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Exploring the Potential Adoption of Metaverse for Higher Education: Structural Equation Modelling Approach in a Business School Context

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Abstract

The evolution of the Metaverse in Higher Education (HE) in Mexico can potentially enhance pedagogy, develop skills, and improve the learning experience. This research aims to estimate the factors guiding the adoption of the Metaverse in a Business School context in Mexico. A survey analysis was conducted to gauge insights from stakeholders on the Metaverse in HE. A total of 117 respondents, comprising students, professors, and staff members, completed the 21-item questionnaire. To determine the relationship between data, a quantitative analysis was performed using a structural equation model (SEM), and a path analysis was computed to illustrate the relationship among the adoption components of the UTAUT model. The study found no correlation between age, gender, and previous experience toward adopting the Metaverse. On the other hand, performance expectancy, effort expectancy, social influence, and facilitating conditions significantly impact the stakeholders' attitudes toward adopting this technology. The R^2 coefficient of 94% obtained explains the model's accuracy. The research reveals that a practical learning exercise in the Metaverse improved student knowledge acquisition. Implementing this model is to be at the service of concerned HE authorities to create an adequate environment for adopting the Metaverse in Universities in Mexico.

Keywords: metaverse, virtual reality, adoption, UTAUT Model, Higher Education

1. Introduction

Adopting virtual and augmented reality technology represents a significant trend in the Higher Education (HE) landscape. This trend is driven by the necessity to enhance interactive and personalized learning experiences and the increasing demand to align different student profiles to labor market needs (Van der Vlies, 2020). According to Statista, Metaverse in Education market report (2023), the global market size is expected to reach $24 billion by 2030, with a CAGR of 45.52% from 2023 to 2030. Furthermore, the number of users is expected to amount to 1.7 million users by 2030.

In Mexico, there is a significant opportunity for growth since 82% of Mexicans between the ages of 25 to 64 do not possess higher education, whereas the OECD average is 63% (Van der Vlies, 2020). With the help of Metaverse technology, a high-quality education can be provided, enhancing innovation and productivity levels (Kremer et al., 2013).

According to the assertions made by Chen (2022), the Metaverse is drawing HE due to its capacity to provide immersive, multisensory, authentic, and practical learning experiences. Consequently, the Metaverse is a feasible method of achieving educational opportunities, breaking down space, time, and cost barriers, and solving complex issues to address in real life.

The metaverse platform VirBELA was the preferred choice for hosting the virtual classes and conferences. According to Liang et al. (2023, p. 75), "*VirBELA contains a campus built in a virtual world, and users can create and use their virtual avatars to access the platform through their computers. After entering this immersive, socially connected virtual campus, students and professors can socialize with others and attend classes in virtual classrooms".* We opted to utilize this platform due to its integration into the virtual laboratory at the Business School of Tecnológico de Monterrey. In addition, our students enjoy unrestricted access to this technology.

VirBELA has established itself as the pioneer enterprise metaverse that enables individuals and teams to collaborate remotely (Virbela, 2012). In addition, as Liang et al. (2023, p. 75) mentioned, *"…this platform meets the three unique characteristics of the metaverse: shared, persistent, and decentralized*". The platform is permanent, user-friendly, and accessible to users worldwide, optimizing remote work (Virberla, 2012).

It is crucial to examine the attitudes and intentions of students and faculty members with varying levels of learning motivation in the metaverse (Arpaci & Bahari, 2023; Chang et al., 2022). UTAUT model has been used to analyze the willingness to adopt mobile learning in universities (Alyoussef, 2021; García Botero, 2018; Alowayr, 2018; and Chand, 2022), the acceptance of the Internet of Things (IoT) in Higher Education (Jain, 2022; Yang, 2019), the continued intention to use online courses in Universities (Li, 2022; Padhi, 2018; Altahi, 2021; Park, 2021) and, the adoption of blended learning in the educational landscape (Martín,2014). To determine the factors that influence the adoption of the Metaverse by higher education stakeholders, this research used the UTAUT model as its theoretical framework, and a quantitative analysis using structural equation modeling (SEM) was performed.

This study aims to raise awareness about the factors that deploy adopting the Metaverse in Higher Education in Business Schools in Mexico. The contribution of this research adds to the literature and unfolds in three significant ways: a: First, identifying the impact in the attitude of the HE stakeholders adopting the Metaverse; Second, analyzing functional practices and applications of the Metaverse and their impact on the higher educational system for private universities and, Third, to specifying how the attitude and behavioral intention of the stakeholders in Business School context could influence the adoption of the Metaverse.

For this purpose, this article is structured as follows: the next section discusses the literature regarding the Metaverse in Higher Education, extended and situated experiential learning, and the components of adopting new technology by HE stakeholders. Section three describes the UTAUT conceptual model and hypotheses. Section four outlines the methodology, results, and discussions. Finally, section five presents the conclusions that emphasize critical discoveries made during this research and general recommendations to Higher Education authorities.

