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Review Article

Understanding adoption of AI-enabled metaverse, AR, and VR for training: An integrated TTF-UTAUT2 model using hybrid SEM-ANN

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ABSTRACT

The determinants of the adoption of artificial intelligence (AI)-based virtual assistants in metaverse-enabled augmented reality (AR) and virtual reality (VR) training environments are the focus of this study, which is based on the need to improve the training experience of students who display anti-social behavior. An integrated approach based on the task-technology fit and the UTAUT2 models is adopted to investigate the factors that affect the training experience in AR and VR environments enabled by metaverse technologies. An online survey conducted in two languages—English and Arabic—yielded 310 participants. The data were then analyzed based on the hybrid approach of structural equation modeling and artificial neural networks. According to the study, the strongest predictor of the behavioral intention to use metaverse-based training systems is the performance expectancy factor, which is 94.1%, followed by the social influence factor, which is 67.5%, and the hedonic motivation factor, which is 66.6%. In addition, the effort expectancy and facilitating conditions factors did not affect the intention to use the training systems. In conclusion, the study revealed that the AI virtual assistant factors and the strategies adopted in the development of the training systems play an essential role in improving the training experience of students who display antisocial behavior in the classroom.

Keywords: metaverse training, AI-powered virtual assistants, augmented reality, virtual reality, educational technology, digital learning environments, artificial intelligence in education, human-computer interaction, intelligent tutoring systems

INTRODUCTION

Research on user acceptance remains limited. Most studies are descriptive, focused on technical implementation or single-domain applications, and do not conduct a systematic analysis of the factors driving adoption. Furthermore, the relationship between metaverse skills and specific training tasks is understudied. This gap impedes the effective implementation of metaverse systems in training environments.

A hypothetical virtual environment that connects to and interacts with the physical environment is called metaverse. It is named by joining the prefix “meta,” which represents “transcendence,” and the word

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"universe." This naming is borrowed from Neal Stephenson's science fiction book Snow Crash in 1992, in which metaverse was used for the first time. Today, metaverse refers to just about every type of technology ranging from augmented reality (AR) and virtual reality (VR), and more lately, to blockchain and Web 3.0, among others (Fast-Berglund et al., 2018). There are numerous metaverse platforms that already exist and have gained popularity simultaneously with huge investments being made in metaverse (Bhattacharya et al., 2023).

To explain the concept of user acceptance for such innovative technology, this paper proposes using the unified theory of acceptance and use of technology 2 (UTAUT2), which mentions the determinants of performance expectancy (PE) and effort expectancy (EE), per (Guest, 2023). However, the use of UTAUT2 alone is insufficient in determining if the technology satisfies the tasks undertaken during the training experience. To fill this gap, we use the task-technology fit (TTF) theory, which determines the fit of the technology and its suitability in relation to the training tasks (Kye et al., 2021).

Although the integration of the two theories has great significance, the existing literature suggests an evident gap that has yet to be addressed: the application of UTAUT2 and TTF has been underexplored for metaverse-based training. Until now, there has been only one study scouting a specific field—the application of the two theories for basketball training knowledge. Although there exist some studies integrating UTAUT2 and TTF in other domains, for example, the application of AR at the tertiary level for education purposes (Faqih & Jaradat, 2021), there has been no study investigating the combined application of the two theories for metaverse training.

To fill the voids in existing literature regarding the use of metaverse-based learning systems, a comprehensive hybrid theoretical model combining both the perceptions of UTAUT2 as well as TTF evaluation of task support is proposed here. To make the results more reliable and accurate, structural equation modeling (SEM) and artificial neural networks (ANN) methods are used. Although not widely used in immersive technology adoption studies, these two methods are now becoming popular due to their ability to accommodate complex non-linear relationships. Additionally, the study is validated using a multilingual and cross-cultural research design.

Innovative Contributions

The contribution made by the research paper under analysis can be seen in the introduction of a multi-dimensional model that is specifically tailored to capture the essence of metaverse usage in training contexts. The integration of perception constructs as embodied in UTAUT2, namely PE, EE, and social influence (SI), with task-specific dimensions as derived from the TTF model, complemented with emerging dimensions such as presence, embodiment, and immersion, enables one to view the problem from a holistic perspective encompassing both perceptions and TTF. As per the findings, PE proves to be an important predictor variable, while engagement and TTF act as important facilitators in the formation of perceived usefulness. In terms of methods, the combined use of SEM and ANN provides researchers with an effective toolset capable of identifying non-linear interactions in the context of immersive technology adoption.

BACKGROUND

Metaverse Overview

The term metaverse can be considered as referring to a fully interactive 3D environment encompassing both real-world and virtual environments and which can be accessed using extended reality (XR). XR represents a framework which is inclusive of AR and VR (Dwivedi et al., 2022). AR is described as superimposing a VR layer on the physical environment in real-time based on sensory inputs like audio, visual, graphics, and GPS information among others (Guest et al., 2018; Wild et al., 2017). On the other hand, VR refers to being immersed in a computer-generated environment using a head-mounted display system, thus completely isolated from any physical environment (Mendoza-Ramírez et al., 2023). Another type of technology, known as augmented virtuality (AV), includes adding a representation of some real-world objects like video and images into the virtual environment, therefore combining VR and AR (Slater & Sanchez-Vives, 2016). The combination of AR and AV results in mixed reality, which is "a subset of VR technologies that involve

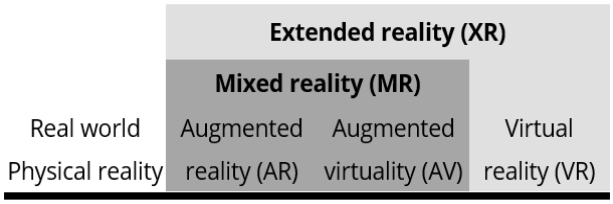


Figure 1. The reality-virtuality continuum (reproduced from Wohlgenannt et al., 2020)

merging real and virtual worlds," among other types of "realities" shown in **Figure 1** (Skarbez et al., 2021; Tlili et al., 2022; Wohlgenannt et al., 2020) .

However, while much advancement has been made in various types of XR applications, studies on the comparative efficacy of various types of XR technologies in the context of training have not yet been empirically carried out. Some of the challenges involved include cost, accessibility, and technological issues.

National Context: Metaverse and Digital Training in the United Arab Emirates

The United Arab Emirates is an interesting setting in which to analyze the use of metaverse-based training, considering the highly advanced nature of the country's digital infrastructure and its ongoing commitment towards digital transformation (Faqih & Jaradat, 2021). Significant amounts of money have been allocated for high-speed connections and initiatives such as smart campuses as part of various national strategies, such as United Arab Emirates digital government strategy, national AI strategy 2031, and smart education framework (Faqih & Jaradat, 2021). The use of such initiatives enables the use of XR and other technological solutions to prepare the current workforce to acquire future skills and learn through technology-based means. Therefore, many educational institutions in the United Arab Emirates are increasingly adopting metaverse technologies to help develop future skills (Brooks, 1999).

In such a technologically enabled environment driven by favorable policies, the need to understand what makes users accept certain technologies becomes essential, especially when it comes to the success of the implementation process and ROI generation. Therefore, the United Arab Emirates can be considered an optimal setting to explore the factors that affect the adoption of the metaverse.

Metaverse Adoption in Training

The trend towards integrating metaverse technology into educational processes has been well-documented through numerous academic works (Goodhue & Thompson, 1995). The increasing need for versatile, engaging, and interactive learning environments has stimulated the consideration of metaverse applications in education and professional training processes . Various works have applied TAM as a theoretical framework when investigating users' acceptance in particular educational communities, such as medical students (Hair et al., 2022), whereas other scholars provided descriptive accounts of user engagement with little emphasis on data analysis (Alawadhi et al., 2022).

