Available online at www.ijournalse.org

Emerging Science Journal

(ISSN: 2610-9182)

Vol. 8, Special Issue, 2024

"Current Issues, Trends, and New Ideas in Education"

Investigating the Adoption of Metaverse-Based Immersive Learning in TESOL

Saja Wardat [1*], Mohammed Akour [2]

[1] *Department of English Language and Literature, Irbid University College, Al-Balqa Applied University, Irbid, 1293, Jordan.*

[2] *College of Computer and Information Sciences, Prince Sultan University, Riyadh, Saudi Arabia.*

Abstract

This study investigates the adoption of Metaverse-based immersive learning in Teaching English to Speakers of Other Languages (TESOL), an area that has been understudied and lacks an understanding of factors influencing the acceptance of this digital platform. In contrast to traditional mobile or e-learning, the Metaverse facilitates all sorts of unique immersive experiences including virtual simulations and cultural dialogues that can aid your process for language acquisition and cultural understanding. However, its reception in the field of TESOL is yet to be substantiated through empirical evidence. The present study explores the effects of constructs such as Perceived ease of use (PEU), Perceived usefulness (PUS), Attitude (ATT), Subjective norm (SBN) and Perceived behavioural control (PBC) on students' Intention to Use Metaverse (IUM) in TESOL context. Data collected from 736 university students in Jordan were analyzed using structural equation modelling (SEM) with a combined Technology Acceptance Model (TAM) and Theory of Planned Behavior (TPB) framework. Results indicate that in terms of direct effects, PEU strongly influences ATT ($\beta = 0.566$) and SBN ($\beta = 0.448$), whereas PUS regulates ATT ($\beta = 0.514$) and SBN ($\beta = 0.482$). Path coefficients for the predictive factors of IUM—ATT, SBN, and PBC were 0.326, 0.641, and 0.516 respectively. A J48 decision tree validated by machine learning was able to predict 91.22% of IUM with good accuracy. The results reveal that Metaverse-based TESOL has gradually become part of student habits despite their limited access to technology. The findings of the study assist in improving TESOL curricula and developing informed policies that recommend immersive language learning.

Keywords:

Immersive Learning;
Machine Learning;
Metaverse;
TESOL.

Article History:

Received:	07	October	2024
Revised:	15	January	2025
Accepted:	23	January	2025
Published:	12	February	2025

1- Introduction

Recent technological advancements have changed the educational scen [1], enabling the immersion and engagement of learners in digitally mediated interactive and visual environments [2-4]. Metaverse, a virtual reality room where users can interact with other users and the setup around them, corresponds to the innovative advancement in this domain [5]. This technological evolution will change the way we learn formally or informally, along with several aspects of Teaching English to Speakers of Other Languages (TESOL) [6]. Recent developments in virtual environments as well as the gradual ease of access to such platforms have paved new pathways for teaching and learning beyond traditional classrooms [7].

By allowing students to visualise, simulate, and experience content in ways that were previously impossible with traditional teaching methods, these digital spaces become more language-inclusive than ever while also providing an

* **CONTACT**: saja.wardat@bau.edu.jo

DOI: http://dx.doi.org/10.28991/ESJ-2024-SIED1-023

increased level of student engagement through their immersive nature and extensibility. This, in turn, boosts students' communication skills and cultural awareness which could be the key aspects of successful language acquisition.

For these advantages to be realised, students and educators must first have the same willingness to apply Metaverse-based tools for TESOL. Even though Metaverse technology has enormous potential, it is still not adopted widely in education. However, the use of Metaverse for educational purposes will vary in scope since the readiness of students to accept this technology even amidst advanced virtual environments is yet to be explored. The Technology Acceptance Model (TAM) [8] and the Theory of Planned Behavior (TPB) [9] have gained much trust empirically through practical observations in the context of technology adoption in different fields including higher education; but research regarding the application of these models on Metaverse, more specifically TESOL is inadequate.

Despite the vast growth of research in mobile learning (m-learning) and e-learning curricula for higher education [10-13], there is only a handful of studies exploring the Metaverse pertaining to TC-LIT, while its application for language learning in TESOL has so far remained at an infancy stage. Especially in regions like Jordan, higher education facilities are increasingly supporting the integration of digital technologies into learning environments [14]. However, little research has been done to explore the determinants of students' intention to use Metaverse platforms in their language learning. Although previous studies focus heavily on SEM-based techniques for technology acceptance, not many have employed a robust machine learning approach to take the analysis forward.

To answer this, the present study examines the factors that shape the inclination to use Metaverse in TESOL in order to fill the existing research void. Therefore, the objective of this study is to formulate a holistic model by integrating TAM and TPB with respect to students' attitudes, subjective norms and behavioural control towards adoption of Metaverse technology. In this research, we will develop the model in detail, based on a mixed-methods approach that uses structural equation modelling (SEM) techniques to identify constructs and machine learning (ML) methods to assess their contribution. It records a review that offers an overview on how the Metaverse Technology can be integrated with TESOL which nurtures actionable insight for educators and policies.

The paper is structured as follows: section 2 outlines the research model and development of hypotheses, describing corresponding relationships between variables being studied. The section also provides an in-depth analysis of the literature surrounding the TAM, the TPB, and the adoption of Metaverse within the educational context, specifically with a focus on TESOL. The Research Methodology (Section 3): The section describes the data gathering process, the participants and the ML methodologies used for analysis (SEM). Empirical results are reported in Section 4, and key SEM and ML findings are summarized. Finally, Section 5 addresses the theoretical and practical implications of these findings, providing salient insights for practitioners, policymakers and researchers. Last, Section 6 concludes the paper by highlighting our main contributions and directions for future research.

2- Research Model and Hypotheses Development

A novel framework combining Subjective Norm (SBN) constructs with TPB and TAM to investigate Metaverse-based immersive learning in the context of TESOL. The theory of planned behaviour (TPB) stresses the role of social norms (SBN), attitudes, and perceived behavioural control (PBC) on intentions to use emerging technologies, while the technology acceptance model focuses on perceived ease of use (PEU) and usefulness (PUS) in technology adoption [15]. PUS, PEU and SBN have a significant effect on the students' intention to interact with Metaverse-based learning. The ease of language learning and its perceived educational benefits, coupled with social encouragement from peers and educators, can increase the likelihood of students using Metaverse. Figure 1 provides an empirical guide for Metaverse adoption drivers in TESOL and consequently fills existing literature gaps through this combined framework.

2-1- Perceived Ease of Use (PEU)

Perceived Ease of Use (PEU) signifies "the degree to which a person thinks using some specific system will require no physical and mental burden" [8]. As such, this is an important element in the Technology acceptance model (TAM) which influences user behavioural intentions to accept new technologies [16]. PEU is vital in the context of Metaverse-based immersive learning in TESOL as learners tend to develop positive attitudes toward using a platform when they find the system easy to use and intuitive. The notable influence of PEU on users ' technology usage attitudes, particularly in the context of mobile learning systems, has been well-established earlier. PEU is also reported to be able to influence the SBN [17] because people who have perceived ease of use believe that their environment will attract social pressure to accept such technology. Based on these findings, this study develops the following hypotheses in the context of Metaverse-based learning in TESOL.

H1: Perceived Ease of Use (PEU) will positively predict the attitude toward the use of Metaverse-based learning platforms (IU) in TESOL.

H2: Perceived Ease of Use (PEU) will positively predict the Subjective Norm (SBN) in the adoption of Metaverse-based TESOL platforms.

