear relationship between determinants and the intention to use metaverse technology in engineering education, identify the significance levels of these determinants and predict the intention to use metaverse technology in scenarios where the parameters changed.

2 Conceptualizations of model and hypotheses development

The Unified Theory of Acceptance and Use of Technology (UTAUT) is a theoretical model used to explain the acceptance and adoption of new technology (Venkatesh et al., 2003). The model proposes that four key factors influence user acceptance and use of technology, including performance expectancy, effort expectancy, social influence, and facilitating conditions. Several studies have proposed that the extended UTAUT model may influence technology adoption, such as trust (Al-Saedi et al., 2020) and security (Tomić et al., 2022). In this study, the proposed model for the behavioral intention to use metaverse technology to learn in engineering education includes the UTAUT. In addition, the authors investigated trust in technology and cyber security. Figure 1 illustrates the research model, which includes the 8 hypotheses developed by this study.

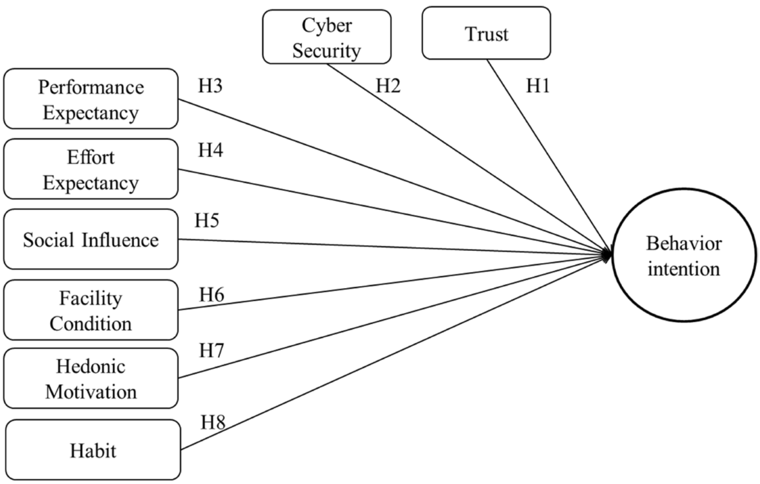

Fig. 1 The research model

2.1 Trust in Technology

Trust in technology means users' confidence to get started or use things, both methods and new technologies, in the long term (Albayatia et al., 2023). No matter how strong the Metaverse is without the user's trust, the technology is immediately useless when it comes to using it in the teaching field, which is deemed to use new technology. According to previous research about the factors related to the intention of a user to apply a method or new technology, it was found that the trust factor is a variable related to the decision-making process (Alkhowaiter, 2022; Kraus et al., 2023; Pal et al., 2022; Shao et al., 2022). Thus, the trust in technology factor was deployed in one of the hypotheses concerning the behavioral intention of users to utilize the Metaverse in engineering education, as follows.

Hypothesis 1 (H1): Trust in technology affects behavioral intention to use metaverse technology in engineering education.

2.2 Cyber security

One of the motivation factors regarding users wanting to be secure, privacy, or able to protect their assets in technology is cyber security (Ogbanufe & Ge, 2023). In digital technology, the protection of personal assets may not be merely tangible. It may refer to protecting something that can distinguish the user's identity in the real world, including username, password, bank account, a digital asset created by the user (character skins, etc.), etc. (Alraja, 2022; Hanif & Lallie, 2021a; Jo, 2022). In terms of the use of the Metaverse in engineering education, cyber security is nearly identical in meaning to the use of other digital technology in which users want to protect privacy, information, and assets. Considering cyber security, which has a significant impact on the decision to employ digital technology in education, some users can learn or participate in learning activities more effectively when they are not the center of attention owing to the ability to remain anonymous and not have their identity exposed (Alvarez-Risco et al., 2022; Lwoga & Lwoga, 2017; Ong et al., 2023). Thus, cyber security was deployed in one of the hypotheses concerning the behavioral intention of users to apply metaverse technology in engineering education, as follows.

Hypothesis 2 (H2): Cyber security affects behavioral intention to use the Metaverse in engineering education.

2.3 Performance expectancy

Performance expectancy is one of the factors that users expect from enhanced ability or performance after using a method or technology (Hooda et al., 2022; Hunde et al., 2023). In terms of the Metaverse in education, the performance expectancy factor means the expectation of increased ability or performance of students or individuals that employed it in education about their topic of interest. According to previous research about intention factors to use a method or technology, the performance expectancy factor affects the behavioral intention of a user to use a method or technology (Benleulmi & Ramdani, 2022; Nordhoff et al., 2020; Ribeiro et al., 2022; Yang et al., 2022). The performance expectancy factor was deployed in one of the hypotheses concerning the behavioral intention of users to apply the Metaverse in engineering education, as follows.

Hypothesis 3 (H3): Performance expectancy affects behavioral intention to use metaverse technology in engineering education.

2.4 Effort expectancy

The effort expectancy factor is based directly on user expectations (Alkhowaiter, 2022). Generally, the effort expectancy factor means the expectation that users want to be comfortable in use, and various facilities are provided, with no effort or minimal effort by the user to obtain them (Hunde et al., 2023; Suki & Suki, 2017). Regarding using the Metaverse in education, the effort expectancy factor refers to convenience, whether user interface (UI) or timely response to users, etc. According to previous research that studied the intention to use new methods or technology, the effort expectancy factor has been suggested to affect the behavioral intention of users (Lee & Kim, 2022; Teng et al., 2022a; Wang & Shin, 2022). Thus, the effort expectancy factor was deployed in one of the hypotheses concerning the behavioral intention of users to apply metaverse technology in engineering education, as follows.

Hypothesis 4 (H4): Effort expectancy affects behavioral intention to use metaverse technology in engineering education.