2. Literature Review

2.1 Metaverse Contemporary Development

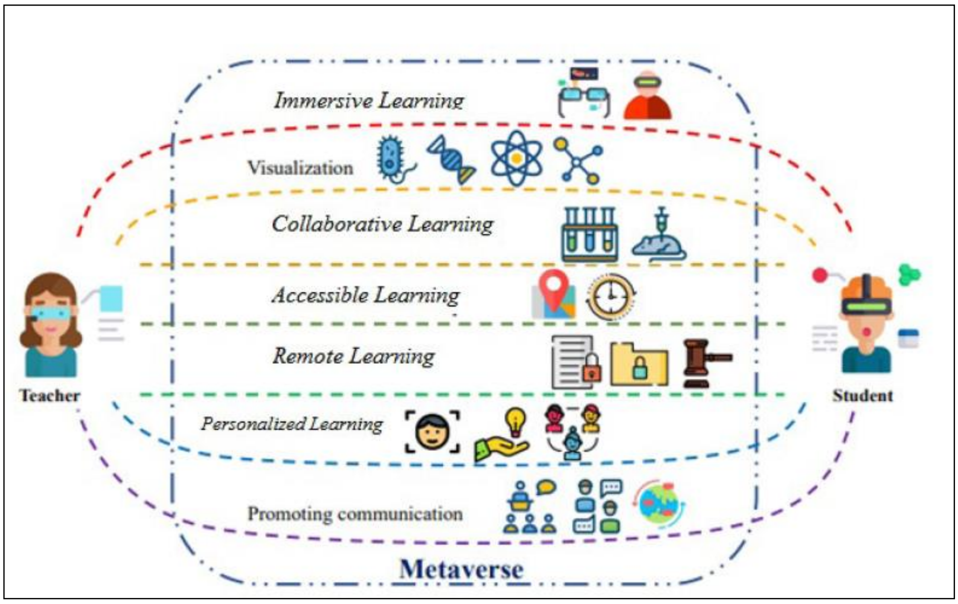
Metaverse was invented and first appeared in Neal Stevenson's science fiction novel "Snow Crash," published in 1992 (Stephenson, 1992). Prakash et al. (2023, p. 2) state that Metaverse "refers to a virtual space where users can engage with each other in various experiences, from gaming and socializing to learning and education." The word Metaverse is a combination of the prefix "meta," implying transcending with the word "universe," which represents a parallel or virtual environment linking to the physical world (Tlili, 2022, p. 2).

Different authors have shaped the definition, adding special features to the Metaverse concept. It has been defined as a collective space in virtuality (Lee et al., 2021), mirror world (Lee et al., 2021), embodied internet (Chayka, 2021), integrated social technology (Ning et al., 2021), a post-reality universe and multiuser environment (Mystakidis et al., 2021) a venue of simulation and collaboration (Lee et al., 2021), and lifelogging (Bruun & Stentoft, 2019).

The backbone of the Metaverse is a protocol called The Street, linking different locations, an analog concept to the information superhighway (Mystakidis, 2022). Metaverse comprises three key elements: Users materialize in this universe through configurable digital bodies called avatars to reflect their identities; this is the first component. These avatars can be customized to resemble human beings, animals, or even fictitious entities. The second element is the environment designed to mimic real-world places or to create new ones. The classroom can be in a museum, laboratory, or even a dangerous crater. The third component consists of virtual objects created by interacting digital items within the virtual space. (Prakash et al., 2023).

According to Prakash et al. (2023), Metaverse can transform traditional teaching methodologies by increasing student engagement and retention of information through collaborative learning, experiential learning, customized learning, and gamification. These elements provide a sense of pride and achievement when students complete tasks or reach educational breakthroughs (Salloum, 2023). Many authors have studied how Metaverse changes education (Lin et al., 2022; Prakash, 2023; Hwang et al., 2023) and the numerous benefits, including interaction, authenticity, and portability. Figure 1 shows seven ways that the Metaverse changes education.

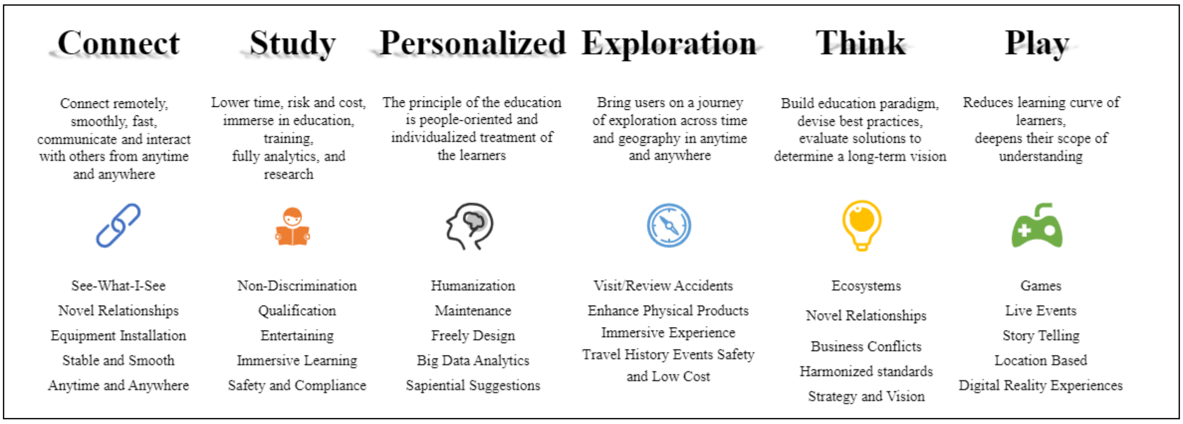
Figure 1: Lin et al.'s (2022) model presents seven ways Metaverse changes education