In support of this idea, Hair et al. (2022) observed that participants were generally positive about using the metaverse for medical training exercises; more precisely, the usefulness of the technology was the most significant determinant. On the contrary, Alawadhi et al. (2022) noted high engagement rates amongst thoracic surgeons using XR technologies; however, no learning outcome analysis was performed during the investigation. Most academic papers in the area are either narrowly specialized or descriptive and lack cross-domain analytics evaluating users' perceptions and the compatibility of learning tasks with various types of XR (Alawadhi et al., 2022; Goodhue & Thompson, 1995; Guest, 2023; Kalinić et al., 2021).

Most adoption studies are descriptive or domain-specific, lacking cross-sector evaluation. Only Joiner (Koo, 2021) applied UTAUT2 to metaverse adoption, but in a narrow context (basketball training). Faqih and Jaradat (Joiner, 2018; Kalinić et al., 2021) merged UTAUT2 and TTF, but only for AR in Jordanian higher education. No study integrates UTAUT2 and TTF for metaverse-based training in a variety of scenarios, nor does it use predictive analytics such as ANN in conjunction with SEM (**Table 1**).

Table 1. Critical comparison of prior adoption studies

Study	Domain	Method	Key findings	Limitations/gaps
Chinta et al. (2021)	Medical training	Survey/TAM	Positive adoption; influenced by perceived usefulness	Limited task-technology analysis; single domain
Koo (2022)	Surgical training	Descriptive	High engagement in 360° sessions	No measurement of learning outcomes; descriptive only
Joiner (2018)	Basketball training	UTAUT2	Attitude, habit, behavioral intention predict usage	Domain-specific; cannot generalize to other training
Faqih and Jaradat (2021)	AR adoption in education	UTAUT2 + TTF	TTF and UTAUT2 constructs enhanced adoption	Limited to AR; single country; PV insignificant

Table 2. Analytical comparison

Domain	Study	Method	Key findings	Limitations/gaps
Healthcare	VR surgical simulations (Alaker et al., 2016)	Experimental	Improved procedural skills	Limited long-term assessment; modality comparison lacking
Technical education	VR/AR machinery training (Wohlgenannt et al., 2020)	Observational	Increased engagement, safety, reduced cost	Hardware accessibility issues; limited generalizability
General training	Metaverse adoption (Lee et al., 2021)	Descriptive review	Interactive, scalable, cost-effective	Few cross-domain comparisons; cultural adaptation not considered

Applications and Benefits of the Metaverse in Training

Recent metaverse improvements have enabled broad training applications in a variety of fields, including healthcare, technical education, and professional skill development (see **Table 2**).

While these studies show the potential of metaverse-based training, they frequently lack an analytical comparison across industries or XR modalities. Accessibility difficulties (hardware and connection), long-term results, cultural adaptation, and task alignment are rarely addressed in a systematic way. This emphasizes the necessity for research that combine user perceptions (UTAUT2) and TTF to provide multidimensional insights (Tlili et al., 2022).

Research Gaps and Justification

The above research reveals three major gaps:

1. Domain specificity and descriptive bias: Most of the research focus on a single domain or provide descriptive data without any comparison analysis.
2. Few studies have combined UTAUT2 and TTF to measure user acceptance and task-technology alignment for metaverse-based training.
3. Methodological limitations: Predictive and explanatory analytics (e.g., SEM + ANN) are rarely used, reducing the strength of the findings.

This study fills those gaps by:

- creating a hybrid model that integrates UTAUT2 with TTF,
- using multilingual survey data for greater application,
- using SEM and ANN to integrate explanatory and predictive analysis, and
- providing cross-domain insights into metaverse use in training.

Research Hypothesis

UTAUT theory was created in 2003 to investigate the possibility of adopting new technologies from an organizational standpoint. It was then expanded into UTAUT2 in 2012, with three new constructs—hedonic motivation (HM), price value (PV), and habit—to investigate the possibilities of embracing and adopting new technology from the user's perspective (Guest, 2023). Gender, age, and experience were identified as modifiers, and they were commonly used in later investigations (see **Figure 2**).

Although UTAUT2 measures individual perceptions, it does not determine whether the technology is appropriate for the training tasks themselves, emphasizing the importance of incorporating TTF.

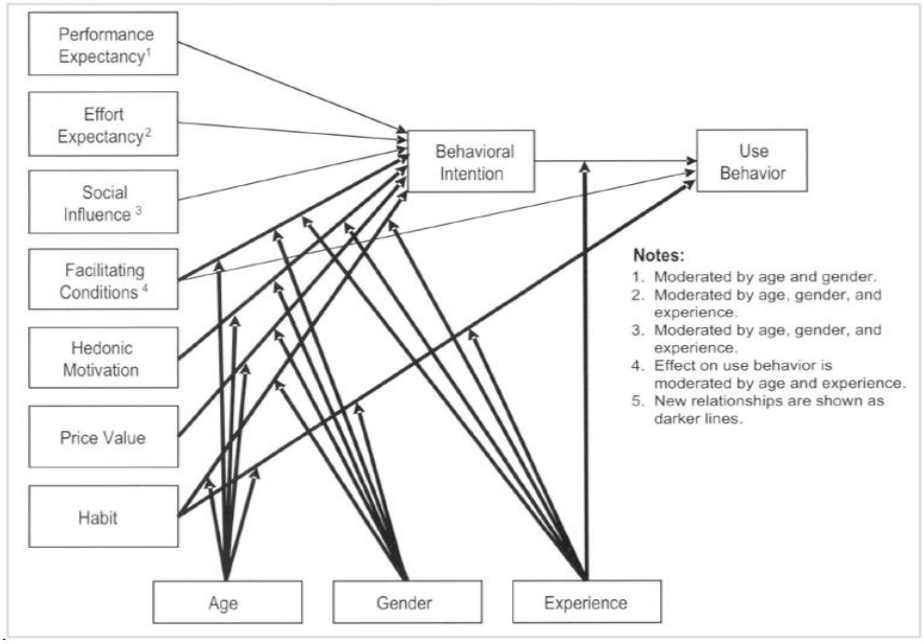


Figure 2. UTAUT2 diagram illustrating the model components of PE, EE, SI, FC, HM, PV, BI, and use behavior (reproduced from Rane et al., 2023)

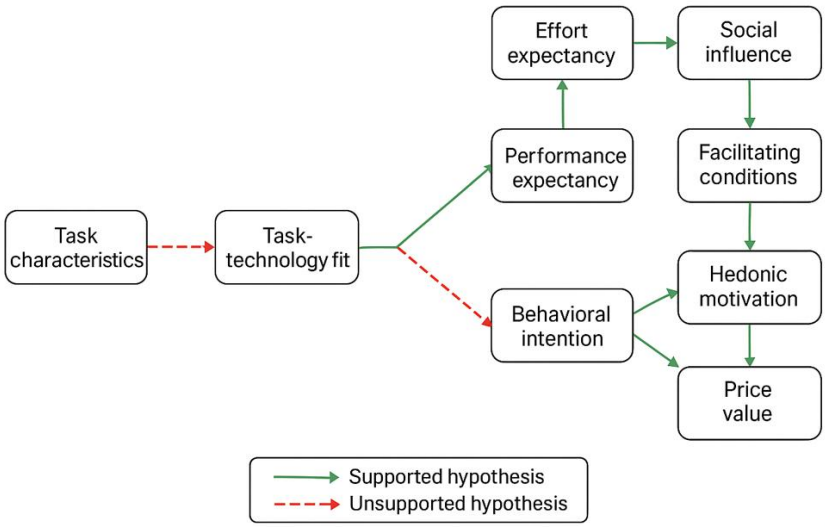


Figure 3. Research model (TTF-UTAUT2 integration for metaverse adoption in training) (the authors' own elaboration)

TTF, by definition, relates to the extent to which technology enables an individual to do specific activities. Many theories of technology adoption and acceptability have been established and tested through empirical investigations and reviews in a variety of information technology disciplines.