2.5 Social influence

The social influence factor refers to the factor that concerns society and its effects on users' decision-making in certain aspects. Users often make decisions based on the conditions and aspects of the surrounding society, whether family, friends, or social influencers (Al-Saedi et al., 2020; Chao, 2019; Dwivedi et al., 2019). Regarding using metaverse technology in education, the social influence factor refers to public relations from Metaverse users, reviews of the Metaverse, user experience, etc. Following previous studies about the intention to use new methods or technology, it can be inferred that the social influence factor affects users' behavioral intention in the case of trying new things (Aranyossy, 2022; Han, 2022; Lai, 2023). Based on evidence from previous research, the social influence factor was deployed in one of the hypotheses concerning the behavioral intention of users to apply metaverse technology in engineering education, as follows.

Hypothesis 5 (H5): Social influence affects behavioral intention to use metaverse technology in engineering education.

2.6 Facility conditions

When users attempt to use new methods and technology, the facility's conditions influence how they select it (Madigan et al., 2017). Regarding digital technology, the facility conditions factor means readiness in terms of hardware and software, such as supported computers and the internet with the standard for users to use technology smoothly. Regarding the application of metaverse technology in the education sector, the meaning of the facility conditions factor is similar to that of other digital technology in the case of prepared resource support for users. Following significant research evidence (Arpaci et al., 2022; Palau-Saumell et al., 2019; Rahi et al., 2018), it can be inferred that the facility conditions factor is one of the factors that affect the behavioral intention of users to apply metaverse technology. Thus, this factor was employed in one of the hypotheses along with other factors.

Hypothesis 6 (H6): Facility conditions affect behavioral intention to use metaverse technology in engineering education.

2.7 Hedonic motivation

Hedonic motivation is one of the factors in the topic that relates to the mental state of users. Hedonic motivation refers to enjoyment or pleasure from using methods or technology (Nikolopoulou et al., 2021; Parhamnia, 2022). In terms of using the Metaverse in the education sector, this method involves high-performance outcomes, but users will not choose to use it if they do not consider it engaging or interesting (Kalinkara & Talan, 2022; Teng et al., 2022a; Weilage & Stumpfegger, 2022). Thus, it can be inferred that hedonic motivation is one of the factors that affect the behavioral intention of users to apply metaverse technology. This factor was employed in one of the hypotheses along with other factors.

Hypothesis 7 (H7): Hedonic motivation affects behavioral intention to use metaverse technology in engineering education.

2.8 Habit

Habits relate to a user's experience and the repetition of behavior (Saputra et al., 2021). The habit factor often depends on the user's mental state; if users have a bad experience related to methods or technology, they will not choose to use it again. Similar to the general meaning of habit, in the Metaverse, the user will decide to use this method depending on experience (Dirsehan & van Zoonen, 2022; Mohd Rahim et al., 2022; Pooyandeh et al., 2022). According to evidence from previous research, the habit factor was deployed in one of the hypotheses concerning the behavioral intention of users to apply metaverse technology in engineering education, as follows.

Hypothesis 8 (H8): Habit affects behavioral intention to use metaverse technology in engineering education.

3 Methods

This study used Google Forms to carry out an online survey and gather data. The measurements for the study were adapted from previous studies on the research context of the Metaverse to ensure the content validity of the questionnaire. PLS-SEM were applied for path analysis, and an ANFIS was used to further analyze the confirmed direct relationships.

3.1 Variables and measurements

The research model in this study consists of 8 constructs measured by 22 measurement items. These items were reviewed from previous related research and adapted to fit the context of the Metaverse. The questionnaire was translated into Thai from English. The assessments used a 7-point Likert scale ranging from "1 = strongly disagree" to "7 = strongly agree." The questionnaire items used in this study are presented in Table 1.

3.2 Data collection

An online survey was conducted using Google Forms from August to October 2022, targeting participants studying in the engineering faculty at a university in Thailand. The data collected from the online survey was validated to confirm its accuracy and consistency. The validation process was essential to ensuring the quality of the data and reinforcing the research results. The validation methods also included construct reliability and validity as well as convergent validity of the measurement model.

The first section of our survey included a definition of metaverse technology and presented a case study illustrating its application in higher education. This was done to ensure a shared understanding among respondents and establish a common framework for interpreting their responses. The second section gathered demographic information such as gender, age, and educational background. The third section included a Likert-scale questionnaire that assessed respondents' intentions to use metaverse technology in engineering education.

The online survey was conducted to gather insights and opinions from 370 students enrolled in the engineering faculty at a university. Initially, the survey was distributed to a larger group of students, but a few failed to complete it fully, leading to incomplete data. After careful consideration of the data, it was decided to exclude these samples, leaving a final sample of 365 for analysis. The results showed that the mean age of respondents was 20.61 years (SD=1.09). The results also revealed a clear gender divide, with 55.35% of respondents being male and 44.65% being female. This emphasizes the significance of gender considerations

Table 1 Construct and measurement items

Construct		Item	Source
Behavior intention	BI	BI1: Metaverse technology will be increasingly important in the future for engineering education.	(Chang et al., 2016; Lee & Lee, 2020; Shuhaiber & Mashal, 2019; Yang et al., 2022)
		BI2: I believe metaverse technology will become an integral part of my daily life, providing valuable learning opportunities in engineering education.	
		BI3: To improve my engineering knowledge, I plan to continue to use metaverse technology.	
Trust in technology	TT	TT1: I believe that metaverse technology has integrity.	(Bawack et al., 2021; Hanif & Lallie, 2021b; Shuhaiber & Mashal, 2019)
		TT2: I can trust metaverse technology.	
		TT3: I believe that metaverse technology is dependable.	
Cyber security	CS	CS1: Metaverse technology can manage cyber security.	(Hanif & Lallie, 2021b; Shuhaiber & Mashal, 2019)
		CS2: I am likely to have a positive opinion towards security in metaverse technology.	
Performance Expectancy	PE	PE1: Using metaverse technology for learning in engineering education would enhance my learning effectiveness.	(Venkatesh et al., 2012; Yang et al., 2022)
		PE2: Using metaverse technology for learning in engineering education would increase my productivity.	
		PE3: Using metaverse technology for learning in engineering education would enhance my learning performance.	
Effort Expectancy	EE	EE1: I would find metaverse technology for learning in engineering education easy to use.	(Venkatesh et al., 2012; Yang et al., 2022)
		EE2: Learning to use metaverse technology for learning in engineering education would be easy.	
		EE3: Interacting with metaverse technology for learning in engineering education would not require much mental effort.	