Note: This model presents seven ways in which Metaverse is changing education. The model by Lin et al. (2022) was presented at the IEEE International Conference on Big Data. Source: Lin, H., Wan, S., Gan, W., Chen, J., & Chao, H. C. (2022, December). Metaverse in education: Vision, opportunities, and challenges. In 2022 IEEE International Conference on Big Data (Big Data) (pp. 2857-2866). IEEE.

Lin et al. (2022) established six components that Metaverse brings to education systems: creating connection, evolving the immersive study, personalizing learning, exploring any geography anytime and anywhere, disrupting thinking, and playing for life learning. These components are depicted in Figure 2.

Figure 2: Revolution of Metaverse in Education



Note: Six components of the Metaverse change education. Source: Lin, H., Wan, S., Gan, W., Chen, J., & Chao, H. C. (2022, December). Metaverse in education: Vision, opportunities, and challenges. In 2022 IEEE International Conference on Big Data (Big Data) (pp. 2857-2866). IEEE.

2.2 Extended and Situated Experiential Learning in the Metaverse

The experiential learning theory was developed by Dewey (1938), establishing the following principle combining motivation and learning:

"*Education and training in school should enable and encourage pupils to use their curiosity and ask questions they want answers to, and in this way create a lifelong learning process when their formal schooling has ended.*" *(Dewey, 1938, p-25)*

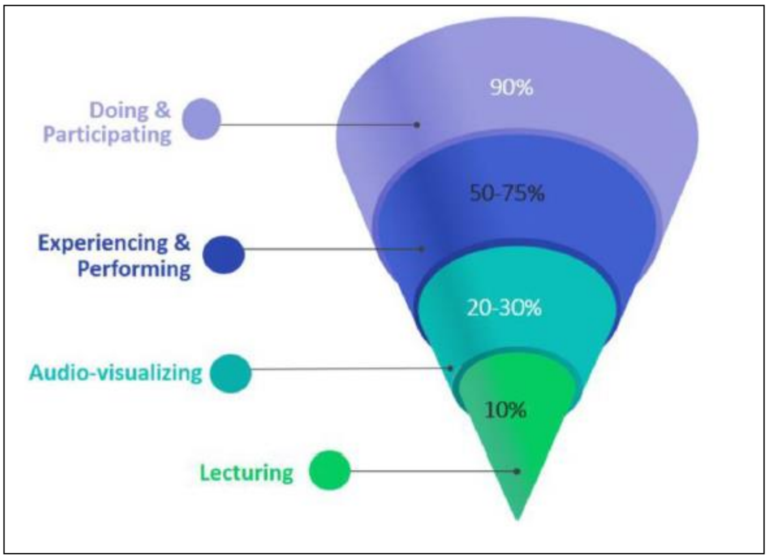
According to this principle, the acquirement of knowledge should be based on real-life experiences that provide a context to process information. The professor becomes a facilitator for students' experiences (Hwanh et al., 2023). Dale (1969) emphasized how different media and materials could maximize learner experiences. In the first edition of Audiovisuals Methods in Teaching (1946), Dale introduced the “Cone of Learning Model” of how much one remembers after two weeks depending on different learning models. The results showed that students remember better when learning by doing, learning through abstractions, and learning through observations.

Hwanh et al. (2023) proposed the “Cone of the Metaverse Learning Model.” This model inverts Dewey’s model and sets a broad base of doing and participating as a top priority. Learning by doing overcomes all other forms of learning, facilitating students' experiences and leading an immersive learning potential. Figure 2 presents the Cone of Metaverse learning model. According to the authors, the Metaverse allows students to access information in any context, combining learning contents.

The environmental context involves connected events and situations that provide a framework for understanding and interpretation. Learning always happens based on actions, including the individual and their context (Lickliert, 2000). This is called situated learning, and according to Hwang et al. (2023), the advantage of learning in the metaverse is the connection with information relevant to students taking place in a virtual environment.

A study by Jovanović and Milosavljević (2022) employed a blend of methodologies (surveys and discussions) to enact an engineering education class on a metaverse platform called VoRtex. The findings indicated that students experienced Comparative studies in divergent subjects, such as English teaching and safety training (Guo & Gao, 2022; Kanematsu et al., 2014) exhibited positive instructional outcomes and immersive experiences marginally enhanced the learning environment; additionally, the features of the platform eased internal dialogue and the dissemination of knowledge amongst the participants.