2-2- Perceived Usefulness (PUS)

Perceived Usefulness (PUS) is defined as "the degree to which a person believes that using a particular system would enhance his or her job performance" [8]. It is a key concept in the widely used TAM that focuses on users' beliefs about the functional utility of a system affecting their performance or results. Therefore, among TESOL-related Metaverse-based immersive learning, perceived usefulness (PUS) is crucial since students are more likely to use the Metaverse if they believe that it will enhance their language acquisition. Existing literature has found that PUS has a substantial effect on these attitudes [16], for instance, buyers perceiving a system as useful, will generally have positive UTAUT-U outcomes. Moreover, PUS impacts SBN [17], which means that whenever users consider technology as innovative or beneficial for them, they may also experience the indirect (social encouragement) or direct (social pressure) effect of increasing use of technology by peers, instructors or institutions. Thus, this study investigates Metaverse-based learning in TESOL and proposes the following hypotheses based on the results of previous research.

H3: Perceived Usefulness (PUS) will positively predict the attitude toward the use of Metaverse-based learning platforms (IUM).

H4: Perceived Usefulness (PUS) will positively predict the Subjective Norm (SBN) in the adoption of Metaverse-based TESOL platforms (IUM).

2-3- Attitude (ATT)

ATT is "an individual’s positive or negative feelings (evaluative effect) about using a particular system," [18] that captures how much an individual likes or dislikes using a given technology. ATT is a critical determinant of learners' intention to learn language via Metaverse in the phenomenon of learning in TESOL. Past studies on m-learning have consistently reported some evidence of a strong correlation between attitude and intention to use (IUM) digital learning systems. Research has shown that a positive attitude towards m-learning has a significant positive impact on students' free will to use these systems. Based on the previous ideas presented in this study, it is reasoned that attitude toward Metaverse will also influence intention to use the technology among TESOL learners. Accordingly, learners with a positive attitude towards Metaverse as a tool in language learning will have greater intention to use it [17, 19, 20]. Therefore, we can postulate that:

H5: Attitude (ATT) will positively predict the intention to use Metaverse-based learning platforms in TESOL (IUM).

2-4- Subjective Norm (SBN)

Subjective Norm (SBN) is defined as "the perceived social pressure to perform or not perform a certain behaviour," [8] reflecting the influence of others' opinions on an individual's decision to use a system. In the context of Metaverse-based learning in TESOL, SBN plays a crucial role as learners may feel encouraged or pressured to adopt immersive learning technologies based on the expectations of peers, educators, or institutions. Prior research has demonstrated that subjective norm significantly influences the intention to use (IUM) various technology platforms [17, 21], including mobile learning (m-learning) systems. When individuals perceive that important people in their lives, such as teachers or classmates, expect them to use a particular system, they are more likely to demonstrate a higher inclination to use that system. There, we hypothesise that:

H6*:* Subjective Norm (SBN) will positively predict the intention to use Metaverse-based learning platforms in TESOL (IUM).

2-5- Perceived Behavioral Control (PBC)

Perceived Behavioral Control (PBC) is defined as "people’s perception of the ease or difficulty of performing the behaviour of interest." [22]. It reflects an individual's sense of control over their ability to perform a particular behaviour, which in this case is the adoption and use of a technology system. In the context of Metaverse-based learning in TESOL, PBC is a key determinant of learners’ intentions to use immersive learning platforms. Learners who perceive that they have sufficient control—whether due to access to technology, digital literacy, or the necessary support systems—are more likely to adopt Metaverse for language learning. Prior research consistently shows that PBC has a significant impact on the intention to use (IU) [17] m-learning platforms and other digital tools, thereby leading to the following hypothesis.

H7: Perceived Behavioral Control (PBC) will positively predict the intention to use Metaverse-based learning platforms in TESOL (IUM).

The proposed research model is built on these seven hypotheses (H1–H7), integrating TAM and TPB to explain the factors influencing the adoption of Metaverse-based platforms in TESOL. As illustrated in Figure 1, the model is first structured as a structural equation model (SEM) to assess the relationships between key constructs like PEU, PUS, ATT, SBN, and PBC. The model is then further evaluated and enhanced using machine learning methods to refine predictions and analyse patterns in the data. This dual approach allows for a robust analysis of both theoretical and empirical factors that influence the adoption of immersive learning technologies in TESOL.

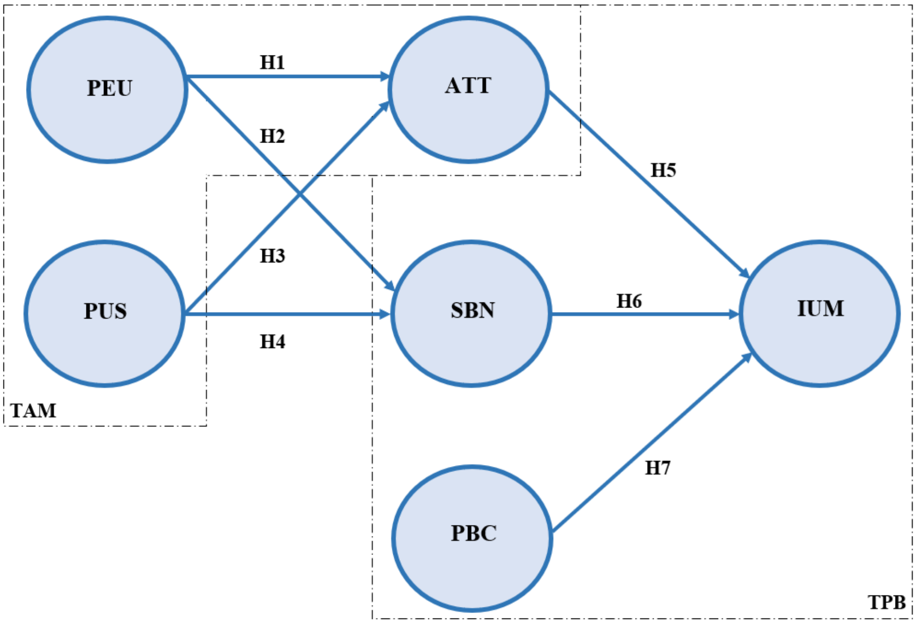

Figure 1. **Theoretical Framework of the Study**

3- Research Methodology

3-1- Data Collection

Online surveys were distributed to university students across Jordan who were collaborating on this study. Data were collected from February 1, 2024 to June 5, 2024. 800 questionnaires were randomly distributed among the students with a very high rate of response (92%). 800 responses were received of which 64 questionnaire forms with incomplete answers were not used for the study. Following the sample size instructions by Krejcie & Morgan (1970) [23], this study achieved its target sample of 306 respondents from a population of 1500. The final sample size exceeded the lower threshold of 736 by far, making it possible to conduct robust analyses. SEM was an appropriate method to test the hypotheses of this study given the sample size. The theories behind the hypotheses for this research were created from existing theoretical frameworks, especially from some Metaverse-based studies. Measurement model assessment was conducted using Structural Equation Modeling (SEM) and SmartPLS Version 3.2.7 [24]. The final path model was then used to perform more advanced analyses and test the proposed hypotheses. Beyond just assisting in the empirical validation of the study conceptual framework, these analyses also helped understand the adoption behaviour of metaverse-based immersive learning in higher education.