Table 1 (continued)

Construct		Item	Source
Social Influence	SI	SI1: Someone close to me has suggested that incorporating metaverse technology into my learning could be beneficial.	(Venkatesh et al., 2012; Yang et al., 2022)
		SI2: Certain individuals who have recommended using metaverse technology for learning in engineering education influence my behavior.	
		SI3: The people I value suggest that using metaverse technology for learning in engineering education may be advantageous.	
Facility Condition	FC	FC1: Metaverse technology provides me with access to a wealth of resources essential for my learning in engineering education.	(Venkatesh et al., 2012; Yang et al., 2022)
		FC2: Through the Metaverse, I have access to a vast amount of information that is crucial for my education in the field of engineering.	
		FC3: Learning engineering education using metaverse technology is compatible with other technologies I use.	
Hedonic Motivation	HM	HM1: Using metaverse technology for learning in engineering education would be fun.	(Venkatesh et al., 2012; Yang et al., 2022)
		HM2: Using metaverse technology for learning in engineering education would be enjoyable.	
Habit	HB	HB1: Learning in engineering education using metaverse technology would become a habit.	(Venkatesh et al., 2012; Yang et al., 2022)
		HB2 I could get addicted to learning in engineering education using metaverse technology.	
		HB3 I must use metaverse technology to learn in engineering education.	

when analyzing data and provides valuable insights into the demographic distribution of the participants.

3.3 Data analysis

Partial least squares (PLS) are based on the principle of latent variables, which are unobservable variables that explain the relationships between predictor and response variables (Hair Jr, 2021). PLS is particularly useful when there are many predictor variables, and their relationships are complex and nonlinear. In this study, SmartPLS software was used to examine the hypotheses in the proposed model. PLS is a well-known statistical technique that provides a systematic approach to simultaneously evaluating measurement and structural models (Hair & Alamer, 2022).

PLS is a valuable tool for gaining deeper insights into data due to its emphasis on individual path coefficients, variance explanations, and the ability to handle complex relationships between variables. The evaluation of the measurement model typically involves using the criteria established for the reflective approach. This approach focuses on construct validity and reliability as well as an analysis of the convergent and discriminant validity of the measurement model (Hair et al., 2019).

The reliability and validity of the construct were assessed using Cronbach's alpha coefficient, composite reliability (CR), and the rho_A coefficient. Cronbach's alpha is a measure of internal consistency that indicates how well scale items measure a single underlying construct; it should be greater than 0.7. CR is a measure of the construct's reliability based on the average of the factor loadings of the items in the construct; recommended values should be greater than 0.7. The rho_A coefficient measures the average inter-item correlation within a construct and should be greater than 0.7. Factor loading represents the strength of the association between a specific item in the construct and the underlying construct being measured (Barclay et al., 1995). When a factor loading exceeds 0.6, it indicates a strong association and confirms the validity of the construct (Hair, 2009).

The average variance extracted (AVE) is a metric commonly used for assessing the convergent validity of a measurement model. It captures the variance explained by the underlying construct in the observed variables. The results showed that the values were more significant than 0.5, confirming convergent validity. The square root of the AVE must be greater than the correlation values between the latent variables to ensure discriminant validity (Barclay et al., 1995).

Following the implementation of the proposed model, the hypotheses were evaluated using a bootstrapping procedure with 5000 samples. The results were compared to the t-statistics at a 5% significance level to assess validity.

3.4 Adaptive neuro-fuzzy inference system (ANFIS)

ANFIS is a widely used algorithm in artificial intelligence modeling. After completing the PLS analysis, the hypothesis parameters that affect behavior intention to use metaverse technology in engineering education were implemented into the ANFIS modeling process to investigate the effects of each and the interaction of hypothesis parameters to the behavior intention in the case that those parameters changed. In this study, the data concerning behavioral intention obtained from the survey method (365 data points) were split into training and testing sets for modeling the ANFIS model on MATLAB programming using the K-Fold cross-validation technique. The ANFIS algorithm can be used in problems characteristic of regression, classification, and clustering. The learning characteristic in the ANFIS modeling begins based on the fuzzy logic or fuzzy inference system, in which the problem data are operated using the classical if-then rule theory (Ani & Agu, 2022; Babarinde & Madyira, 2022). The ANFIS algorithm may be different from the original fuzzy inference system in the aspect of updated model accuracy during the modeling phase with neural network learning architecture. For a more straightforward approach to explain the learning process for the ANFIS model in the case applied to continuous or regression data characteristics, similar to this study, the learning architecture for the ANFIS model is represented in the case of 2 inputs (X and Y) and 1 output (f), which employs the if-then rule in Eq. (1) and (2), and architecture shown in Fig. 2. The learning of each layer in the ANFIS model can be expressed as follows (Olatunji et al., 2022; Wiangkham et al., 2021).