Figure 3: Cone of Metaverses learning model by Hwang et al. (2023)



Note: This model presents four levels of learning engagement: lecturing, audio-visualizing, experience and performing, and doing and participating. Source: Hwang, Y., Shin, D., & Lee, H. (2023). Students’ perception of immersive learning through 2D and 3D metaverse platforms. Educational technology research and development, 1-22.

Many researchers (e.g., Shin et al., 2021; Coveney et al., 2013; Golden & Baddeley, 1975) in many fields highlight the context-dependent memory, establishing that the higher the learning and authentic environments, the higher the learning effect. Shin et al. (2021) reported that the learning environment can boost context-dependent memory to create knowledge. This is one of the principles of the Metaverse in education. According to Hwang et al. (2023), *"metaverse amplifies student's learning experiences by offering persistent self-presence as well as decentralized high levels of interaction and freedom" (*Hwang et al., 2023 p-6*)*. Hence, in the metaverse, students can experience extended experiential and situated learning processes that lead to knowledge acquisition.

2.3 Adoption of new technologies: Metaverse in HE

In Technology literature, users' acceptance of new automation processes plays a crucial role in ensuring the success of any technology. Therefore, it is crucial to identify the factors that affect the Higher Education community´s acceptance of immersive experiential learning, such as the metaverse. To perceive learning users' needs and requirements, many models have been developed to examine the users' acceptance of new technology and their intention to use such technology.

From studies of literature review, researchers found that the Unified Theory of Acceptance and Use of Technology, UTAUT model has the highest explanatory power compared to other relevant theories (i.e., TAM, TAM2, TRA, TBP) (Almaiah et al., 2019). A meta-analysis study by Walldén et al. (2016) demonstrated that the UTAUT model is valid and robust based on empirical evidence in 69 studies. The focus on factors for successful implementation positioned the UTAUT model as the most popular in technology acceptance (Al-Mamary et al., 2015).

According to Venkatesh et al. (2003), the UTAUT model explains almost 70% of the variance regarding behavioral intention, and it is considered helpful in interpreting users' intention to adopt a modern technology like Metaverse (Chatterjee & Bhattacharjee, 2020). In Higher Education, this theoretical framework has been used to analyze the willingness to adopt mobile learning in universities (Alyoussef,2021; García Botero, 2018; Alowayr, 2018; Chand,2022), the acceptance of the Internet of Things (IoT) (Jain, 2022; Yang 2019,), the continued intention to use online courses in universities (Li, 2022; Padhi, 2018; Altahi, 2021; Park, 2021) and in the context of blended learning (Martín,2014).

This research uses UTAUT theory to develop a conceptual model to understand why Higher Education (HE) stakeholders (i.e., students, professors, researchers, and staff) accept or reject extended experiential and immersive learning through the metaverse. As established by Venkatesh et al. (2023), the model consists of four constructs: effort expectancy, performance expectancy, social factors, and facilitating conditions) Moreover, four moderating variables (i.e., age, gender, education, and voluntariness of use). The combination of constructs and moderating variables affects the behavioral intention of users (Venkatesh et al., 2003).

According to Chong (2013), the variable attitude has been widely acknowledged in interpreting users' intention to accept new technology. In Higher Education, it is necessary to realize students' motivation and attitudes toward learning with new technology (Dang & Liu, 2022). Following the study of Chatterjee Bhattacharjee (2020), we took the variable of attitude as the mediating variable between Performance Expectancy and Behavioral Intention, Effort Expectancy and Behavioral Intention, Social Influence and Behavioral Intention, and Facilitating Conditions and Behavioral Intention as has been done in several studies (Alshare & Lane, 2011; Cox, 2012). Contrary to Chatterjee and Bhattacharjee's (2020) model, this study considers the moderators of age, gender, and experience affecting the attitude of the HE stakeholders.

The studies of Hwang & Chien (2022), Downie et al. (2021), and Han & Greng (2023) have explored the effect of learners' motivation and attitude in the adoption of new technologies.

The model proposed in this study also measures the effect on stakeholders' attitudes towards adopting Metaverse. Finally, to interpret the Adoption of Metaverse in Higher Education (AD), the constructs of Performance Expectancy (PE), Effort Expectancy (EE), Social Intention (SI), Facilitating Condition (FC), Attitude (ATT), and Behavioral Intention (BI) have been chosen along with Age (A), Gender (G) and Experience (EX) to understand the potential of adoption of new technology in HE. The following section provides an individual explanation of the constructs with the hypotheses and the model.

3. Conceptual Model and hypotheses

3.1 Performance Expectancy (PE)

Performance Expectancy (PE) is one of the most observed factors influencing the adoption and acceptance of a virtual reality environment (Alfaisal et al., 2022). Venkatesh et al. (2023) established the relationship between PE and the user's belief in using new technology to accomplish a specific task. The research of Chatterjee and Bhattacharjee (2020) and the study of Lin et al. (2011) considered that PE has a significant and positive impact on attitude (ATT). Therefore, the following hypothesis is developed:

H1: Performance Expectancy (PE) has a positive and significant impact on the Attitude (ATT) of stakeholders adopting the Metaverse in Higher Education (AD).