While all technology adoption theories have some elements, they also have distinct features that set them apart. For example, the UTAUT theory measures how much a person adopts new technology; nevertheless, individuals' views of technology alone may not be sufficient for adoption, potentially leading to inconsistencies in actual usage data (Kollar Isabelle, 2022). This is where incorporating another theory, such as TTF, is critical. TTF analyzes whether the adopted technology is appropriate for the goal for which it was designed—in this example, the metaverse (Morris et al., 2004) (see **Figure 3**).

The intricacy of metaverse technology presents difficulties for instructors and learners in grasping its interactive tactics, making metaverse adoption in training an important topic. To be effective, metaverse technology's qualities must be compatible with the training tasks entrusted to it. Most empirical studies that combine UTAUT and TTF focus on associating PE, EE, and behavioral intention (BI) from UTAUT or UTAUT2

with task features, TTF, and technological characteristics from TTF (Mystakidis, 2022). Based on the integrated UTAUT2-TTF model, the following hypotheses are proposed:

H1: Task characteristics (TAC) significantly influence TTF.

H2: Technology characteristics (TEC) significantly influence TTF.

H3: TTF significantly influences BI.

H4: PE significantly influences BI.

H5: EE significantly influences BI.

H6: SI significantly influences BI.

H7: Facilitating conditions (FC) significantly influence BI.

H8: HM significantly influences BI.

H9: PV significantly influences BI.

H10: TTF significantly influences PE.

H11: TEC significantly influence EE.

The proposed research framework, as seen in **Figure 3**, incorporates tasks from TTF and UTAUT2 theories to examine factors determining metaverse adoption during training settings. Such a framework captures inter-relationships between TAC, TEC, TTF, PE, EE, SI, FC, HM, and PV, leading to BI. In **Figure 3**, the hypotheses that have been supported by statistically significant results using strong green lines include **H2**, **H4**, **H5**, **H6**, **H8**, **H10**, and **H11**. On the other hand, the hypotheses that have failed to be supported using dashed red lines include **H1**, **H3**, **H7**, and **H9**. This framework combines task and technology factors, as well as social and motivational factors and perspectives of end-users. This provides a well-rounded perspective of immersive technology usage in a training environment.

MATERIALS AND METHODS

This study uses a quantitative research approach to investigate the factors that influence the use of metaverse technology in training. The process is divided into three major phases: data collection, research instrument development, and data analysis. A systematic online questionnaire was utilized to collect responses from Twitter users, taking use of the platform's broad reach to include people from diverse backgrounds. The parts that follow go into detail about each phase.

Data Collection

A bilingual (Arabic and English) online questionnaire was used in the present study to evaluate determinants of adoption of metaverse training technologies. The process of data collection was divided into two stages. In the first stage, data were collected between November 14 and 24, 2022; in the second stage, additional data were collected between April 7 and 30, 2025, leading to the receipt of 197 responses. Thus, after screening the responses for completeness, 310 valid responses were obtained.

Potential respondents were found via online social media platforms (mainly, X/Twitter), educational, and professional communities. The purpose was to obtain responses from different segments of the population, considering individuals' education and career, and thus to receive a wide variety of responses concerning new immersive technologies for training and learning. Furthermore, to avoid any technology bias, respondents were not recruited only from technology-related communities but from the general pool of learners and educators.

Participation in the study was voluntary; inclusion criteria included being 18 years or older and able to complete the questionnaire either in Arabic or English. Prior experience with metaverse, VR, and AR was not considered necessary.

The study strictly follows ethical standards of research. Personal information was not collected, and all responses were anonymous. Participants were acquainted with the purpose of the study and voluntary nature of participation.

Table 3. Respondents' demographic characteristics

Characteristics	Values	Frequency (n)	Percentage (%)
Gender	Female	91	29
	Male	219	71
Age	18-25	71	23
	26-40	106	34
	41-55	118	38
	+55	15	5
Education	High school	32	10
	Diploma/high diploma/bachelor	201	65
	Master	58	19
	PhD	19	6

In addition to demographic characteristics, such as gender, age, and educational level, other information was collected using close-ended questions with multiple-choice answers (see **Table 3**). Gender (male/female/other), age group, and educational level were coded categorically (binary for gender, three categories for others). Moreover, responses to all questions (except demographic questions) were obtained using a five-point Likert scale (1 – strongly disagree; 2 – disagree; 3 – neutral; 4 – agree; 5 – strongly agree).

Research Instrument

The items corresponding to each construct were carefully selected or tailored to the context of adopting metaverse technologies for training. Regarding TAC, items were mainly based on Mystakidis (2022) because the mentioned scale is based on TTF and UTAUT models. This framework highlights the importance of task analysis in relation to technological fit. More specifically, Mystakidis (2022) scale was relevant for the present study since it allows obtaining valid measurements in accordance with task variability, flexibility, complexity and the need for completing them in a timely manner, regardless of place and time limitations, which are essential characteristics of metaverse technology.

In turn, items pertaining to TAC were also adopted because the scale integrates TTF with UTAUT2 in an educational setting. It was found particularly helpful to obtain relevant measurements of training in terms of task variability, complexity and organizational support. Thus, TAC4 and SI3 were modified according to the current study needs.

Lastly, the following constructs (except for TAC) have been adopted mainly from (Kollar Isabelle, 2022). It should be noted that the latter is characterized by thorough discussion of adoption of AR technology. This framework is highly relevant in the present study due to its applicability for evaluating technology-related variables, associated with metaverse.

Necessary adjustments have been made to adapt the items to the specifics of metaverse and their utilization in the context of training. References for mobile banking and AR were replaced with references to the metaverse to make the scale clear to respondents.

The main constructs explored in this study are:

- TAC: Assessing the requirement for training in various settings (e.g., anytime, anywhere, and real-time).
- TEC: Evaluate the availability, dependability, and security of metaverse-based training.
- TTF: Determines the compatibility of technical infrastructure and training requirements.
- PE: Analyzing the perceived benefits of metaverse-based training.
- EE: Measuring the usability of metaverse technologies.
- SI: Examining the effect of peer and organizational support on metaverse adoption.
- FC: An assessment of resource availability and technical compatibility.
- HM: investigates the enjoyable and engaging components of metaverse training.
- PV: Determines the cost-effectiveness of metaverse training systems.
- BI: predicts the likelihood of metaverse adoption for training purposes.

Each construct is made up of several items that have been altered from previous research to guarantee that the relevant variables are accurately captured. **Table 4** summarizes the items and their sources.