Rule 1: If X is A_1 and Y is B_1, then

$$f_1 = d_1A_1 + e_1B_1 + g_1 \tag{1}$$

Rule 2: If X is A_2 and Y is B_2, then

$$f_2 = d_2A_2 + e_2B_2 + g_2 \tag{2}$$

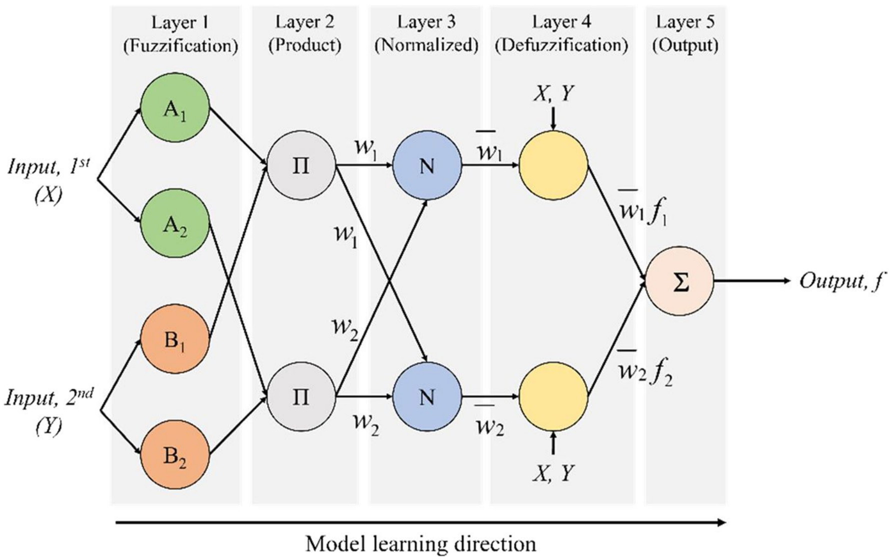

Fig. 2 The architecture for adaptive neuro-fuzzy inference system (ANFIS) modeling

where f_1 and f_2 are the outputs of fuzzy rules 1 and 2 and (d_i, e_i, g_i) that $i = 1, 2$ represents nodal parameters obtained during the training phase of the ANFIS model.

1st Layer (Fuzzification) In the first learning layer of the ANFIS model, the input data (X and Y) were placed into the fuzzy inference system process, also called the fuzzification process, which was the Takagi-Sugeno fuzzy-based selection. The data were converted into the membership function, which is initially the level of membership and membership shape that can be adjusted randomly by the user; in this study, the Gaussian membership function shape was selected. The nodes in this layer are of the adaptive type, and the output of the nodes (ON) can be expressed as

$$ON_i^1 = \begin{cases} uA_i(X) \\ uB_i(Y) \end{cases} \tag{3}$$

where uA_i and uB_i represent the membership function corresponding to the linguistic variables of rules 1 and 2, respectively.

2nd Layer (Product) In the second learning layer of the ANFIS model, the product of the fuzzy inference system rules was generated. All nodes represented the products mentioned above and were fixed node types, which can be expressed as:

$$ON_i^2 = w_i = uA_i(X) \times uB_i(Y) \tag{4}$$

where w_i are the products generated by fuzzy rules at node i.

3rd Layer (Normalized) In the third learning layer of the ANFIS model, the products of fuzzy rules generated in the previous layer were converted to the normalization form following

$$ON_i^3 = \overline{w_i} = \frac{w_i}{w_1 + w_2} \tag{5}$$

where $\overline{w_i}$ is the normalized products generated by fuzzy rules at node i

4th Layer (Defuzzification) In the fourth learning layer of the ANFIS model, the process that reconverts the data that was previously converted into the fuzzification form into the original form or also the defuzzification process was performed. All nodes in this layer were of the adaptive type, similar to the first layer and the defuzzification process, which can be expressed as

$$ON_i^4 = \overline{w_i} f_i = \overline{w_i}\left(d_i A_i + e_i B_i + g_i\right) \tag{6}$$

5th Layer (Output) In the fifth learning layer of the ANFIS model, which is the last layer, the prediction outputs were generated. The conversion process of all results from previous layers into the output of the problem can be expressed as

$$ON_i^5 = \sum_{i=1}^{2} \overline{w_i} f_i \tag{7}$$

According to the ANFIS model that was used as a surrogate model for investigating the effects of the hypothesis parameters on behavioral intention to use metaverse technology in the education sector, the performance of the model is one of the factors that demonstrated the ability to surrogate behavior of those hypothesis parameters. According to the characteristics of data for behavioral intention in this study, the wide use of regression performance metrics, namely coefficient of determination (R^2) (Chong & Zak, 2013), and the percentage-based error metric, namely mean absolute percentage error (MAPE) (Naser & Alavi, 2020), were used to evaluate the prediction performance of the ANFIS models, which can be expressed as

$$\text{Coefficient of determinition}, R^2 = 1 - \frac{\sum_{i=1}^{n} \left(Y_{ac,i} - Y_{pr,i}\right)^2}{\sum_{i=1}^{n} \left(Y_{ac,i} - \overline{Y_{ac}}\right)^2} \tag{8}$$

$$\text{Mean absolute percentage error}, MAPE = \frac{\sum_{i=1}^{n} \left| \frac{Y_{ac,i} - Y_{pr,i}}{Y_{ac,i}} \right|}{n} \times 100 \tag{9}$$

where $Y_{ac,\ i}$ is the actual value that represents the value of the behavior intention to use metaverse in the education sector at index i, $Y_{pr,\ i}$ is the prediction value via the ANFIS model at index i, $\overline{Y_{ac}}$ is the mean of the actual value, and n is the number of observations.