3.2 Effort Expectancy (EE)

Effort Expectancy (EE) relates to user expectations regarding ease of use. Many authors in other fields (Zhou et al., 2010; Chaouali et al., 2016) demonstrated that “when users feel that a certain technology does not require much effort, they would have high chances of adopting such technology” (Rahi et al., 2019, p.3). Therefore, and based on empirical evidence (Chaouali et al., 2016; Oliveira et al., 2016), the Effort Expectancy (EE) of users will influence their Attitude (ATT) toward the adoption of new technology. Thus, Effort Expectancy is proposed as:

H2: Effort Expectancy (EE) has a positive and significant impact on the Attitude (ATT) of stakeholders adopting the Metaverse in Higher Education (AD).

3.3 Social Influence (SI)

Social Influence (SI) is the pressure exerted on individuals to adopt new technology (Chaouali et al., 2016; Martinsetal, 2014). According to Fishbein’s Theory of reasoned action (Fishbein, 1980), “an individual develops beliefs about the extent to which other people who are important to them think they should or should not perform” (Bozan et al., 2016, p.518). In technology, the influence of peers and superiors strongly determines a person's behavior (Mathieson, 1991). Following the above arguments, Social Influence (SI) is expressed as:

H3: Social Influence (SI) has a positive and significant impact on the Attitude (ATT) of stakeholders adopting the Metaverse in Higher Education (AD).

3.4 Facilitating Conditions

Urumsah et al. (2011) argued that quality, agility, stability, and availability of technical infrastructure and user training lead to the easy adoption of new technology. As Venkatesh et al. (2003) reported, if the physical conditions support using a new system, the stakeholders will be more inclined to embrace it. The absence of technological infrastructure could demotivate users to adopt technology (Rahi & Nhag., 2019). It is Hence, the following hypothesis is outlined:

H4: Facilitating Conditions (FC) have a positive and significant impact on the Attitude (ATT) of stakeholders adopting the Metaverse in Higher Education (AD).

3.5 Moderating Role of Age, Gender, and Experience

Demographic variables such as age (A) and gender (G) have significant effects on social factors studies (Mazman, 2011) modifying the individual's attitude (ATT). According to Morris and Venkatesh (2000), older individuals tend to be more cautious when making decisions but are also more susceptible to social influences. Dabaj's (2009) study showed that older students prefer attending face-to-face classes. Regarding gender, the results demonstrated that female students have a better perception of online education than male students. Users with limited experience prefer technology that requires minimal effort. (Vankatesh et al., 2003). Thus, this study presents a relationship between the experience level (EX) and the user's effort expectancy (EE). Considering the above arguments, the moderating role of Age (A), Gender (G), and Experience (EX) are expressed as:

H5: Age (A) and Gender (G) moderate the relationship between the Attitude (ATT) and Behavioral Intention (BI) of stakeholders toward the Adoption of the Metaverse in Higher Education (AD).

H6: Level of Experience (EX) moderates the relationship between the Attitude (ATT) and Behavioral Intention (BI) of stakeholders toward the Adoption of the Metaverse in Higher Education (AD).

3.6 Attitude

The Theory of Technology Acceptance Model (TAM) postulates that Behavioral Intention (BI) is assessed by the Attitude (ATT) of an individual regarding the usage of a system (Davis et al., 1989). According to Aboelmaged (2010) and Cox (2012), attitude (ATT) is a solid mediating variable for interpreting behavioral intention (BI). Janssen et al. (2017) established that attitude is essential to adopting new technology. Au and Enderwick (2000) define Attitude (ATT) as the “cognitive process affected by six beliefs: compatibility, enhanced value, perceived benefits, adaptive experiences, perceived difficulty, and commitment.” Thus, the following hypotheses are proposed:

H7: Attitude (ATT) positively and significantly impacts adopting the Metaverse in Higher Education (AD).