Table 4. Constructs, items, and their resources

Construct	IC	Items	Reference
TAC	TAC1	"I think that I need to do training at any time."	Kollar Isabelle (2022); Mystakidis (2022); Wild et al. (2017)
	TAC2	"I think that I need to do training at anywhere."	
	TAC3	"I think that I need to do training in real-time."	
	TAC4	"I frequently deal with ad-hoc, non-routine problems in training."	
TEC	TEC1	"I think the use of metaverse for training will be available without interruption in service."	Kollar Isabelle (2022); Mystakidis (2022)
	TEC2	"I think the use of metaverse will provide real time training."	
	TEC3	"I think the use of metaverse in training will be quickly available."	
	TEC4	"I think the use of metaverse in training will be secure."	
TTF	TTF1	"I think the available technical equipment meets the minimal requirements to complete my metaverse-based training."	Kollar Isabelle (2022); Mystakidis (2022)
	TTF2	"I think the available technical equipment is appropriate to complete my metaverse-based training."	
	TTF3	"I think the available technical equipment meets all the needs of my metaverse-based training."	
PE	PE1	"I think the use of metaverse will be more beneficial to my training."	Kollar Isabelle (2022)
	PE2	"I think the use of metaverse increases my chances of achieving targets that are important to me in my training."	
	PE3	"I think the use of metaverse will enable me to conduct training more quickly."	
EE	EE1	"I think that I will find metaverse easy to use in training."	Kollar Isabelle (2022)
	EE2	"I think my interaction with metaverse in training is clear and understandable."	
	EE3	"I think that it is easy for me to become skillful at using metaverse in training."	
SI	SI1	"People who influence my behavior think that using the metaverse in training is important to me."	Kollar Isabelle (2022); Mystakidis (2022); Wild et al. (2017)
	SI2	"People who are important to me think that using the metaverse in training is important to me."	
	SI3	"I believe the facility or organization I belong to will support the use of the metaverse in training."	
FC	FC1	"I think that I have the necessary resources to use metaverse in my training."	Kollar Isabelle (2022); Wild et al. (2017)
	FC2	"I think that I have the necessary knowledge to use metaverse in my training."	
	FC3	"I think that the use of metaverse in my training is compatible with other technologies I use."	
	FC4	"I think that I can get help from others when I have difficulties using metaverse in my training."	
HM	HM1	"I think the use of metaverse in my training is fun."	Kollar Isabelle (2022)
	HM2	"I think the use of metaverse in my training is enjoyable."	
	HM3	"I think the use of metaverse in my training is very entertaining."	
PV	PV1	"I think the use of metaverse in my training will be available at reasonable expenses."	Kollar Isabelle (2022);
	PV2	"I think the use of metaverse in my training will provide me a good value for the paid expenses."	
BI	BI1	"If I were to adopt metaverse technology, I intend to use it in training."	Mystakidis (2022); Wild et al. (2017)
	BI2	"If I were to adopt metaverse technology, I predict that I would use it in training."	
	BI3	"I plan to use metaverse technology frequently in training."	

A hybrid structural equation modeling-artificial neural network (SEM-ANN) technique is used in this study to examine correlations and predict behavioral intents. This integrated method combines the explanatory power of SEM, which is suitable for assessing causal paths, model fit, and capturing certain non-linear effects, with the predictive capability of ANN, which can identify more complex, high-order, and non-parametric non-linear relationships that SEM alone may not be able to detect.

The justification for using SEM-ANN over standalone approaches stems from the exploratory character of metaverse adoption, in which behavioral components may interact in nonlinear ways. While SEM validates the theoretical framework through hypothesis testing and reliability checks, ANN enhances it by providing robust prediction capabilities and variable relevance ranking. This dual approach improves analytical depth and practical insight.

This tool, which was subjected to repeated pilot testing and reliability checks, was validated to establish its appropriateness in the context of training adoption in the metaverse.

Table 5. Summary of constructs and measurement focus in the metaverse training adoption study

Construct	Focus/description
TAC	Flexibility, real-time, ad-hoc training tasks
TEC	System reliability, security, availability, user knowledge
TAF	Compatibility of system with training needs
PE	Belief that Metaverse improves training effectiveness
EE	Perceived ease of use
SI	Impact of peers and organizational support
FC	Resources, support, and knowledge availability
HM	Fun, enjoyment, engagement
PV	Cost-effectiveness and value
BI	Likelihood of adoption and frequent use

Measurement Items and Constructs

The section discusses measuring items adopted from prior research, with a particular emphasis on several variables such as FC, HM, PE, PV, BI, and others. It discusses the sources of these items, the adaption process to match the metaverse setting, and the importance of assuring validity and relevance in assessment tools. As shown in **Table 5**, the measurement model's validity and reliability were evaluated using a variety of metrics, showing the robustness of the constructs utilized in the study.

These findings confirm that the study successfully established discriminant validity, convergent validity, and internal consistency reliability, supporting the robustness of the measurement model.

Data Analysis

The proposed research model and hypotheses embodied in this research can be verified using a combination of partial least squares structural equation modeling (PLS-SEM) techniques and ANN. The selection of the PLS-SEM technique over the covariance-based structural equation modeling (CB-SEM) technique is based on a variety of reasons that are aligned to the proposed research. First, the nature of the research is exploratory and predictive since it aims to find important predictors of metaverse adoption for more effective training. PLS-SEM is preferable for exploratory and theoretic development studies than for confirming a theory, where CB-SEM is more appropriate. Second, the combination of UTAUT2 and TTF models is relatively complex since it involves several latent variables with many relations, and PLS-SEM is superior when dealing with complex models without imposing data distribution assumptions.

Third, PLS-SEM does not require normality in the data and can handle medium-sized samples, which are common in the context of emerging technology adoption studies. By contrast, CB-SEM needs large sample sizes and multivariate normality to obtain sound estimates. Fourth, the adopted research methodology using PLS-SEM has its continuity in the succeeding implementation of the ANN model. Both methods share the common goal of focusing on the explanatory and predictive capabilities of the variances against the overall goodness-of-fit measures. This makes the PLS-SEM particularly compatible with the implementation of the ANN model.

Therefore, PLS-SEM can be used to explore linear causality and test hypotheses, whereas the potential nonlinear relationships can be captured by means of the ANN. By combining the SEM and the ANN, it has become possible to achieve explanatory power and robustness in prediction, which cannot be obtained by either methodology alone.

PLS-SEM analysis

PLS-SEM was chosen for its capacity to

- analyze large theoretical models that contain several constructs,
- identify the essential factors impacting the BI to use metaverse-based training, and
- handle constructs based on UTAUT2 and TTF theories.

ANN analysis

Because PLS-SEM has difficulty handling nonlinear interactions, ANN was used in this study. ANN is extremely good at detecting and modeling complicated, non-linear correlations between variables, which

typical linear approaches may miss. To do this, a multi-layer perceptron (MLP) with a single hidden layer made up of three neurons was employed to capture these interactions and rank the most relevant metaverse adoption factors.

The ANN model used supervised learning with the backpropagation algorithm, with the sigmoid activation function in both the hidden and output layers to help learn nonlinear patterns. The input features were PE, EE, HM, and PV. To avoid overfitting and improve model generalizability, a ten-fold cross-validation strategy was used (Ramírez-Correa et al., 2019; Rauschnabel et al., 2022), with the dataset divided into 90% training and 10% testing for each fold. The hyperparameters were tweaked depending on the model's performance throughout folds.

This work uses PLS-SEM and ANN to conduct a detailed and rigorous evaluation of the factors influencing metaverse acceptance in training scenarios. This combination strategy capitalizes on the strengths of both methods—PLS-SEM for confirmatory analysis and linear relationships, and ANN for modeling complex, nonlinear interactions—to improve forecast accuracy and strengthen the study's theoretical contributions (Ali et al., 2025; Oliveira et al., 2014).

RESULTS

Respondents' Demographic Characteristics

The demographic characteristics of the respondents are presented in **Table 4**. There were 310 people involved in the study. The sample included 71% (n = 219) male respondents and 29% (n = 91) female respondents. Regarding age differences, 23% of the respondents fell into the age group of 18-25 years, 34% into the age group of 26-40 years, 38% into the age group of 41-55 years, and 5% were older than 55 years. This pattern in the age distribution implies that the participants of the research predominantly belong to the category of working adults who continue their professional education and training.

As for the educational level of the sample members, 65% had a diploma, higher diploma or a bachelor's degree, 19% had a master's degree, 6% had a doctorate degree, and 10% only graduated from a high school. This data implies that most of the participants had an experience of studying in contemporary digital environments.

Overall, the sample includes a rather diverse population characterized by differences in age and education. Such a demographic situation allows obtaining comprehensive information regarding the implementation of metaverse-based training technologies in educational environments. Even though all respondents were attracted to participate in the study through online resources, the researchers aimed at attracting participants not only from the community of educational technologies but also from the general audience.