4 Results and Discussion

This research revealed the behavioral intention factors used in metaverse technology for learning in engineering education. Based on the UTAUT model, hedonic motivation, habit, trust in technology, and cyber security are included in the original model. An online survey was conducted to gather opinions from users. After such a data collection process, a statistical analysis is typically undertaken to evaluate the research model. In this case, the research model utilized a PLS structural equation model to test the hypotheses. The results show that four of the eight hypotheses were supported.

4.1 Personal demographic information

The personal statistics of the survey for 365 participants are presented in Table 2. The table shows that 55.35% of the participants were male, and 44.65% were female. The mean age of the participants was 20.61 years (S.D. = 1.09).

Table 2 Demographic statistics

		Frequency	Percentage
Gender	Male	202	55.35
	Female	163	44.65
College Years	1	75	20.55
	2	108	29.59
	3	98	26.85
	4	84	23.01

4.2 Descriptive statistics

Table 3 shows the mean and standard deviation for various constructs. Behavioral intention has a mean score of 5.39 and an S.D. of 1.30; this construct appears to be moderately high, indicating that participants have a strong intention to use metaverse technology. The results suggest that participants have a positive attitude towards learning in engineering education by using metaverse technology. Habit has a lower mean of 4.12, indicating that participants may not have an established pattern of using metaverse technology. However, the relatively high SD of 1.50 suggests a wide range of attitudes towards habit, with some participants having a robust habit of using metaverse technology.

4.3 Assessment of the measurement model

Data were analyzed to determine to construct reliability and validity, as well as convergent and discriminant validity. According to the results in Table 4, all eight constructs met the required standard limits. All item loadings were more significant than 0.6. Furthermore, the CR, Cronbach's alpha, and rho_A values for each construct were more significant than 0.7, indicating that the reliability and validity of the data were strong. In Table 5, the square roots of the AVE values for each construct are

Table 3 The results of mean and standard deviation

Construct	Mean	SD
Behavioral intention	5.39	1.30
Trust in technology	4.69	1.44
Cyber security	5.62	1.32
Performance expectancy	4.98	1.47
Effort expectancy	5.07	1.46
Social influence	5.42	1.37
Facility condition	4.48	1.78
Hedonic motivation	5.43	1.34
Habit	4.12	1.50

Table 4 The results for the reliability and validity of the measurement model

	Item	Loading	Cronbach's Alpha	rho_A	CR	AVE
Behavioral intention	BI1	0.863	0.838	0.841	0.903	0.756
	BI2	0.918				
	BI3	0.825				
Trust in technology	TT1	0.701	0.836	0.928	0.898	0.750
	TT2	0.937				
	TT3	0.938				
Cyber security	CS1	0.925	0.724	0.792	0.875	0.778
	CS2	0.837				
Performance expectancy	PE1	0.775	0.784	0.807	0.872	0.695
	PE2	0.843				
	PE3	0.881				
Effort expectancy	EE1	0.838	0.786	0.791	0.875	0.700
	EE2	0.855				
	EE3	0.817				
Social influence	SI1	0.875	0.781	0.783	0.873	0.697
	SI2	0.858				
	SI3	0.769				
Facilitating conditions	FC1	0.730	0.742	0.737	0.851	0.657
	FC2	0.840				
	FC3	0.855				
Hedonic motivation	HM1	0.907	0.788	0.788	0.904	0.825
	HM2	0.909				
Habit	HB1	0.914	0.908	0.774	0.920	0.793
	HB2	0.788				
	HB3	0.961				

Table 5 The results of discriminant validity

	BI	TT	CS	PE	EE	SI	FC	HM	HB
BI	0.870								
TT	0.504	0.866							
CS	0.765	0.472	0.882						
PE	0.637	0.656	0.590	0.834					
EE	0.570	0.658	0.546	0.804	0.837				
SI	0.660	0.559	0.691	0.648	0.638	0.835			
FC	0.436	0.641	0.419	0.654	0.653	0.539	0.810		
HM	0.260	0.101	0.165	0.189	0.142	0.144	0.160	0.908	
HB	0.071	0.074	0.063	0.011	0.022	0.069	0.051	-0.021	0.891

BI, behavioral intention; TT, Trust in technology; CS, Cyber security; PE, Performance expectancy; EE, Effort expectancy; SI, Social influence; FC, Facilitating conditions; HM, Hedonic motivation, HB, Habit more significant than their corresponding correlation coefficients, indicating that all constructs had satisfactory discriminant validity. This finding highlights that all values met the recommended criteria for demonstrating distinctiveness between the constructs.

4.4 Analysis of the structural model

The results of the structural equation modeling presented in Table 6 show the relationship between the 8 constructs and behavioral intention. The study tested 8 hypotheses, each representing a relationship between one construct and behavioral intention. The path coefficients indicate the strength and direction of the relationship between each construct and behavioral intention, while the t-statistics measure the significance of the relationships.

The results show that 4 of the 8 hypotheses were supported, including hypotheses H2, H3, H5, and H7, indicating that cyber security, performance expectancy, social influence, and hedonic motivation have a significantly positive relationship with behavioral intention. Cyber security has the most decisive influence on behavior intention (H2: $\beta = 0.511$; $p < 0.001$), followed by performance expectancy (H3: $\beta = 0.208$; $p < 0.01$), and social influence (H5: $\beta = 0.143$; $p < 0.05$). Hedonic motivation had the least effect (H7: $\beta = 0.118$; $p < 0.001$).

The results of the PLS structural equation model indicate that cyber security has a positive impact on behavioral intention, consistent with numerous studies in other domains that suggest attitude plays a crucial role in determining intention (Gani et al., 2023; Renaud & Ophoff, 2021). The results indicate that an individual's behavioral intention to adopt a specific technology, including the Metaverse, is significantly influenced by cybersecurity. Users are more likely to trust a platform and feel more secure using it when they believe it has robust cybersecurity measures. This finding can encourage them to adopt the Metaverse and boost their attitudes.