3-2- Students' Personal Information / Demographic Data

Figure 2 provides an overview of the demographic and personal information of the participants. A total of 58% of respondents were females, while 42% were males. The majority of participants (73%) fell within the age group of 18 to 29 years, with the remaining respondents being over 29 years old. In terms of educational background, most participants held a university degree, with 72% having a Bachelor's degree, 26% holding a Master's degree, and 3% possessing a PhD. According to Anwar et al. (2024) [25] study, the purposive sampling approach can be employed when participants demonstrate a willingness to volunteer, which was applicable in this study. The participants came from various universities, representing different age groups with diverse educational qualifications. To analyse the demographic data, IBM SPSS Statistics version 23 was used, ensuring an accurate and thorough evaluation of the dataset.

The demographic results of the participants, as outlined in Table 1, provide a detailed breakdown of the students' backgrounds and experiences with Metaverse-based learning. The majority of respondents, accounting for 63%, were from TESOL programmes, followed by Language Studies (23%), with fewer representations from Education (6%) and Information Technology (8%). Most students were enrolled in public universities (62%), while 38% attended private universities. In terms of academic level, 44% of respondents were in their first year, 31% in their second year, 13% in their third year, 7% in their fourth year, and 6% were graduate students. While analysing their experience with Metaverse technologies, 30% of students reported having no prior experience, while 32% identified themselves as beginners with less than a year of experience. Another 29% had intermediate-level experience (1-3 years), and 9% were advanced users with over three years of experience. Regarding access to technology, the survey showed that half of the respondents (50%) had no regular access to technology, while 20% used personal laptops/desktops, 7% had access to university-provided devices, and 23% utilised public computers, such as those in libraries. Lastly, when it came to the use of Metaverse in learning, 44% reported they had never used it, 11% used it rarely, 23% used it sometimes, and 21% used it often or always. These findings highlight the diversity in both the backgrounds and the levels of technological exposure among the participants, offering a comprehensive view of the sample for further analysis.

The results from Table 1 provide valuable insights into the participants' educational backgrounds, technological exposure, and their interaction with Metaverse-based learning. A significant portion of the participants are enrolled in TESOL programmes, with most of them attending public universities, suggesting that Metaverse adoption in TESOL could have broader relevance in public education. The varying levels of experience with Metaverse technologies—ranging from no experience to advanced users—demonstrate that while some students are familiar with these platforms, a substantial proportion lacks prior exposure. Additionally, the fact that 50% of participants report no regular access to technology highlights a potential barrier to widespread Metaverse adoption in educational contexts. Furthermore, while 44% of students have never used Metaverse in their learning, a growing minority (21%) are already integrating it into their educational routines. These findings suggest that while there is an opportunity for expanding Metaverse-based learning in TESOL, efforts should focus on improving both access to technology and familiarity with these immersive platforms to maximise educational outcomes among learners.

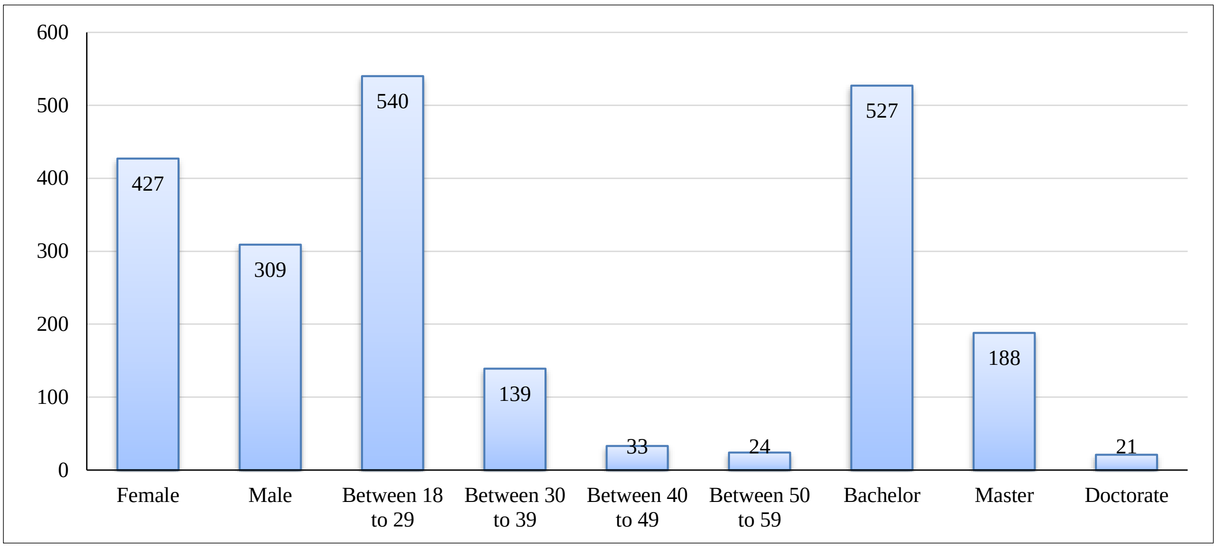

Figure 2. Demographic data of the respondents (n= 736)

Table 1. The demographic results of the participants

Category	Factor	Frequency	Percentage
Field of Study	TESOL	461	63%
	Education	46	6%
	Language Studies	172	23%
	Information Technology	57	8%
Academic Institution	Public University	453	62%
	Private University	283	38%
Year of Study	1st Year	322	44%
	2nd Year	225	31%
	3rd Year	97	13%
	4th Year	49	7%
	Graduate Student	43	6%
Experience with Metaverse Technologies	None	221	30%
	Beginner (Less than 1 year)	234	32%
	Intermediate (1-3 years)	216	29%
	Advanced (3+ years)	65	9%
Access to Technology	Personal Laptop/Desktop	147	20%
	University-provided Devices	53	7%
	Public Computers (e.g., library)	167	23%
	No regular access to technology	369	50%
Use of Metaverse in Learning	Never	325	44%
	Rarely	82	11%
	Sometimes	169	23%
	Often	152	21%
	Always	8	1%

3-3- Study Instrument

The research instrument used in this study consisted of two main sections. The objective of the first part was to obtain the participants' demographic data, while the second one sought responses about the factors incorporated in the conceptual model. A "5-point Likert scale" was used to measure items in the second section [26]. PEU and PUS were measured using items adapted from previous research sources. The constructs of ATT, SBN, PBC, and Intention to Use the Metaverse-based TESOL platform (IUM) were measured using items adapted from established studies [9]. Table 2 presents a list of constructs and their underlying items.

Table 2. Constructs and their sources

Constructs	Item	Source
Attitude (ATT)	I would enjoy my language courses more if I used Metaverse-based learning platforms.	Cheon et al. (2012) [17]
	Using the Metaverse in my coursework would be a pleasant experience.	
	Using the Metaverse in my language studies is a wise idea.	
Subjective Norm (SBN)	Most people who are important to me think it would be fine to use Metaverse-based platforms for university courses.	Cheon et al. (2012) [17]
	I think other students in my classes would be willing to adopt Metaverse-based immersive learning for language learning.	
	Most people who are important to me would be in favor of using Metaverse platforms for university courses.	
Perceived Behavioral Control (PBC)	I have sufficient knowledge to use Metaverse-based learning platforms.	Cheon et al. (2012) [17]
	I feel in control when deciding to use Metaverse technology for my TESOL studies.	
	I have enough confidence to make a decision to adopt Metaverse-based learning for language learning.	
Perceived Ease of Use (PEU)	The Metaverse-based learning environment is clear and easy to understand.	Bao et al. (2013) [27], Tan et al. (2014) [28]
	I found it easy to get the Metaverse platform to perform the tasks I wanted.	
	Overall, the Metaverse-based learning system is easy to use.	
Perceived Usefulness (PUS)	Using the Metaverse can improve my language learning performance.	Bao et al. (2013) [27], Tan et al. (2014) [28]
	Using the Metaverse-based TESOL platform increases my productivity in language studies.	
	I find the Metaverse to be useful in enhancing my TESOL coursework.	
Intention to Use the Metaverse-based TESOL platform (IUM)	I intend to increase my use of Metaverse-based learning platforms in the future.	Bao et al. (2013) [27], Tan et al. (2014) [28]
	Assuming that I had access to a Metaverse-based TESOL platform, I intend to use it.	