Measurement Model Evaluation

Before conducting the analysis of the structural model, the measurement model was tested for reliability, convergent validity, and discriminant validity. Reliability was examined with Cronbach's alpha (CA) and composite reliability (CR). The CA is a popular measure of reliability, showing to what extent items are related to each other and reflect the same latent variable. According to Hair et al. (2022), the value greater than 0.70 indicates acceptable reliability, higher than 0.80 is interpreted as good, and the value exceeding 0.90 means excellent reliability. As one can see from **Table 6**, CA coefficients range between 0.699 and 0.897, while CR values are between 0.815 and 0.936. All measures meet the requirement for at least acceptable levels of reliability since their values are above the critical point of 0.70. Despite the slightly lower value of the CA for TAC (0.699), the reliability of this construct is still considered acceptable when doing an exploratory study and supported by satisfactory CR (0.815) and average variance extracted (AVE) (0.535). Hence, all constructs were included in further analyses (Paulo et al., 2018; Qasem et al., 2020).

Inclusion of all indicators was supported due to exceeding the recommended loading value of 0.40. Even though TAC4 loading was 0.478, removing this item would not significantly increase reliability and validity of this construct, therefore, this item was left in the study. Also, all CRs exceeded the threshold value of 0.70 (ranging from 0.815 to 0.936).

Table 6. Measurement model assessment results including factor loadings, CA), CR, AVE, and construct correlations

Construct	Indicator	Loading	CA	CR	AVE	BI	EE	FC	HM	PE	PV	SI	TAC	TATF	TEC
BI	BI1	0.905	0.848	0.908	0.768	**0.876**	0.424	0.520	0.703	0.790	0.588	0.589	0.685	0.332	0.503
	BI2	0.880													
	BI3	0.842													
EE	EE1	0.871	0.859	0.914	0.780	0.424	**0.883**	0.312	0.620	0.618	0.494	0.198	0.272	0.263	0.558
	EE2	0.922													
	EE3	0.854													
FC	FC1	0.691	0.744	0.834	0.558	0.520	0.312	**0.747**	0.386	0.346	0.538	0.720	0.434	0.558	0.484
	FC2	0.689													
	FC3	0.822													
	FC4	0.778													
HM	HM1	0.922	0.879	0.926	0.807	0.703	0.620	0.386	**0.898**	0.728	0.473	0.216	0.552	0.119	0.522
	HM2	0.937													
	HM3	0.833													
PE	PE1	0.918	0.888	0.931	0.818	0.790	0.618	0.346	0.728	**0.904**	0.429	0.282	0.499	0.263	0.642
	PE2	0.924													
	PE3	0.871													
PV	PV1	0.817	0.735	0.875	0.779	0.588	0.494	0.538	0.473	0.429	**0.882**	0.447	0.371	0.403	0.358
	PV2	0.944													
SI	SI1	0.869	0.770	0.868	0.689	0.589	0.198	0.720	0.216	0.282	0.447	**0.830**	0.541	0.540	0.394
	SI2	0.885													
	SI3	0.727													
TAC	TAC1	0.840	0.699	0.815	0.535	0.685	0.272	0.434	0.552	0.499	0.371	0.541	**0.732**	0.206	0.543
	TAC2	0.851													
	TAC3	0.694													
	TAC4	0.478													
TTF	TTF1	0.913	0.897	0.936	0.829	0.332	0.263	0.558	0.119	0.263	0.403	0.540	0.206	**0.910**	0.474
	TTF2	0.948													
	TTF3	0.870													
TEC	TEC1	0.766	0.776	0.856	0.599	0.503	0.558	0.484	0.522	0.642	0.358	0.394	0.543	0.474	**0.774**
	TEC2	0.870													
	TEC3	0.730													
	TEC4	0.721													

Convergent validity was estimated using factor loadings and AVE. All the items' loadings exceed the required level of 0.708 except for TAC4. Besides that, all constructs have values of AVE higher than 0.5, including TAC, whose AVE is 0.535. It means that constructs capture more than 50% of variance of the indicators and, therefore, are suitable from the point of view of convergent validity. Finally, discriminant validity was estimated using the Fornell-Larcker criterion and Heterotrait-Monotrait (HTMT) ratio. In accordance with the criteria, square roots of AVE are higher than correlation with other constructs, which shows adequate discriminant validity of the measures. Also, all HTMT values do not exceed the critical level of 0.85; the largest coefficient is 0.813.

Structural Model Assessment

Following validation of the measurement model, the structural model was evaluated to determine its predictive capabilities and construct relationships (Hair et al., 2022). The structural model was estimated using a bootstrapping resampling technique with 5,000 resamples, yielding non-bootstrapped and bootstrapped estimates. We evaluated the model's relevance and appropriateness using R^2, path coefficients, t-values, p-values, and PLS-SEM fit indices (SRMR and NFI).

Table 7 displays the values of the structural model path coefficients, t-values, p-values, and R-squared (R^2) for each proposed hypothesis in the model. It is observed that the p-values of hypotheses **H1**, **H3**, **H7**, and **H9** are greater than 0.05. This means that hypotheses **H1**, **H3**, **H7**, and **H9** failed to predict the hypothesis of BI. In this case, hypothesis **H7** is statistically significant ($p < 0.001$) with a negative coefficient of -0.150. This hypothesis is expected to be positive based on the principles of UTAUT2 theory. Additionally, it appears that TTF is influenced by TEC but does not significantly affect BI. **Table 7** offers a clear description of the significance of the hypothesized relationships proposed in the model.

Table 7. Results of hypothesis testing

Hypothesis	Path	Path coefficient	t-value	p-value	Supported	Interpretation
H1	TAC → TTF	0.011	0.209	0.834	No	TAC did not significantly influence TTF, likely due to the overriding role of immersive features.
H2	TEC → TTF	0.409	7.105	0.000	Yes	TEC significantly improved TTF.
H3	TTF → BI	-0.008	0.178	0.859	No	TTF did not directly impact BI, perhaps reflecting a focus on individual perceptions over task-technology alignment.
H4	TTF → PE	0.241	3.181	0.001	Yes	A positive effect of TTF on PE was observed.
H5	TEC → EE	0.463	6.817	0.000	Yes	Technology attributes significantly enhanced EE.
H6	PE → BI	0.463	10.042	0.000	Yes	PE strongly influenced BI.
H7	EE → BI	-0.150	3.653	0.000	No	EE did not significantly affect BI, indicating that perceived usefulness outweighs ease of use.
H8	SI → BI	0.267	6.221	0.000	Yes	SI had a significant positive impact on BI.
H9	FC → BI	0.050	1.009	0.313	No	FC did not significantly influence BI.
H10	HM → BI	0.261	4.907	0.000	Yes	HM contributed positively to BI.
H11	PV → BI	0.164	3.672	0.000	Yes	PV was a significant predictor.

Four of the six constructs hypothesized to influence BI in adopting the metaverse for training (**H6**, **H8**, **H10**, and **H11**) were found to be significant, implying that PE, SI, HM, and PV all have a positive impact on BI.

Furthermore, three additional hypotheses (**H2**, **H4**, and **H5**) were identified as significant but not directly related to BI. Instead, they contributed to TTF, which **H2** supports TTF from the TEC, **H4** supports PE from the TTF, **H5** supports the EE from TEC.

These findings shed light on the important elements impacting the adoption of metaverse technology for training, stressing the importance of technical characteristics and individual user expectations.

The R^2 values for endogenous constructs were generated to assess the structural model's capacity to predict the dependent variables and explain their variance. Existing research classifies R^2 values as low (0.02-0.12), moderate (0.13-0.25), and considerable (≥ 0.26) (Ramayah, 2018)

Figure 4 shows the R^2 values for the endogenous constructs: TTF (0.171), PE (0.058), EE (0.214), and BI (0.650). The moderate R^2 value of TTF (22.4%) indicates that TEC is the primary contributor to its variance, with TAC playing a minor part due to the unsubstantiated **H1**.

The moderate R^2 value of TTF suggests that TEC explains a notable portion 17.1% of its variance, while TAC contribute minimally, likely due to the unsupported **H1**. The low R^2 value for PE indicates that TTF explains only 5.8% of its variance, whereas the moderate R^2 for EE 21.4% reflects the influence of TEC. Most notably, the substantial R^2 value of 0.650 for BI suggests that the four supported predictors PE, SI, HM, and PV collectively account for 65% of the variance in users' intention to adopt the metaverse for training. Unsupported hypotheses are **H1**, **H3**, **H7**, and **H10**.