3.7 Behavioral Intention

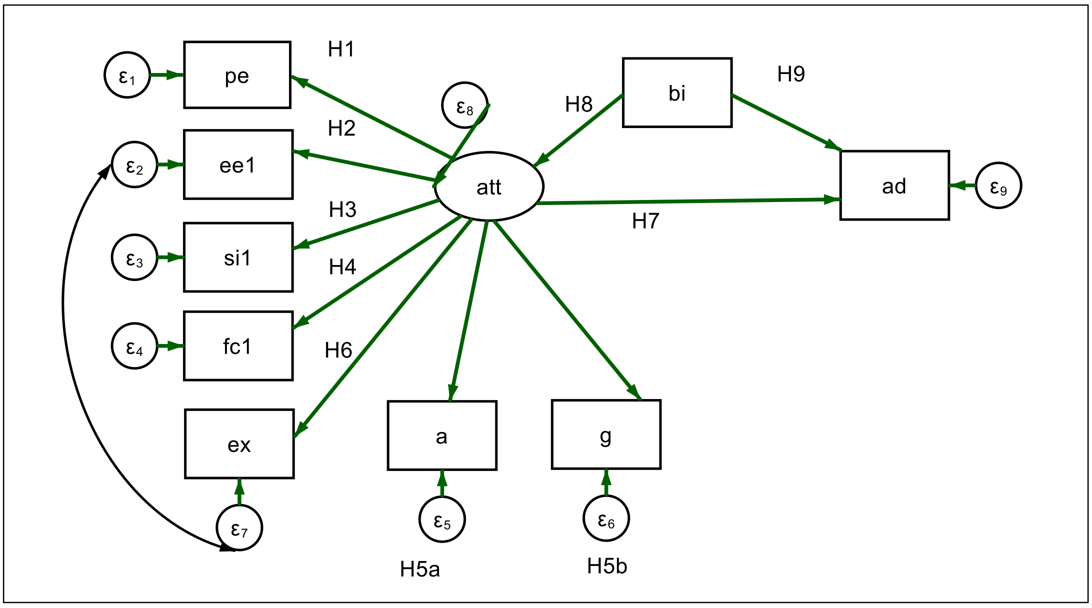
According to Nasrallah (2014), Behavioral Intention (BI) is a mediating variable that influences performing an intended activity or task. Behavioral intention is linked to the strength of the desire to perform a specific action (Fishbein & Ajzen, 1975). Therefore, the following hypothesis is being proposed:

H8: The Behavioral Intention (BI) of stakeholders has a positive and significant impact on the Attitude (ATT) towards the adoption of the Metaverse (AD).

H9: Stakeholders' Behavioral Intention (BI) positively and significantly impacts adopting the Metaverse in Higher Education (AD).

The model's constructs are exhibited in the research model shown in Figure 4. The hypotheses conceptually formulated were validated using the Partial Least Square (PLS) regression analysis. To establish the relationship between the variables, the Structural Equation Modelling (SEM) and a Path Analysis present the strength level between the constructs. The model's methodology and validation are explained in the next section.

Figure 4: Research Model for the Adoption of Metaverse in Higher Education

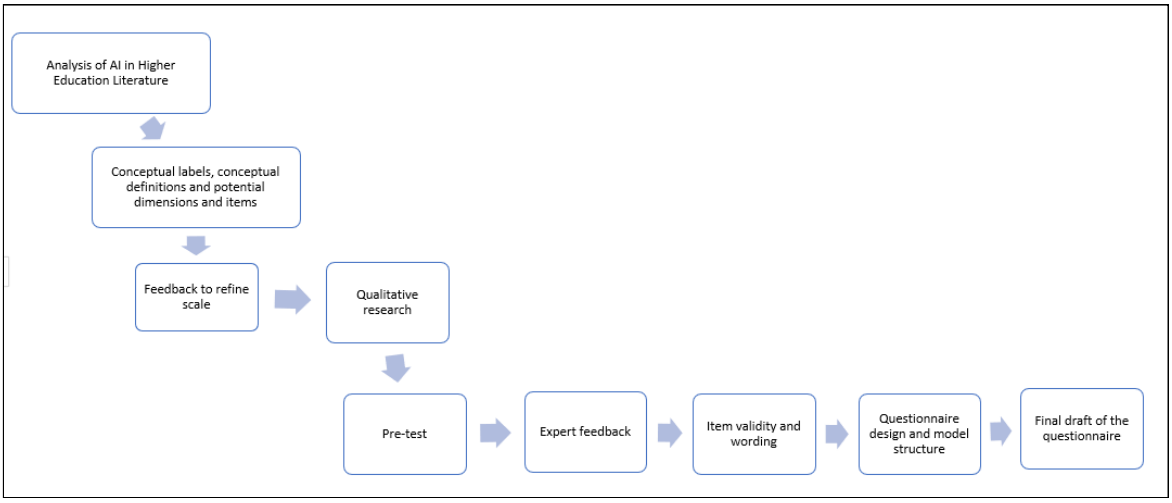


Note: This model was produced by Chatterjee and Bhattacharjee (2020), summarising the primary constructs of the UTAUT model (EE, PE, FC, and SI). This research adds the effect of Age (AG), Gender (G), and Experience (EX) of users and the effect on Attitude (ATT) towards the Adoption (AD) of the Metaverse—source: Own work.

4. Methodology

Factor Analysis (FA) and Partial Least Square (PLS) regression analysis were conducted to validate the conceptual model and the hypotheses. It has been determined that the required survey work is necessary. To prepare the questionnaire, the methodology of Carpenter (2018) was followed along with the assistance of experts. The methodology is depicted in Figure 4. The final questionnaire contained 21 questions in the form of statements, including three initial questions identifying relevant characteristics of the sample (i.e., Age, Gender, and Status). The questions addressed different aspects of the Metaverse for the Higher Education sector. Some of the questions were related to how Metaverse could improve the teaching-learning process. A few of the questions were also related to the necessity to create more educational content to understand thoroughly climate change and sustainability in business. The questionnaire has also covered the level of experience and effort different stakeholders need to meet their individual needs. The summary of the questions in statements and the answers collected are presented in Appendix Table 5 and Figure 9, respectively.