3-4- Common Method Bias (CMB)

To ensure that the collected data were free from Common Method Bias (CMB), Harman's single-factor test was conducted using seven variables [29]. This method helps identify whether a substantial amount of common variance exists among the variables, which could indicate CMB issues. In this analysis, ten factors were loaded into a single factor to examine the extent of variance explained. The results showed that the newly created single factor accounted for 24.13% of the total variance, which is significantly lower than the acceptable threshold of 50% [29]. This finding indicates that there was no significant common method bias present in the dataset, thereby confirming the validity of the data collection process for subsequent analyses.

4- Results

This study applies Weka (ver. 3.8.3), using a number of well-known machine learning (ML) classifiers such as OneR, BayesNet, J48 and Logistics [30]. Using such classifiers, the model can aid in analyzing the relationships between elements of this research by applying an extensive number of approaches towards classification. Neural networks, Bayesian networks, and other machine learning-based algorithms have been successfully applied in earlier work to identify relationships and characteristics within data sets that would be otherwise imperceptible. These techniques assist in revealing concealed connections in the information that may not be discovered via standard techniques.

Apart from ML, Partial Least Squares Structural Equation Modeling (PLS-SEM) is also applied to test the theoretical model driven by general Information Systems (IS) principles [31]. PLS-SEM is used to study causal relationships between latent variables in the research model along with the structural and measurement model validity. These two complementary approaches — SEM and ML — are used to ensure the completion of the model evaluation. The relationships between the latent variables are evaluated using structural model analysis, while measurement model analysis evaluates construct reliability and validity.

The dual evaluation process facilitated by this research with ML ensuring the assessment of predictive accuracy and classification ability of the models, PLS-SEM rigorously iterates through model theory testing of constructs and relationships–outspanning the more focused assessments afforded by singular use.

4-1- Convergent Validity

While evaluating the measurement model, construct validity—comprising both discriminant and convergent validity—and construct reliability were assessed according to the established guidelines [32]. Construct reliability was measured using Cronbach's alpha (CA) and composite reliability (CR). As shown in Table 3, Cronbach's alpha values ranged from 0.813 to 0.895, exceeding the recommended threshold of 0.7, indicating a high level of reliability for the constructs [33]. Similarly, the composite reliability (CR) scores, which ranged from 0.819 to 0.897, also surpassed the acceptable cutoff point of 0.7, further confirming the model's reliability. For convergent validity, the study assessed the average variance extracted (AVE) and factor loadings [32]. Table 3 reveals that all factor loadings exceeded the standard criterion of 0.7, demonstrating strong item-to-construct associations. Additionally, the AVE values ranged from 0.625 to 0.798, surpassing the minimum required value of 0.5. These results collectively indicate that the model achieved convergent validity, meaning that the constructs in the model are well-correlated with their respective indicators. Overall, these findings suggest that the measurement model meets the necessary criteria for reliability and validity, supporting the robustness of the constructs within the study.

4-2- Discriminant Validity

For the actual assessment of discriminant validity, Hair et al. (2017) [32] contemplated the reconsideration of two main criteria for discriminant validity - the Heterotrait-Monotrait ratio (HTMT) and the Fornell-Larcker criterion [32]. As shown in Table 4, the Fornell-Larcker criterion was satisfied since the square roots of each construct's average variance extracted (AVE) exceeded the correlations with other constructs, confirming its discriminant validity as per this criterion [34].

In addition, the outcomes of the HTMT ratio presented in Table 5 further reveal that all constructs had an HTMT value below 0.85 [35], indicating the Heterotrait-Monotrait ratio of correlations-confirmed discriminant validity. The results imply that the constructs are distinct enough from one another. To summarize, these findings support the convergence and discriminant validity and reliability of the measurement model setting firm grounds to use this set of data for an overall evaluation of the structural model ensuring that we can study our research model at higher levels owing to good measurement quality.

Table 3. **Convergent validity results which assures acceptable values (Factor loading, Cronbach's Alpha, composite reliability ≥ 0.70 & AVE > 0.5)**

Constructs	Items	Factor Loading	Cronbach's Alpha	CR	AVE
ATT	ATT1	0.776	0.885	0.897	0.721
	ATT2	0.881			
	ATT	0.881			
IUM	IUM1	0.783	0.813	0.854	0.736
	IUM2	0.823			
PBC	PBC1	0.833	0.852	0.842	0.627
	PBC2	0.772			
	PBC3	0.855			
PEU	PEU1	0.863	0.821	0.819	0.625
	PEU2	0.708			
	PEU3	0.803			
PUS	PUS1	0.858	0.895	0.894	0.771
	PUS2	0.870			
	PUS3	0.854			
SBN	SBN1	0.724	0.885	0.875	0.798
	SBN2	0.847			
	SBN3	0.722			

Table 4. **Fornell-Larcker Scale**

	ATT	IUM	PBC	PEU	PUS	SBN
ATT	**0.818**					
IUM	0.544	**0.814**				
PBC	0.384	0.520	**0.805**			
PEU	0.361	0.358	0.461	**0.798**		
PUS	0.423	0.421	0.667	**0.847**	**0.825**	
SBN	0.229	0.328	0.361	0.428	0.426	**0.843**

Table 5. Heterotrait-Monotrait Ratio (HTMT)

	ATT	IUM	PBC	PEU	PUS	SBN
ATT						
IUM	0.572					
PBC	0.681	0.633				
PEU	0.756	0.441				
PUS	0.520	0.571	0.477			
SBN	0.445	0.437	0.382	0.499	0.521	

4-3- Hypotheses Testing Using PLS-SEM

The variability of each path in the study model was evaluated using R^2 values and the significance of the path connections. Figure 3 and Table 6 display the normalised path coefficients and path significances, providing a detailed view of the relationships between the variables. The testing of the nine hypotheses was performed through structural equation modelling (SEM), which offered empirical support for the model's predictions.

The constructs demonstrated moderate predictive power, as indicated by the R^2 values for Intention to Use Metaverse (IUM), Subjective Norms (SBN), and Attitude (ATT), ranging from 0.492 to 0.729 (refer to Table 7). These values reflect the model's ability to explain a moderate percentage of variance in these constructs.

According to the analysis, the following hypotheses were confirmed:

- H1: Perceived Ease of Use (PEU) significantly influenced Attitude (ATT) ($\beta = 0.566$, $P < 0.001$).
- H2: PEU significantly influenced Subjective Norms (SBN) ($\beta = 0.448$, $P < 0.05$).
- H3: Perceived Usefulness (PUS) significantly impacted Attitude (ATT) ($\beta = 0.514$, $P < 0.001$).
- H4: PUS significantly affected SBN ($\beta = 0.482$, $P < 0.001$).
- H5, H6, H7: Intention to Use Metaverse (IUM) significantly influenced ATT ($\beta = 0.326$, $P < 0.001$), SBN ($\beta = 0.641$, $P < 0.001$), and Perceived Behavioral Control (PBC) ($\beta = 0.516$, $P < 0.01$).