The pattern of accepted and unsupported assumptions gives substantial theoretical consequences when translated onto the UTAUT2 and TTF frameworks. The considerable effects of PE, SI, HM, and PV agree with UTAUT2's basic hypotheses that perceived utility, social endorsement, experiential enjoyment, and value perception drive BI (Küçükuncular & Ertugan, 2025; Mishara, 2024). In contrast, the non-significance of EE and FC is consistent with recent literature demonstrating that usability and resource-based predictors play a lessened role among digitally experienced users engaging with immersive systems (Rauschnabel et al., 2022; Selvam & González Vallejo, 2025; UNESCO, 2021). Furthermore, the absence of significant associations for TAC and TTF shows difficulties in the classic TTF model when applied to immersive metaverse environments. This supports recent calls to extend TTF to include presence, immersion, and embodied interaction to more accurately reflect user perceptions in XR-based training .

ANN Results

Figure 5 illustrates the ANN model formulated to forecast the BI, which emerged as the lone endogenous construct with statistically significant antecedents in the PLS-SEM analysis. The two remaining endogenous constructs, PE and EE, with single antecedents TTF and TEC, respectively, were thus excluded as dependent variables when building the ANN model.

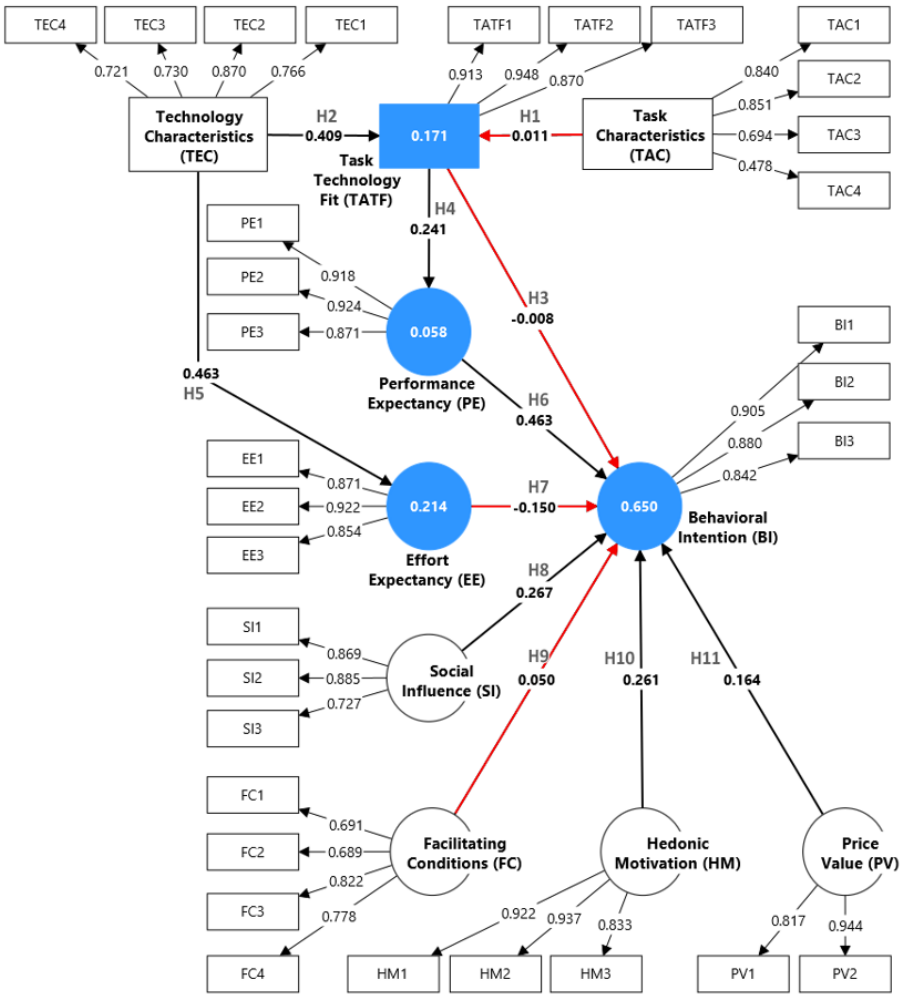


Figure 4. PLS algorithm results (the authors' own elaboration)

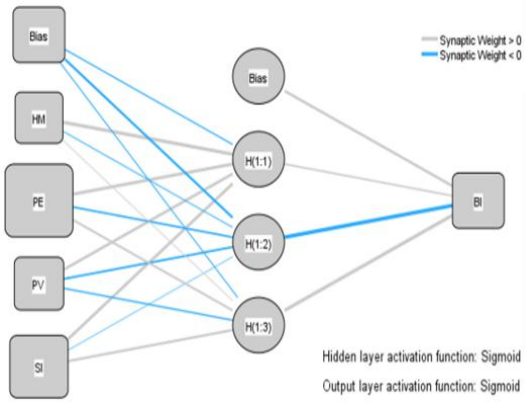


Figure 5. ANN model (the authors' own elaboration)

Though theoretically affected by TAC and TEC as antecedents of TTF, TTF was not considered as a parameter for the analysis of ANN since only one antecedent had statistical backing as indicated in **Table 6**. Supported by the PLS-SEM results, PE, EE, HM, and PV served as inputs to model BI (**Table 6** & **Figure 4**).

The analysis using the ANN was performed using SPSS version 29, which utilizes the MLP neural network model. Consistent with existing modeling best practices for ANN, the design included only one hidden layer to achieve optimal model complexity and generalization performance (Oliveira et al., 2014). With reference to **Figure 5**, the final design includes four input neurons (PE, EE, HM, PV), one hidden layer containing three neurons, and one output neuron (BI).

Table 8. RMSE values of the ANN model

Network	RMSE (training)	RMSE (testing)
1	0.092	0.119
2	0.085	0.110
3	0.083	0.097
4	0.083	0.090
5	0.104	0.129
6	0.096	0.106
7	0.082	0.103
8	0.098	0.115
9	0.083	0.110
10	0.088	0.109
Mean	0.089446593	0.108650182

To reduce overfitting and improve generalization capabilities, a ten-fold cross validation method was adopted that split the dataset into 90% for training and 10% for testing purposes. This method also assists in assessing the strength of the predictors over various networks designs (Ramírez-Correa et al., 2019; Rauschnabel et al., 2022). The sigmoid activation function is used in both the hidden and output layers, as in other ANN models on behavioral issues (Schmitz et al., 2022).

For model training, the scaled conjugate gradient algorithm was used, and the parameters were set at the default values of SPSS (learning rate = 0.4, momentum = 0.9). For early stopping of the training, which needed to be controlled to avoid over-fitting of the model, there are limitations of using hyperparameter optimization tools available on SPSS software. However, there is room for improvement using recent advances offered by deep learning libraries such as TensorFlow and Keras.

The accuracy of the ANN model in making predictions was measured using the root mean square error (RMSE), with ten runs, according to prescribed methodologies (Alnsour et al., 2025; Bulut & Beiting-Parrish, 2024). The RMSE values, according to **Table 8**, range between 0.082 and 0.104 for training, and 0.090 and 0.129 for testing. The standard deviation of these values is 0.0079 and 0.0109, respectively. The standard deviations show a moderate variation. Even though the ANN model was unable to optimize the level of precision because of the apparent fluctuations in the RMSE values, the prediction trends of the model generally corresponded with the PLS-SEM outcomes. The small deviations could be ascribed to the deletion of various non-significant predictors discovered under the structural model, which contributed to the learning dynamics of the ANN model and the variability of the RMSE values. Although there was a process of cross-validation, the variability apparent from the differences in RMSE values during training and testing could imply the current sensitivity of the model to the over-fitting problem.