Figure 5: Methodology of Carpenter (2018) Step-by-step scale of development.



Source: Carpenter, S. (2018). Ten steps in scale development and reporting: A guide for researchers. Communication methods and measures, 12(1), 25-44.

For the respondents' selection, this research focused on three main stakeholders: students, staff, and professors from the Accounting and Finance Academic Department of the Business School of Tecnológico de Monterrey. The students belong to the bachelor's in accounting and finance academic program. In this project, students, staff, and professors were contacted through an e-mail request to answer the questionnaire. The questionnaire was sent with a request to send feedback within three days. Their e-mails, as well as their consents, were collected in a period of 12 days, from May 26th to June 6th.

117 users answered the questionnaire without bias and with incomplete responses. According to Deb & David (2014), this is within the acceptable range of 1:4 to 1:10 (no. of questionaries: no. responses). The survey work took June and July 2023, excluding the time of feedback collection. The demographic profile of the 117 respondents is shown in Table 1.

Table 1: Profile of respondents

Participants	Number	Proportion (%)
Students	95	81%
Professors	20	17%
Staff	2	2%
	117	100%

Source: Own work

Metaverse engagement was tested in the course Financial Management and Controllership code CF302B conducted in the summer of 2023. The course consisted of integrating sustainability reporting and data analytics for ten weeks. The course aimed to assess the financial impact of decisions, both financial and non-financial, within an international context for a cement company located in Mexico. Based on creative problem-solving tasks with divergent thinking (creative, disruptive, design, lateral), students were asked to participate in relevant conferences in the Metaverse and guided visits to Mostla Lab as part of Tecnológico de Monterrey facilities. The Metaverse conferences were operated using the VirBELA platform.

VirBELA is a virtual 3D university campus that brings students, companies, and professors together in a 3D world and connects them for expert collaboration (Mora-Beltrán et al., 2020). It also offers three specific advantages of use: remote work, remote learning, and virtual events. In this 3D campus, all participants create a 3D character before starting any educational process. VirBELA has other functions and features, including public chats, private bubbles, resolution, window display settings, exposition halls, conference rooms, and classrooms, among other things (Volkow & Howland, 2018). See Figure 4.

The students had a conference call: "Digital payments and the future of accounting." The students participated in a Q&A session with the speaker at this conference and shared ideas through the VirBELA chat. Figure 5 depicts a sample scene of this conference. It is essential to highlight that during the conference, students were engaged, and the knowledge retention level increased. The speaker shared a video, browsed the web, and dropped links during the conference. Therefore, the students and staff observed higher participation and satisfaction.

Figure 6: VirBELA 3D Campus Tecnológico de Monterrey

Note: This is the initial screen after login to VirBELA. The user can participate in a variety of educational content. Source: VirBELA- Tecnológico de Monterrey (2023)

Figure 7: Sample scene of conference lesson in Virbela 3D Campus

Note: Students, professors, and staff were gathered to attend the conference. Source: VirBELA- Tecnológico de Monterrey (2023)

4.1 Computations of LF, AVE, and CR

Exploratory Factor Analysis (EFA) is a statistical method widely used in the social sciences (Costello & Osborne, 2005). EFA helps to validate the constructs of a questionnaire by analyzing the interrelationships between the responses to a set of items. Some of the issues

EFA deals with are principal components and factor analysis, the number of factors to retain, orthogonal and oblique rotations, and the adequation of sample size. In this study, one of the first steps was to test if the questionnaires were reliable concerning their construct. Ten factors were retained from the Eigenvalues more significant than 1 rule or the Kaiser's criterion.

In factor analysis, each item is given a score for each factor. Field (2013) states that loading factors (LF) below 0.3 must be suppressed. Scores greater than 0.4 are considered stable (Guadagnoli & Velicer, 1988). The Fornell-Larcker (1981) has been commonly used to evaluate the degree of shared variance between the model's variables. According to this criterion, the convergent validity of the measurement of the model can be assessed by the Average Variance Extracted (AVE) and Composite Reliability (CR).

AVE measures the level of variance captured by a construct versus the level due to measurement error. Values above 0.7 are considered reasonable, and 0.5 is acceptable. CR is a less biased reliability estimate than Cronbach's Alpha (α); the acceptable value of CR must be 0.7 and above. The estimated values for the LF are within an acceptable range. For the CR values, EE and FC did not meet the criteria. All the variables' levels for the AVE were below 0.5. Nevertheless, "the choice of a single statistic to summarize the accuracy of an instrument is not the best report that can be made" (Cronbach & Shavelson, 2004, p. 414). According to this principle, this study considered both constructs. All the results are shown in Appendix Table 2.