These results provide strong empirical support for the relationships outlined in the study's conceptual model, confirming the significance of PEU and PUS in predicting Attitude, Subjective Norms, and ultimately, Intention to Use the Metaverse for immersive learning in TESOL.

Table 7. Hypotheses-testing of the research model (significant at p < = 0.01, p* < 0.05)**

H	Relationship	Path	*t*-value	*p*-value	Direction	Decision
H1	PEU → ATT	0.566	12.463	0.000	Positive	Supported**
H2	PEU → SBN	0.448	6.549	0.012	Positive	Supported*
H3	PUS → ATT	0.514	13.352	0.000	Positive	Supported**
H4	PUS → SBN	0.482	16.521	0.000	Positive	Supported**
H5	ATT → IUM	0.326	14.210	0.000	Positive	Supported**
H6	SBN → IUM	0.641	10.503	0.000	Positive	Supported**
H7	PBC → IUM	0.516	9.802	0.003	Positive	Supported**

Table 6. R^2 of the endogenous latent variables

Construct	R^2	Results
ATT	0.729	High
SBN	0.548	Moderate
IUM	0.492	Moderate

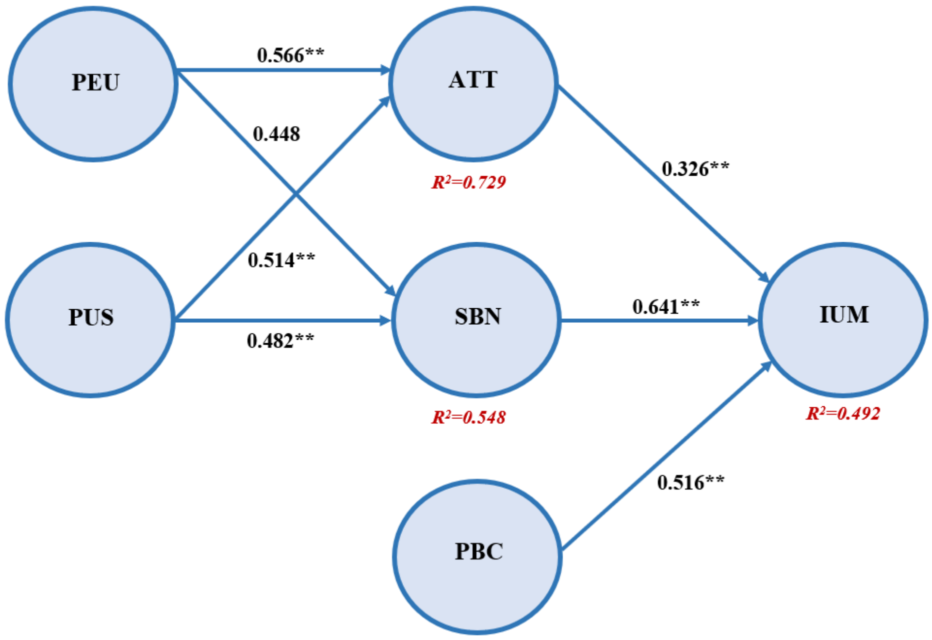

Figure 3. Path coefficient of the model (significant at p < = 0.01, p* < 0.05)**

4-4- Hypotheses Testing Using Classical Machine Learning Algorithms

The results of this analysis confirm our first, third, fifth and seventh hypotheses providing considerable support for the relationships proposed in the conceptual framework of the study. A range of machine learning (ML) methods such as Bayesian network, neural network and decision tree algorithms were used to evaluate the hypotheses. These ML approaches, were implemented in the conceptual model to associate the relationships among variables [30]. Conf.waterfall plots illustrated changes of prediction were validated by Weka(v. 3.8.3; with classifiers including J48, OneR and BayesNet [30] . J48 was found to perform best among the classifiers specifically for ATT evaluation as shown in Figure 4. The most accurate model (J48 with 89.24% accuracy) predicted an attitude-related outcome using ten-fold cross-validation. In addition, J48 [36] obtained highest results for other performance metrics as well: 89.12% precision, 89.18% recall and more than 82.48% F-Measure which underscored the effectiveness of it in our analysis. The final section of this paper shows that with these results the J48 decision tree is quite appropriate for type of predictive modelling, and thus reasonably accurate and fairly stable outcomes are obtained for testing research hypotheses.

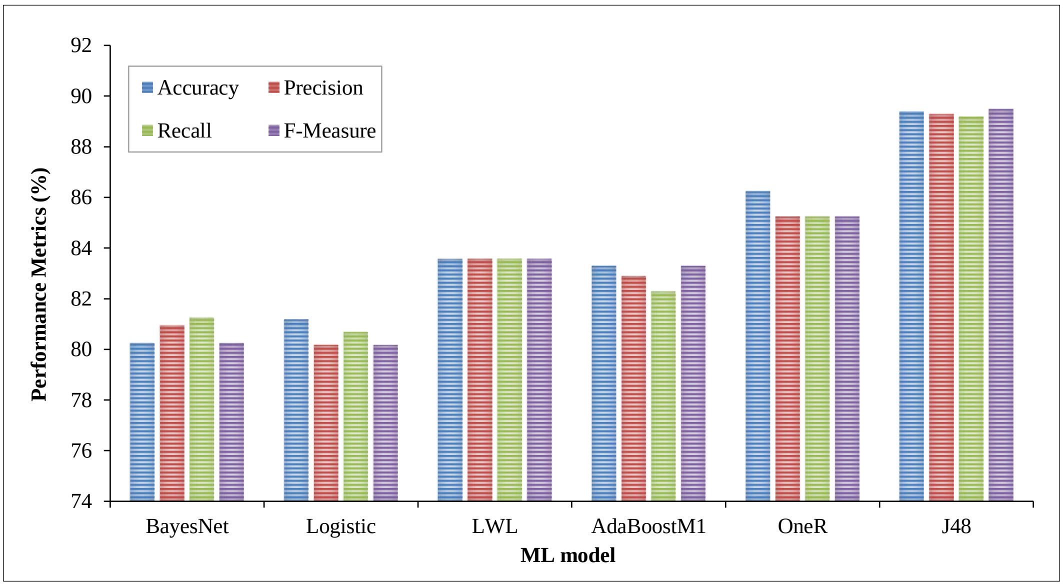

Figure 4. Impact of PEU & PUS on ATT

These results are also in line with the second and fourth research hypotheses, which further bolsters the conceptual frameworka (Figure 5). As with prior findings, the best J48 classifier accurately predicted SBN. J48 correctly classifies SBN with an accuray of 82.67% as showed in Figure 5 The stable performance of J48 at each of the proposed hypotheses has reinforced the efficiency and stability of using it for predicting important variables in this study.