Sensitivity Analysis

A sensitivity study was performed to determine the impact of each predictor on BI to use the metaverse for training. To calculate normalized importance, each input's relative significance was divided by the optimal relative value (Chinta et al., 2024).

According to **Figure 6**, the sensitivity analysis results suggest that PE is the most significant predictor, with a normalized relevance of 97.5%, followed by SI at 67%. Conversely, HM and PV had the least influence on BI, with normalized significance values of 94.1%. This is followed by SI and HM at 67.5% and 66.6%, respectively. In contrast PV exhibits lower level of influence with normalized importance value of 46.9%.

Figure 6 shows the architecture of a MLP ANN model for predicting BI in metaverse training adoption. **Figure 6** depicts three hidden neurons, and the input components used as predictors—PE, EE, HM, and PV, with BI serving as the output.

DISCUSSION

Evaluation of Constructs Affecting Metaverse Adoption in Training

These findings reveal that PE and SI are the main factors affecting the intention to accept metaverse-based training systems. Such a conclusion is in accordance with previous research focused on the role of users'

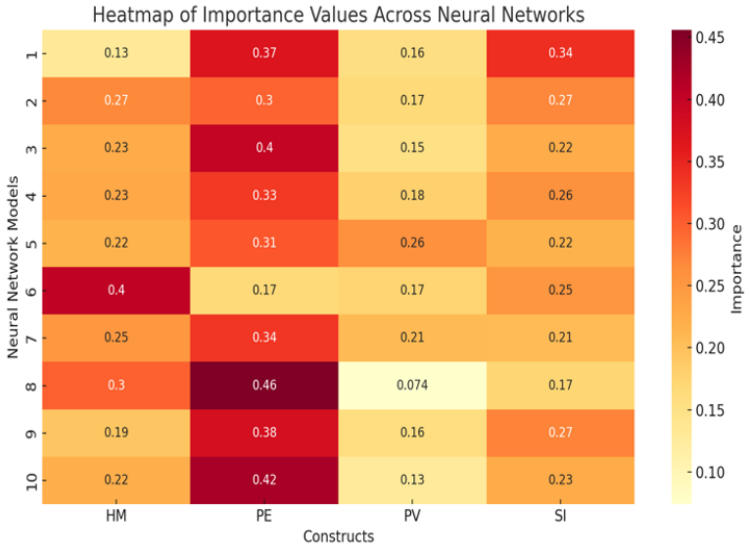


Figure 6. Heatmap-sensitivity analysis for NNR model (the authors' own elaboration)

beliefs in the acceptance of immersive technology in general, where perceived usefulness and social connectedness were shown to be the most important drivers for the implementation of immersive solutions (Küçükuncular & Ertugan, 2025; Slater & Sanchez-Vives, 2016; Wild et al., 2017).

As expected, the study shows that the effect of PE is pre-dominant (94.1%) and confirms the previous findings related to medical and surgical training using XR technology. At the same time, neither EE nor FC had any direct impact on BI. It can be explained by high level of digital literacy and intuitive design in most immersive technologies. Recent studies confirm such tendencies showing that in the age of advanced technologies and increased digital skills, ease-of-use becomes an implicit variable for the technology acceptance (Brooks, 1999; UNESCO, 2021).

The secondary importance of TTF is another feature of the findings in question, which is in accordance with the emphasis on experience-focused approaches in the contemporary context. Specifically, in line with recent studies, the current investigation demonstrates that such elements of TTF as presence, embodiment, and immersion play a key role as mediating variables. In other words, rather than task fit, users' perception of presence mediates PEs. Thus, the results obtained by the author confirm the hypothesis according to which immersive technologies require the presence dimension to serve as a facilitator (Hair et al., 2022; Koo, 2021; Wohlgenannt et al., 2020).

Additionally, the importance of SI as a mediator is confirmed by numerous studies emphasizing social aspects of immersive environments and highlighting the key role of peer recognition in the promotion of metaverse technologies.

Finally, the ANN model reveals the complex and nonlinear relations between the variables studied. Specifically, while PE remains the largest driver of BIs, engagement and presence variables have complicated relations among themselves, which implies the necessity to take both into account when studying the technology acceptance process (Alaker et al., 2016; Selvam & González Vallejo, 2025).

It should be noted that all aspects identified in the current research correspond to recent trends observed in the field of immersive learning.

ANN Validation and Theoretical Insights

Our proposed hybrid SEM-ANN model helps extend our knowledge by proving that adoption in metaverse training environments is driven mostly by benefits with "PE" playing a mediating role here. Indeed, this is consistent with modern paradigms suggesting the transition from purely behavioristic, utilitarian approaches to those considering experiential aspects and perceptions based on such qualities as embodiment (Bhattacharya et al., 2023; Küçükuncular & Ertugan, 2025).

The role of TTF constructs, namely presence and embodiment, as the indirect determinants of performance and thus adoption is compatible with new theories of TTF stressing the role of experiential fit beyond mere task and technology alignment. The implication here is that in order to ensure successful immersive training in the metaverse, one should focus first on creating engaging and immersive environments to foster users' performance perceptions.

From a practical point of view, the result means that while designing metaverse immersive training environments, developers need to focus on developing not only usability but especially the dimension of perceived usefulness through enhancing the levels of presence and embodiment, among other immersive factors. Finally, we see the role of SI as a strong determinant of adoption of immersive environments (Rane et al., 2023).

Methodologically, another implication of using SEM and ANN together is seen in the benefits of the approach itself when dealing with complex non-linear processes. Indeed, this contributes to the growing recognition of the advantages of using hybrid methods to investigate complex phenomena in various fields, including adoption (Alaker et al., 2016; UNESCO, 2021).

Future Directions for Research: Further research needs to include longitudinal analysis of how perceptions of immersion in the metaverse environment impact adoption. At the same time, cross-cultural validation seems needed, considering the cultural sensitivity of some factors, such as SI. The inclusion of more constructs, namely of those related to presence and embodiment, could be helpful, as indicated in previous immersive research literature (Guest et al., 2018; Speicher et al., 2019).

Ethical Aspects of AI-Powered Metaverse Technologies in Training

Metaverse platforms can alter educational and training paradigms. However, their adoption presents important ethical considerations that go beyond technology innovation and include user rights, fairness, and society impact. Integrating established ethical standards and regulatory frameworks promotes responsible development and deployment (Küçükuncular & Ertugan, 2025; UNESCO, 2021).

Data privacy and surveillance risks

AI-powered metaverse systems capture comprehensive behavioral, biometric, and contextual data, including eye-tracking (gaze fixation), motion trajectories and posture, voice interactions, and emotional reactions. While such data improve adaptive learning, they also raise problems relating to monitoring, profiling, and permission, which may undermine users' informational autonomy. Ethical data management necessitates the adoption of privacy-by-design, data reduction, transparent informed consent procedures, and strong cybersecurity safeguards. (Alnsour et al., 2025; Küçükuncular & Ertugan, 2025).

Compliance with recognized data protection regulations, such as the general data protection regulation, is required (Alnsour et al., 2025). These regulations require a clear articulation of data collection purposes, storage duration, and sharing practices, as well as user rights to access, modify, or delete their data. Adopting such regulatory compliance together with rigorous cybersecurity measures is essential to protect sensitive information and foster user trust.

Digital equity and inclusion

Access to metaverse training generally requires high-end gear (VR headsets), consistent Internet, and technological literacy — conditions that may disadvantage certain communities and deepen the digital divide. To enhance inclusiveness, stakeholders should (Krsmanovic & Deek, 2024).

- Prioritize affordable hardware (or alternative low-cost devices), mobile-friendly interfaces, and offline-capable modules.
- Provide material in many languages and assure accessibility (e.g., for disabled people) by following to recognized accessibility criteria.
- Consider institutional support mechanisms (such as equipment lending programs and community-based learning centers) to help democratize access.