Performance expectancy is also positively associated with behavioral intention, indicating that individuals are more likely to have a positive attitude toward adopting the Metaverse when they perceive a high-performance expectancy regarding its use. The platform will provide them with the desired functionality and ease of use,

Table 6 The results of hypothesis testing

Hypothesis	Path	Path coefficient	T-Statistics	Significance	Hypothesis test result
H1	TT -> BI	0.062	1.304	0.192	Not supported
H2	CS -> BI	0.511	9.841	***	Supported
H3	PE -> BI	0.208	2.887	**	Supported
H4	EE -> BI	0.015	0.217	0.828	Not supported
H5	SI -> BI	0.143	2.459	*	Supported
H6	FC -> BI	-0.061	1.275	0.203	Not supported
H7	HM -> BI	0.118	3.462	***	Supported
H8	HB -> BI	0.027	0.629	0.530	Not supported

*p <0.05, **p <0.01, and ***p <0.001

motivating them to use the Metaverse. These results can lead to higher adoption among users (Arpaci et al., 2022; Ren et al., 2022).

Social influence and behavioral intention exhibit a positive relationship. This result means that individuals are more likely to intend to use metaverse technology themselves when they perceive others in their social networks are using it for engineering education. Furthermore, social influence can improve an individual's perception of the utility and ease of use of metaverse technology in engineering education. If they see their peers and respected individuals in their network using the technology successfully, they are more likely to regard it as a valuable learning tool. The increased prevalence of the Metaverse among people is expected due to its potential social impact on how people interact with each other and the digital world (Arpaci et al., 2022; Teng et al., 2022b).

Hedonic motivation showed significant effects on behavioral intention. The findings of this study align with a recent study in the literature (Arpaci et al., 2022; Han et al., 2022). The positive relationship observed between hedonic motivation and behavioral intention to use metaverse technology for learning in engineering education suggests that educators can use this motivation to increase technology adoption. Using metaverse technology to create engaging and enjoyable learning experiences, educators can appeal to students' desire for pleasure and foster a more positive attitude toward technology. As a result, students are more likely to use technology in the future and achieve better learning outcomes.

Hypotheses H1, H4, H6, and H8 were not supported. The results of this study indicate that trust in technology, effort expectation, facility condition, and habit do not significantly affect the behavioral intentions to use metaverse technology for learning in engineering education. Engineering students may already have high trust in technology as it is a core component of their field of study and future profession. As a result, trust in technology may not be a differentiating factor in the decision-making process when using metaverse technology for learning. Behavioral intention was not affected by effort expectation to use metaverse technology for learning since engineering students tend to be highly familiar with technology and possess the skills and knowledge required to use metaverse technology for learning. Therefore, the effort needed to adopt and use metaverse technology may not be a significant barrier or challenge. These results align with (Yang et al., 2022), whose findings revealed that effort expectancy had no significant effect on the behavioral intention to learn basketball using the Metaverse.

Facility conditions showed no significant effects on behavioral intention. Generally, engineering students tend to be well-versed in using various forms of technology in different educational settings such as classrooms, laboratories, and online environments. This familiarity with technology may indicate that facility conditions may not be a significant determinant of their intentions to use metaverse technology for learning. Similarly, the study found no significant relationship between habit and behavioral intention to use metaverse technology for learning in engineering education. Metaverse technology for learning in engineering education may be an emerging technology for students. They may have not yet developed a strong habit or routine around using this technology for their studies.

The R^2 values illustrated in Fig. 3 indicate that 66.3% of the variance in the behavioral intention to use metaverse technology for learning in engineering education can be accounted for by the proposed model.

BI, behavioral intention; TT, Trust in technology; CS, Cyber security; PE, Performance expectancy; EE, Effort expectancy; SI, Social influence; FC, Facilitating conditions; HM, Hedonic motivation; HB, Habit

4.5 Effects of hypotheses parameters on behavioral intention via the ANFIS model

The prediction performance of the ANFIS model used as a surrogated model to investigate the effects of hypotheses parameters at various regression performance metrics are shown in Fig. 4. The evaluation of model performance shows that the prediction results for the behavioral intention to use metaverse technology in engineering education are nearly identical to the actual results obtained from the survey method; the model had an R^2 value equal to 0.942, while the MAPE value indicated a prediction error in terms of a percentage equal to 3.875%. Following the interpretation of the MAPE according to Lewis's research (Lewis, 1982), it was found that the ANFIS model had high prediction performance (MAPE < 10%). The partial dependence plot (PDP) of the input factors to output factor of the ANFIS model indicated the importance of each input factor in the model, as shown in Fig. 5. The PDP for all input factors indicated the nonlinear relationship to behavioral intention to use the Metaverse, which is the output of the prediction model. Following the PDP interpretation (interpretation from the range of values in the y-axis, where

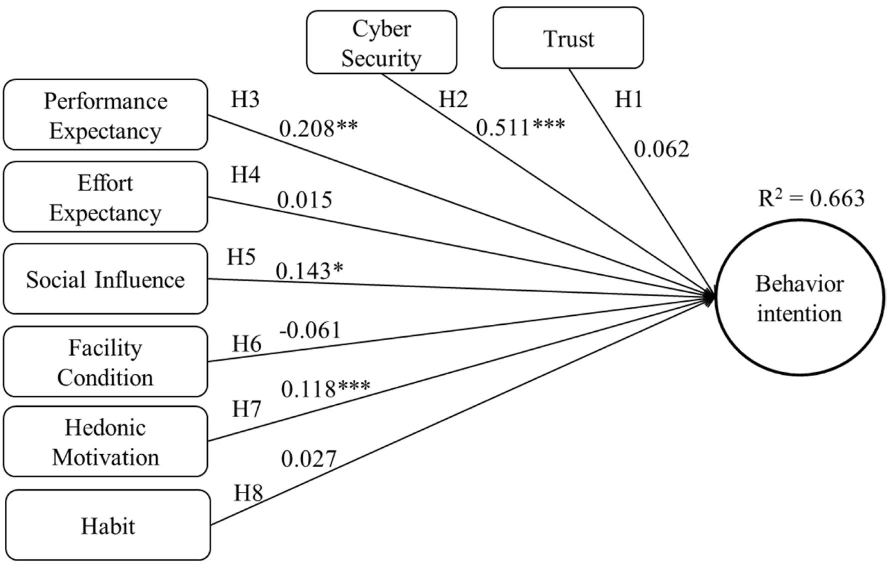

Fig. 3 Assessment of the structural model. *Note:* *p <0.05, **p <0.01, and ***p <0.001