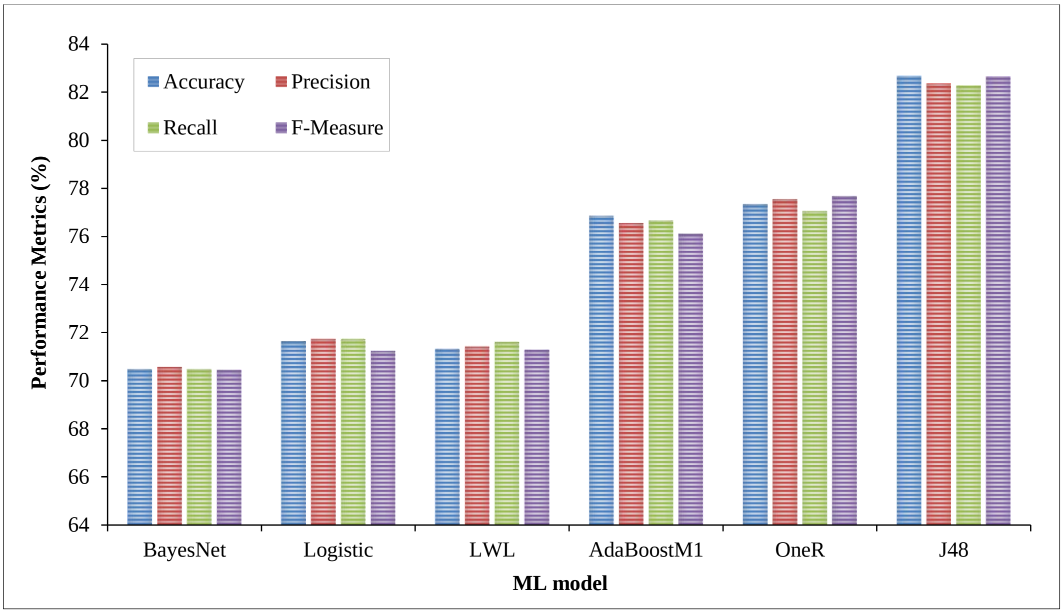

Figure 5. Impact of PEU & PUS on SBN

The J48 classifier also demonstrated the highest performance in predicting the IUM by utilising key features such as ATT, SBN, and PBC. As shown in Figure 6, J48 accurately estimated IUM 91.22% of the time, further validating the model's predictive capability. As a result, the fifth, sixth, and seventh hypotheses were also confirmed, showcasing J48's effectiveness in predicting various constructs within the study and providing strong empirical support for the conceptual framework.

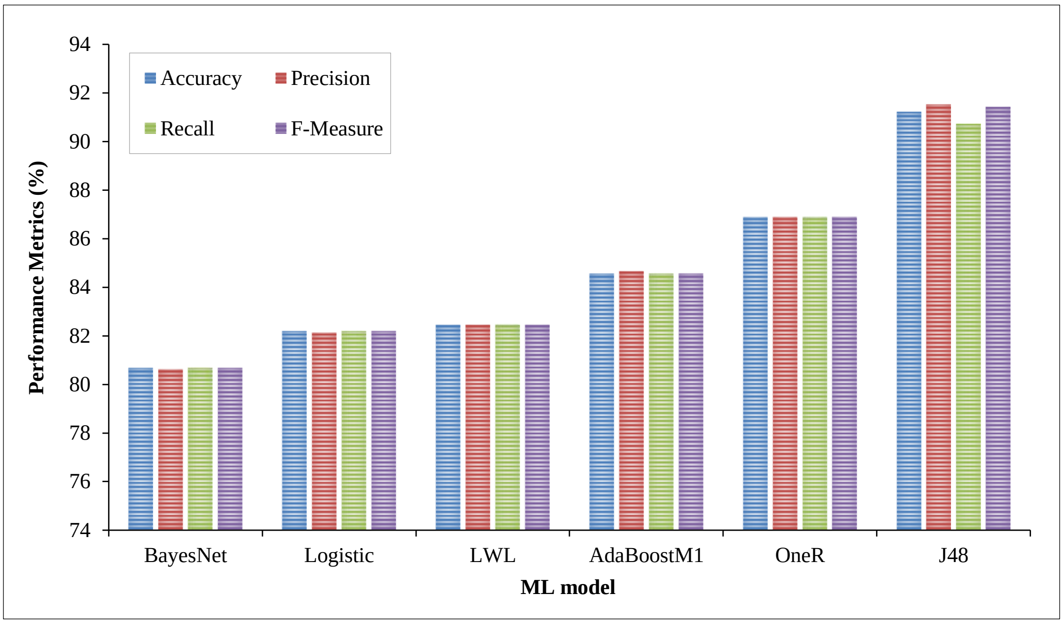

Figure 6. Impact of ATT, SBN & PBC on IUM

5- Discussion

The findings provide an in-depth understanding of the determinants for Intention to Use Metaverse (IUM) concept in immersive learning settings for TESOL context. By utilizing SEM and ML algorithms, this analysis provided a comprehensive examination of significant constructs including PEU, PUS, ATT, SBN and PBC. Utilizing SEM and ML not only gave the relationships concerning the research model a stronger validation but also revealed regions in which ML was superior to traditional SEM techniques.

SEM analysis suggested the research model has moderate predictive power (R^2 from embedded IUM to SBN, M2 = 0.492; attached SBN to ATT, M4 = 0.729). These is an indication that the model explains a large portion of variance in participants' intention to use Metaverse-based learning platforms. Of the nine hypotheses tested, the results provided strong support for seven of them (H1, H2, H3 and H4 in particular).

The results demonstrated that PEU influenced ATT (β = 0.566; $P < 0.001$) and SBN (β = 0.448, $P < 0.05$). These findings underscored that the perceived ease of use of Metaverse technologies among learners is a key factor in influencing their attitudes and social norms concerning adoption. Our findings are in line with earlier research on technology acceptance, which have found that perceived ease of use is one of the key predictors of attitudes toward emerging technologies [8].

PUS also had considerable direct effects on ATT (β = 0.514, $P < 0.001$) and SBN (β = 0.482, $P < 0.001$), indicating the vital role of perceived usefulness in generating good attitudes as well as social norms to accept Metaverse-based learning experiences positively. According to the Technology Acceptance Model (TAM) that claims perceived usefulness refers as an important variable which has a high predicting value on formulating users attitude towards technology acceptance [37], similar results could be found from the study mentioned earlier.

In the case of IUM, SEM analysis further corroborated that ATT, SBN, and PBC were significant predictors (H5, H6, H7) of learners' intention to adopt Metaverse. The path coefficients were 0.326 of ATT, 0.641 SBN and then 0.516 PBC, which indicate that both external (social norms) and internal (perceived control over using the technology) are strong motivators of adoption. These findings are in line with prior research highlighting the predictive role of perceived control for intention-to-behavior links, especially in a learning context [22].

Compared to SEM, the machine learning methods produced even more robust prediction performance where the J48 decision tree classifier outly performed OneR and BayesNet approaches. The performance of J48 algorithm confirmed its effectiveness on ATT (H1, H3) to achieve 89.24% accuracy, as well as precision (89.12%) and recall (89.18%), while predicting different constructs. The accuracy of this level indicates the superiority of J48 in modeling intention toward Metaverse technologies with an acceptable level of precision better than traditional SEM methods. ML, in particular decision trees, are thus highly capable of capturing the effects nature of social norm on learners behaviour again in predicting SBN (H2,H4), J48 perform best among all achieving an accuracy of 82.67%, referring to Figure 5.

These results are consistent with recent literature that highlights the advantages of ML algorithms in improving prediction accuracy and identifying complex patterns in data [38].

Most notably, J48 achieved the highest performance in predicting IUM, with an accuracy of 91.22%, as illustrated in Figure 6. This result indicates that ML is particularly well-suited for estimating behavioural intentions in technology adoption studies. The superior performance of ML in this context aligns with findings from similar studies that have used ML to predict user behaviour, where machine learning often exceeds the predictive capabilities of traditional methods like SEM.