These efforts are consistent with the ethical principles of fairness and equity outlined in major AI-in-education guidelines, which emphasize that AI systems should provide equal opportunity and accessibility to all users, regardless of socioeconomic status or physical ability (Chinta et al., 2024; Krsmanovic & Deek, 2024).

Ethical applications of AI and behavioral adaptation

AI-driven customization in immersive training has the potential to greatly improve learning results. Nonetheless, it poses concerns such as autonomy, algorithmic bias, and opacity. Adaptive feedback mechanisms should avoid manipulative or coercive behavior, as well as the reinforcement of stereotypes. Instead, AI applications should adhere to concepts of openness, explainability, fairness, accountability, and non-maleficence (Bulut & Beiting-Parrish, 2024; Chinta et al., 2024). To implement these principles:

- AI decision-making and adaptability logic should be clear and explainable to users and educators, rather than a "black-box" (Krsmanovic & Deek, 2024).
- Developers should detect and mitigate prejudice, ensure that training data reflects demographic diversity (including underrepresented groups), and assess AI outputs on a regular basis for fairness and unexpected negative social consequences (Chinta et al., 2024).
- Establish accountability: humans (developers, educators, stakeholders) must be held accountable for AI actions and their repercussions, rather than outsourcing complete responsibility to the (Küçükuncular & Ertugan, 2025).

Governance, ethical stewardship, and multi-stakeholder collaboration

The implementation of AI-powered metaverse training necessitates rigorous governance and constant oversight. Governance for AI in education should be interdisciplinary and incorporate all key stakeholders, including developers, educators, policy-makers, and the user community (Alnsour et al., 2025; Küçükuncular & Ertugan, 2025).

Such governance should incorporate ethical oversight by documenting fairness criteria, monitoring compliance with privacy and equity standards, conducting regular impact assessments (including discrimination impact assessments where applicable), and providing clear channels for redress or withdrawal of consent (Bulut & Beiting-Parrish, 2024).

Implications

The results of this research have tremendous implications for the concerned bodies as well as the community of practitioners attempting to apply the metaverse to the space of training. In practice, the following types of training programs will benefit from the application of the findings of this study. Matters of corporate employee training, sports and educational instruction, simulations of dangerous or hard to reach areas, the use of complicated or infrequently accessible machinery, as well as sophisticated medical procedures such as highly unusual surgeries will all benefit from the application of the metaverse to training. This will become possible through increased awareness of the metaverse and its benefits to users, the development of the digital infrastructure (specifically the development of the 5G network and fast Internet access), appropriate use instructions for the system, as well as lowering access costs.

On the theory side, the research suggests that traditional technology Acceptance and TTF theories do not fully explain immersive learning experiences. Theoretical frameworks such as EE, FC, TAC, and TTF have limited explanatory power, suggesting that the experiential cognitive processes involving immersive technologies can be better explained by incorporating theories such as presence, immersion, engagement, and flow theories along with flow theory, technology immersion theory, and embodied cognition theory. Moreover, the dimensions for TTF should move beyond productivity measures to incorporate spatial and sensory inputs, including embodied engagement, while a more diverse population in the next research study may help to inform the inclusion of untapped theories. On the research methods side, a combination of SEM-ANN and other nonlinear methods can provide a more precise representation of the complex interrelations between the predictors of the sensory and utilitarian type, offering improved explanations and applications.

Overall, these findings have helped to provide a broad spectrum for planning, implementing, and evaluating effective metaverse-based training intervention approaches. These will help researchers, practitioners, and policy-makers to make the most effective use of metaverse technology in education.

Limitations and Future Work

Even while this study has provided several insightful findings and conclusions, there are still several issues which should be considered when developing directions for further investigation.

Sample size and sample characteristics: The current sample, which is comprised of 310 people, gives sufficient grounds for thorough analysis, yet the enlargement of the sample as well as its diversification regarding demographics and culture are crucially important for achieving external validity in the future.

Digital literacy and demographics: Since social networks were used in the process of recruitment, there is a high possibility that this method favored attracting individuals who are better versed in technology. The consideration of such variables as digital literacy level, as well as age, gender, education, economic background, and place of residence (urban/rural), is crucial for gaining a comprehensive picture of driving forces behind the behavior.

Model modification: Several constructs, such as TAC, TTF, EE, and FC demonstrated weak direct effects in the model. This might be an indication that some refinements are required, especially considering the peculiarities of the investigated context. It is also important to add the constructs which have been identified as crucial for immersive experience: perceived presence, embodiment, sensation, immersion, and social connectedness, since this factor plays a major role in the studied process.

Methodology improvements: To gain more information concerning the factors that affect the behavior, the use of a mixed-methods approach seems to be very useful. It will allow incorporating different types of data, ranging from survey questions to behavioral observations.

Advanced methods of analysis: The usage of advanced analytical tools such as deep learning and other hybrid models which incorporate both SEM and ANN models could help reveal more complicated interrelationships between constructs.

Longitudinal and cross-cultural research: The development of longitudinal studies which would investigate users' perceptions and preferences over time will help identify factors that may affect their decisions over time. Besides, it is important to conduct cross-cultural studies to see if the chosen theoretical frameworks are universal and whether any cultural moderators exist within the accepted model.

Technical barriers: Alongside practical challenges which arise when conducting research, the problem of hardware accessibility, network infrastructure issues, and usability should be solved. Moreover, it is vital to consider the long-term implications of immersive technologies from psychological and educational perspectives.

CONCLUSIONS

The adoption of a metaverse-based training system, examined through the integrated framework of UTAUT2 and TTF, analyzed through the SEM-ANN technique, reveals PE as the key antecedent in determining adoption in immersive settings. This is in line with the importance attached to task alignment in experiential technologies. Although TTF, EE, and FC failed to have direct influences on BI, this research has made significant theoretical contributions in understanding the role of task alignment and engagement in creating foundation-level FC in an indirect manner through PEs. This result indicates an important paradigm shift in adoption theories from the conventional focus on decision-making in immersive settings from the perspective of performance and quality.

On the theoretical side, the results improve current adoption theory by confirming the UTAUT2 scale's construct validity in immersive contexts, as well as generalizing the TTF to include the concepts of presence, embodiment, and interaction. From the methodological standpoint, the combination of SEM and ANN represents a powerful and complete approach to the interpretation of the dynamics related to the technology adoption.

Collectively, this body of research provides not only empirical findings, but theoretical contributions as well, for learning systems that utilize the metaverse, providing a verified foundation for future studies on the incorporation of experiential and embodied learning into immersive technologies.

Author contributions: AM: conceptualization, validation, visualization, writing – original draft, writing – review & editing; **KA-Q:** conceptualization, data curation, formal analysis, investigation, methodology, resources, software, validation; **MG:** investigation, writing – review & editing; **KS:** project administration, supervision, validation. All authors approved the final version of the article.

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Ethics declaration: This study was approved by the Research Ethics Committee at the British University in Dubai. Participation in the study was voluntary. Before completing the anonymous online questionnaire, participants were provided with information about the purpose of the study, the voluntary nature of their participation, and the confidentiality of their responses. Completion and submission of the questionnaire were considered to indicate participants' informed consent to participate. No personally identifiable or sensitive personal information was collected. All responses were anonymous and analyzed in aggregate to protect participants' privacy and confidentiality.

AI statement: During the preparation of this manuscript, the authors used ChatGPT (OpenAI) solely to improve the language, grammar, readability, and overall clarity of the manuscript. The generative AI tool was not used to generate the scientific content, develop the research methodology, analyze or interpret the data, or formulate the study's conclusions. Following the use of this tool, the authors carefully reviewed, edited, and verified all AI-assisted text and took full responsibility for the ac-curacy, integrity, and originality of the published work.

Declaration of interest: The authors declared no competing interest.

Data availability: Data generated or analyzed during this study are available from the authors on request.

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