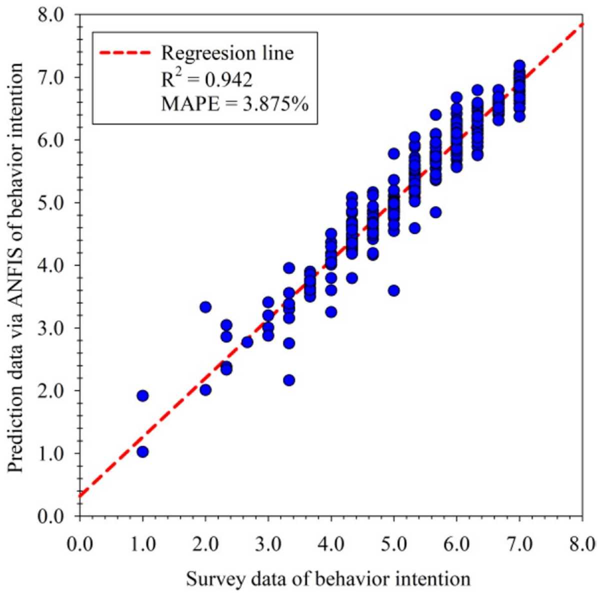

Fig. 4 Comparison of results between the survey and prediction of behavioral intention to use the Metaverse

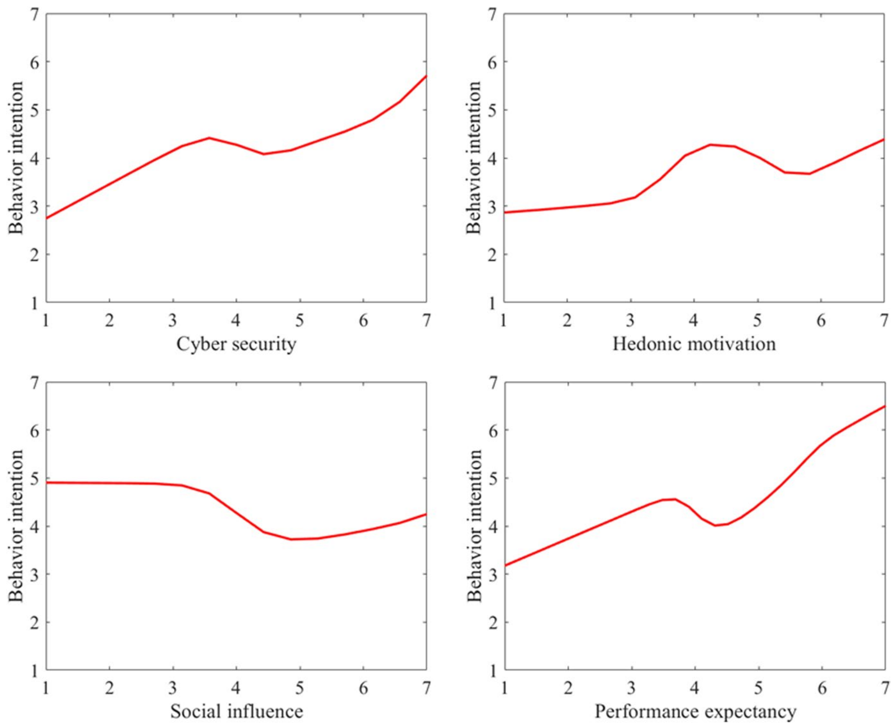

Fig. 5 A partial dependence plot of hypothesis parameters for behavioral intention to use the Metaverse

a significant value means high importance to the output model and a small value means low importance), it was found that the performance expectancy factor among all input factors, representing the users' expectation of performance after they use the Metaverse, was the factor with the highest importance to the behavioral intention to use the Metaverse in the education section. Further, the output factor had a nearly positive linear relationship, except in a range between 3.5 and 4.5. Subsequent to the performance expectancy factor, the cyber security factor was the second most important in behavioral intention to use the Metaverse in the education section, which indicates the concerns about security or privacy in the case of using digital technology. The relation to the output factor is represented in linear form ranging from 1 to around 3.5. After that, the form was changed to slightly nonlinear. Regarding the hedonic motivation factor and social influence factor, which were directly related to the state of mind of the user concerning the performance of the Metaverse platform, they were found to be inconsequential to the behavioral intention to use the Metaverse in the education section compared to other factors. It was also found that both factors (hedonic motivation factor and social influence factor) were of similar importance.