The findings from this study are consistent with prior research on technology adoption and the use of advanced modelling techniques. For example, , in their studies on TAM [8, 37], found that PEU and PUS are key determinants of user attitudes toward technology, a result corroborated by the current study. Similarly, studies using Ajzen (1991)'s [22] Theory of Planned Behavior (TPB) support the finding that SBN and PBC are significant predictors of IUM, as evidenced by this study's path coefficients of 0.641 and 0.516, respectively.

Nevertheless, the application of ML algorithms differentiates this study from much of existing research. Although SEM is often the only statistical method used to test hypotheses in this context, this study highlights better predictions brought by ML techniques such as J48. For example, Santos & Goncalves (2012) [39] found that similar studies usually produce higher R^2 values and predictive accuracy with ML models than traditional SEM techniques, which is consistent with the results of this study. Specifically, while IUM ML-based predictions were accurate up to 91.22%, the corresponding SEM R^2 value was low at 0.492, indicating that especially in more complex models lettered it can provide a much richer input to support behavioural intentions.

6- Conclusion

This research investigated the significant factors affecting Intention to Use Metaverse (IUM) among TESOL learners for immersive learning, applied either Structural Equation Modeling (SEM) or Machine Learning (ML) algorithms on the reported questionnaire-based data, and synthesized comprehensive evaluative conclusions. This study explored the impact of important variables including Perceived Ease of Use (PEU), Perceived Usefulness (PUS), Attitude (ATT), Subjective Norms (SBN) and Perceived Behavioral Control (PBC) in the adoption of Metaverse-based learning platform in TESOL field, especially at higher education institutions. The results showed that PEU and PUS, however, have a direct effect on students' Attitudes (ATT) and SBN that affect student use of the Metaverse. The SEM results indicated that in particular PEU significantly affected both ATT (β = 0.566) and SBN (β = 0.448), while PUS similarly significantly affected both ATT (β = 0.514) and SBN (β = 0.482). We found that users perspectives regarding ease of use and usefulness is a very important factors for the adaptation of some technology which aligns with several theories in this area like Technology Acceptance Model (TAM). In addition, ATT, SBN and PBC were identified as significant predictors of IUM; SBN had the strongest path coefficient (β = 0.641), suggesting that social influences are imperative for technology adoption. On the other hand, we showed that ML algorithms—J48 in particular—outperformed SEM for prediction. The J48 reached an accuracy of 91.22% on IUM prediction which was significantly higher than SEM R2 of 0.492. These results emphasize the advantage of machine learning methods for improving predictive accuracy and modelling more complex relationships in behavioral research.

The study's findings have several important implications for both educational institutions and policymakers. First, the strong impact of PEU and PUS on learners' attitudes and social norms suggests that user-friendly design and clear demonstrations of the learning benefits of Metaverse platforms are essential for encouraging adoption. Given that 50% of the participants reported irregular access to technology, addressing infrastructure challenges and providing students with greater access to digital tools is crucial for promoting equitable adoption of immersive learning platforms in TESOL. Furthermore, the significant role of SBN and PBC in predicting IUM highlights the importance of creating a supportive social and institutional environment that encourages the use of innovative educational technologies. Universities and educators should foster a culture that promotes the use of immersive learning platforms, providing necessary resources and training to ensure that both students and faculty can effectively integrate these technologies into their curricula. Despite the robust findings, this study has several limitations. The sample was limited to students in Jordan, which may reduce the generalisability of the results to other cultural and educational contexts. Moreover, the study primarily focused on TESOL programs, and thus future research could explore the adoption of Metaverse-based learning in other disciplines to broaden the scope of the findings. Another limitation is the self-reported nature of the survey data, which may introduce bias in responses related to technology use.

Additionally, while the combination of SEM and ML provided a comprehensive analysis, future studies could employ longitudinal data to track changes in technology adoption behaviour over time. Future research could address these limitations by expanding the sample to include participants from different regions and educational systems. Studies could also explore how different teaching methods and curriculum designs can be adapted to fully leverage the capabilities of Metaverse-based learning platforms. Moreover, investigating the role of institutional support and faculty training in facilitating technology adoption would provide valuable insights into the mechanism of overcoming barriers to its widespread use. In addition, given the superior performance of ML techniques in this study, future research should further explore the integration of AI and ML models for personalised learning experiences in the Metaverse. By developing adaptive learning algorithms that cater to individual student needs, institutions can optimise the learning outcomes of immersive educational technology.

7- Declarations

7-1- Author Contributions

Conceptualization, S.W. and M.A.; methodology, S.W. and M.A.; software, M.A.; validation, S.W. and M.A .formal analysis, M.A.; investigation, S.W.; resources, S.A.; data curation, S.A.; writing—original draft preparation, S.A.; writing—review and editing, M.A.; visualization, M.A.; supervision, S.W.; project administration, S.W.; funding acquisition, M.A. All authors have read and agreed to the published version of the manuscript.

7-2- Data Availability Statement

The data presented in this study are available on request from the corresponding author.

7-3- Funding and Acknowledgments

The authors would like to acknowledge the support of Prince Sultan University for paying the Article Processing Charges (APC) of this publication.

7-4- Institutional Review Board Statement

Not applicable.

7-5- Informed Consent Statement

Not applicable.

7-6- Conflicts of Interest

The authors declare that there is no conflict of interests regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancies have been completely observed by the authors.

8- References

[1] Akour, M., & Alenezi, M. (2022). Higher Education Future in the Era of Digital Transformation. Education Sciences, 12(11), 784. doi:10.3390/educsci12110784.

[2] Hussain, T., Yu, L., Asim, M., Ahmed, A., & Wani, M. A. (2024). Enhancing E-Learning Adaptability with Automated Learning Style Identification and Sentiment Analysis: A Hybrid Deep Learning Approach for Smart Education. Information (Switzerland), 15(5), 277. doi:10.3390/info15050277.

[3] Kayyali, M. (2024). Immersive technologies: Virtual and augmented reality in higher education. Reshaping Learning with Next Generation Educational Technologies, 99–114. doi:10.4018/979-8-3693-1310-7.ch007.

[4] Marks, B., & Thomas, J. (2022). Adoption of virtual reality technology in higher education: An evaluation of five teaching semesters in a purpose-designed laboratory. Education and Information Technologies, 27(1), 1287–1305. doi:10.1007/s10639-021-10653-6.

[5] Hennig-Thurau, T., Aliman, D. N., Herting, A. M., Cziehso, G. P., Linder, M., & Kübler, R. V. (2023). Social interactions in the metaverse: Framework, initial evidence, and research roadmap. Journal of the Academy of Marketing Science, 51(4), 889–913. doi:10.1007/s11747-022-00908-0.

[6] Wu, J. G., Zhang, D., & Lee, S. M. (2024). Into the Brave New Metaverse: Envisaging Future Language Teaching and Learning. IEEE Transactions on Learning Technologies, 17, 44–53. doi:10.1109/TLT.2023.3259470.

[7] Childs, E., Mohammad, F., Stevens, L., Burbelo, H., Awoke, A., Rewkowski, N., & Manocha, D. (2024). An Overview of Enhancing Distance Learning Through Emerging Augmented and Virtual Reality Technologies. IEEE Transactions on Visualization and Computer Graphics, 30(8), 4480–4496. doi:10.1109/TVCG.2023.3264577.

[8] Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly: Management Information Systems, 13(3), 319–339. doi:10.2307/249008.

[9] Ajzen, I. (1985). From Intentions to Actions: A Theory of Planned Behavior. Action Control, 11–39. doi:10.1007/978-3-642-69746-3_2.

[10] Benbaba, A., & Lindner, J. (2021). Tesol Teachers' Attitudes Toward Learning Management Systems in Online Teaching in Alabama and Mississippi. The Quarterly Review of Distance Education, 22(1), 17–27.

[11] Haleman, K. N., & Yamat, H. (2021). The Acceptance of E-Learning Among ESL Primary School Students During Covid-19. Journal of English Language Teaching and Applied Linguistics, 3(1), 08–18. doi:10.32996/jeltal.2021.3.1.2.

[12] Jung, H. J. (2015). Fostering an english teaching environment: Factors influencing english as a foreign language teachers' adoption of mobile learning. Informatics in Education, 14(2), 219–241. doi:10.15388/infedu.2015.13.

[13] Mohd Shahrol, S. J., Sulaiman, S., & Mohamed, H. (2023). Acceptance Factors Towards Mobile Technologies in Learning English among Rural Students. International Journal of Innovative Computing, 13(2), 37–47. doi:10.11113/ijic.v13n2.387.

[14] Hasan, M., AlMajaly, S., Alkhatatbeh, R., & Agha, N. (2024). Digital Transformation Revolution and Higher Education Universities in Jordan: Exploring the Students' Attitude Toward the Use of eLearning Platforms in the COVID-19 Pandemic. Studies in Systems, Decision and Control, 489, 243–252. doi:10.1007/978-3-031-36895-0_20.

[15] López-Belmonte, J., Pozo-Sánchez, S., Moreno-Guerrero, A.-J., & Marín-Marín, J.-A. (2023). We've reached the GOAL. Teaching Methodology for Transforming Learning in the METAVERSE. A teaching innovation project. Metaverse Basic and Applied Research, 2, 30. doi:10.56294/mr202330.

[16] Seliaman, M. E., & Al-Turki, M. (2012). Mobile Learning Adoption in Saudi Arabia. World Academy of Science, Engineering, and Technology, 6(9), 356–358.

[17] Cheon, J., Lee, S., Crooks, S. M., & Song, J. (2012). An investigation of mobile learning readiness in higher education based on the theory of planned behavior. Computers and Education, 59(3), 1054–1064. doi:10.1016/j.compedu.2012.04.015.

[18] Karjaluoto, H., Mattila, M., & Pento, T. (2002). Factors underlying attitude formation towards online banking in Finland. International Journal of Bank Marketing, 20(6), 261–272. doi:10.1108/02652320210446724.

[19] Khanh. (2014). Factors Influencing Mobile-Learning Adoption Intention: an Empirical Investigation in High Education. Journal of Social Sciences, 10(2), 51–62. doi:10.3844/jssp.2014.51.62.

[20] Prieto, J. C. S., Miguelánez, S. O., & García-Peñalvo, F. J. (2014). Mobile learning adoption from informal into formal: An extended TAM model to measure mobile acceptance among teachers. ACM International Conference Proceeding Series, 595–602. doi:10.1145/2669711.2669961.

[21] Liu, Y. (2008). AN adoption model for mobile learning. MCCSIS'08 - IADIS Multi Conference on Computer Science and Information Systems; Proceedings e-Commerce 2008, 235–240.

[22] Ajzen, I. (2012). The theory of planned behavior. Handbook of Theories of Social Psychology: Volume 1, 50(2), 438–459. doi:10.4135/9781446249215.n22.

[23] Krejcie, R. V., & Morgan, D. W. (1970). Determining Sample Size for Research Activities. Educational and Psychological Measurement, 30(3), 607–610. doi:10.1177/001316447003000308.

[24] Chuan, C. L., & Penyelidikan, J. (2006). Sample size estimation using Krejcie and Morgan and Cohen statistical power analysis: A comparison. Jurnal Penyelidikan IPBL, 7(1), 78-86.

[25] Anwar, M. S., Choi, A., Ahmad, S., Aurangzeb, K., Laghari, A. A., Gadekallu, T. R., & Hines, A. (2024). A Moving Metaverse: QoE challenges and standards requirements for immersive media consumption in autonomous vehicles. Applied Soft Computing, 159, 111577. doi:10.1016/j.asoc.2024.111577.

[26] Joshi, A., Kale, S., Chandel, S., & Pal, D. (2015). Likert Scale: Explored and Explained. British Journal of Applied Science & Technology, 7(4), 396–403. doi:10.9734/bjast/2015/14975.

[27] Bao, Y., Xiong, T., Hu, Z., & Kibelloh, M. (2013). Exploring gender differences on general and specific computer self-efficacy in mobile learning adoption. Journal of Educational Computing Research, 49(1), 111–132. doi:10.2190/EC.49.1.e.

[28] Tan, G. W. H., Ooi, K. B., Leong, L. Y., & Lin, B. (2014). Predicting the drivers of behavioral intention to use mobile learning: A hybrid SEM-Neural Networks approach. Computers in Human Behavior, 36, 198–213. doi:10.1016/j.chb.2014.03.052.

[29] Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common Method Biases in Behavioral Research: A Critical Review of the Literature and Recommended Remedies. Journal of Applied Psychology, 88(5), 879–903. doi:10.1037/0021-9010.88.5.879.

[30] Arpaci, I. (2019). A hybrid modeling approach for predicting the educational use of mobile cloud computing services in higher education. Computers in Human Behavior, 90, 181–187. doi:10.1016/j.chb.2018.09.005.

[31] Mangrulkar, S. (1990). Artificial neural systems. ISA Transactions, 29(1), 5-7. doi:10.1016/0019-0578(90)90024-F.

[32] Hair, J., Hollingsworth, C. L., Randolph, A. B., & Chong, A. Y. L. (2017). An updated and expanded assessment of PLS-SEM in information systems research. Industrial Management and Data Systems, 117(3), 442–458. doi:10.1108/IMDS-04-2016-0130.

[33] Sitgreaves, R. (1979). Review of Psychometric theory (2nd ed.). Contemporary Psychology: A Journal of Reviews, 24(7), 599–599. doi:10.1037/018882.

[34] Fornell, C., & Larcker, D. F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. Journal of Marketing Research, 18(1), 39. doi:10.2307/3151312.

[35] Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. Journal of the Academy of Marketing Science, 43(1), 115–135. doi:10.1007/s11747-014-0403-8.

[36] Frank, E., Hall, M., Holmes, G., Kirkby, R., Pfahringer, B., Witten, I. H., & Trigg, L. (2009). Weka-A Machine Learning Workbench for Data Mining. In Data Mining and Knowledge Discovery Handbook, 1269–1277. doi:10.1007/978-0-387-09823-4_66.

[37] Grover, P., Kar, A. K., Janssen, M., & Ilavarasan, P. V. (2019). Perceived usefulness, ease of use and user acceptance of blockchain technology for digital transactions–insights from user-generated content on Twitter. Enterprise Information Systems, 13(6), 771-800. doi:10.1080/17517575.2019.1599446.

[38] Shmueli, G., & Koppius, O. R. (2011). Predictive analytics in information systems research. MIS Quarterly: Management Information Systems, 35(3), 553–572. doi:10.2307/23042796.

[39] Santos, V., & Gonçalves, R. (2012). A Social Shopping Model Proposal. Proceedings of Mediterranean Conference on Information Systems, MCIS2012, 1–7.