According to the interactive relationship between the hypothesis parameters, a partial dependence plot of the paired parameters is shown in Fig. 6. The paired PDP of performance expectancy and cyber security demonstrate consistent behavior and a positive relationship with behavioral intention to use the Metaverse, while the paired PDP of cyber security and hedonic motivation is quite negative to behavior intention to use the Metaverse in the case of low values for cyber security and increased hedonic motivation. Regarding the paired PDP of cyber security and social influence and the paired PDP of performance expectancy and social influence, there seems to be no interactive relationship in the case of low values for cyber security. The paired PDP of performance expectancy and hedonic motivation will behave quite similarly to the paired PDP of cyber security and hedonic motivation. Regarding the paired PDP of hedonic motivation and social influence, which are directly related to the state of mind of users, it was found that behavioral intention to use the Metaverse increased slightly when social influence increased in the case of low hedonic motivation. In the case of low social influence, the behavioral intention to use the Metaverse increased in the beginning and then decreased slightly. In the case of increased hedonic motivation and social influence, the behavioral intention to use the Metaverse increased accordingly.

4.6 Limitations and future research

This study has certain limitations that offer potential avenues for future research. Firstly, the data collected was limited to universities in Thailand. Consequently, the technology readiness, social, cultural, and environmental factors may differ across various countries. Therefore, future research should investigate the effects of different countries on the subject matter. Second, although this study introduced metaverse technology in engineering education before conducting the survey. However, participants may have different levels of experience with metaverse technology.

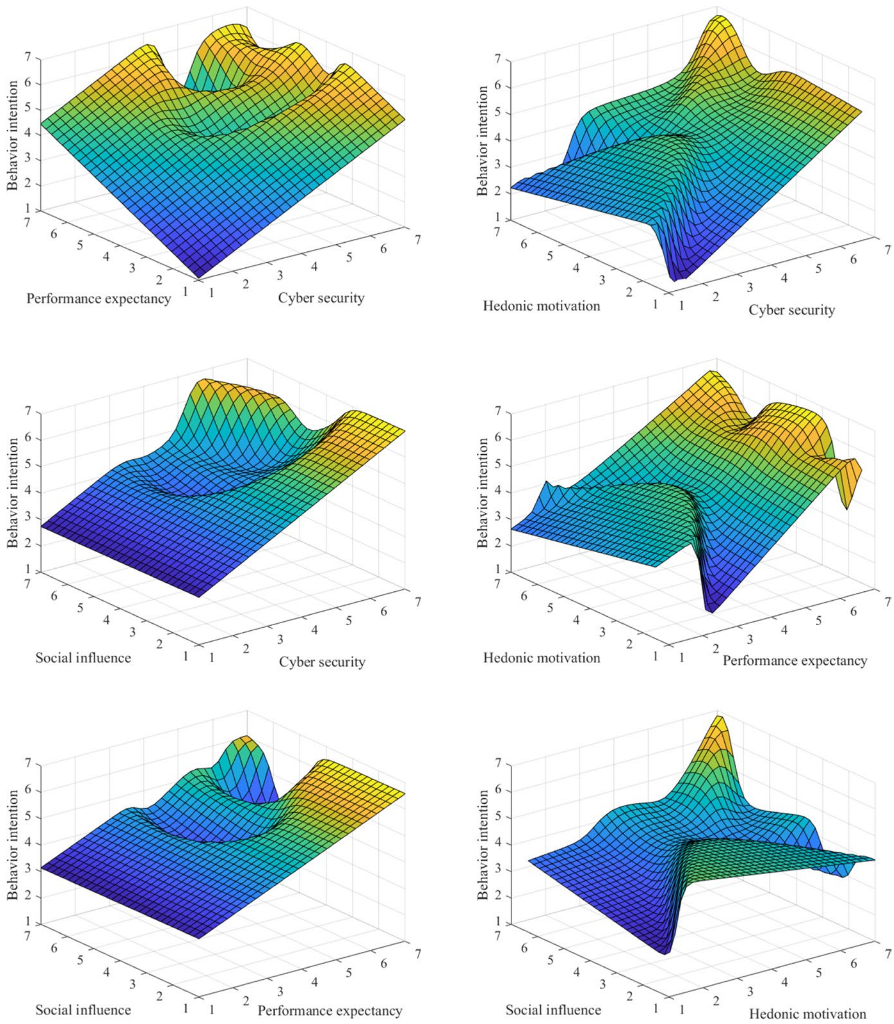

Fig. 6 A partial dependence plot of the relationship between the hypothesis parameters and behavioral intention to use the Metaverse

Therefore, future research should consider evaluating the participants' level of experience in using metaverse technology to analyze the distribution of behavioral intention to use metaverse technology in engineering education. Lastly, given that the study focused on engineering students, it is crucial to explore the applicability of the findings to other groups with distinct characteristics. Furthermore, evaluating the data for long-term use may also be necessary. It is important to note that the development of metaverse technology is still in its nascent stage, with ongoing exploration into future directions and specific operational methods.

5 Conclusion

Metaverse technology is a rapidly developing virtual environment that can provide limitless opportunities for social interaction, collaboration, education, and commerce. It has a wide range of potential uses, and its potential effects on various facets of life are anticipated to be significant. While metaverse technology has enormous potential for social interaction, collaboration, and education, it also raises concerns about inclusivity, accessibility, privacy, and user behavior. Addressing these issues will ensure that the technology is widely adopted and accepted. This study investigates the factors that influence user behavior and intention to utilize metaverse technology in education, which can help provide guidance concerning the design and implementation of more effective and interesting metaverse applications. This study utilized Google Forms to collect data, adapted measurements from previous studies, and employed PLS and ANFIS for path analysis. These methods confirmed direct relationships within the research context of the Metaverse. The results demonstrated that cyber security, performance expectancy, social influence, and hedonic motivation had significantly positive influences on behavioral intention, with cyber security having the most compelling effect. These results provide valuable insights for organizations seeking to improve their cyber security practices and promote positive user behavior.

Data availability Data will be made available on reasonable request.

Declarations

Conflicts of Interest The authors affirm that they are not affiliated with or involved in any organization or entity with any interest, financial or otherwise, in the subject matter or materials discussed in this manuscript.

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