4.2 Discriminant validity test

The construct's reliability can be measured through Cronbach´s alpha. According to Zikmund (1994), it provides a clear indicator regarding the internal consistency of items. For the sample, all the constructs showed values above 0.90. The average of the 17 items of the scale were 0.9531 and 0.7729 for the nine constructs of the model. According to Cresswell (2005), Pallant (2001), and Sekaran (1992), for a small sample, it can be concluded that items have good internal stability and consistency.

Ordinary least squares (OLS) linear regression was computed to test multicollinearity and validate the model. The Variance Inflation Factor (VIF) of each construct was obtained, and as a rule of thumb, VIF above 4 indicates that multicollinearity might exist. The mean VIF is 2.06, which is considered acceptable, and the model did not present multicollinearity (Johnston et al., 2018).

Discriminant analysis "is a statistical technique which allows the researcher to study the differences between two or more groups or objects concerning several variables simultaneously" (Klecka, 1980, p. 7). With this technique, this study determined which of the presented variables helped predict a result, how variables might be combined into a mathematical equation to predict the most likely outcome, and the accuracy of the derived equation (Klecka, 1980).

Testing for discriminant validity can be done using the Average Variance Extracted analysis (AVE). The first step is computing the square root of the corresponding AVE; the result is the Average Variance (AV). The AV of each construct must be more significant than any correlation coefficient among any pair of latent constructs (Gefen & Straub, 2005). If this is true, then the items of the construct explain more variance than those of the other constructs. The value of AV is shown in a diagonal place, and these values are more significant than the corresponding correlation coefficients shown in off-diagonal places of the matrix. This confirms the discriminant validity test (Fornell & Lacker, 1981). All the results are shown in Table 3.

Table 3: Discriminant Analysis, reliability and VIF

	EX	PE	AD	BI	FC	EE	SI	G	A	AVE	α	VIF	AV	Item No.
EX	**0.45**									0.20	0.78	1.11	0.45	1
PE	0.17	**0.74**								0.54	0.71	3.28	0.74	4
AD	0.17	0.85	**0.91**							0.84	0.69	6.75	0.91	5
BI	0.20	0.82	0.89	**0.86**						0.74	0.70	4.45	0.86	5
FC	0.18	0.49	0.54	0.50	**0.56**					0.31	0.74	1.50	0.56	1
EE	0.24	0.43	0.48	0.46	0.43	**0.49**				0.24	0.75	1.40	0.49	1
SI	0.19	0.68	0.75	0.77	0.40	0.39	**0.79**			0.62	0.70	2.62	0.79	1
G	0.06	(0.01)	(0.03)	0.03	(0.11)	(0.04)	0.01	**0.12**		0.01	0.85	1.03	0.12	1
A	0.14	(0.05)	(0.04)	(0.05)	(0.04)	(0.02)	(0.15)	(0.02)	**0.26**	0.07	0.79	1.06	0.26	1

Source: Own work.

4.3 Structural Equation Modelling (SEM)

Structural equation modeling (SEM) is a collection of statistical techniques that allow a set of relationships between one or more independent variables (IVs) and one or more dependent variables (DVs) to be examined (Ullman & Bentler, 2012). SEM confirms if the structure of the model represents the data and if it is in order and correct. To establish the global fit of the model, the chi-square, the root mean squared error of approximation (RMSEA), the comparative fit index (CFI), the Tucker-Lewis index (TLI), and the size of residuals measured with the standardized root mean squared residual (SRMR) indices were obtained.

Table 4 shows that all these parameters are within standard acceptable limits, and the adequacy of the model fit has been established. In Figure 6, the path analysis is presented, showing the relationships in the model. To estimate the portion of the variance in the dependent variable, which can be predicted from the independent variable, the coefficient of the determinant known as R^2 has been computed. The results are shown in Table 5.

Table 4: Model Fit summary

Fit Statistic	Recommended value	Value in Model
Likelihood ratio $p>\chi^2$	>0.000	0.16
Root mean squared error of approximation (RMSEA)	<0.50 (Hamid, 2019)	0.048
90% CI, Lower bound	<0.05 (Whittaker & Schumacker, 2022)	0.00
Upper bound	<0.10 (Whittaker & Schumacker, 2022)	0.093
Probability of RMSEA (pclose)	<0.05 (Pituch & Stevens, 2016)	0.493
Comparative Fit Index (CFI)	> .93 (Hair et al., 2006)	0.988
Tucker Lewis index (TLI)	> .90 (Pituch & Stevens, 2016)	0.983
Standardized root mean squared residual (SRMR)	>0.05 (Pituch & Stevens, 2016)	0.055

Source: Own work.

The chi-square (χ^2) goodness of fit test is better considered a “badness of fit” test. The chi-square goodness of fit test is insignificant, $\chi^2(25)=31.623$, $p>.169$, suggesting a good fit of the model to the data. The Root Mean Square Error of Approximation (RMSEA) and Standardized Root Mean Square Residual (SRMR) fall into a class of indices referred to as ‘absolute fit indices’ (Whittaker & Schumacker, 2022). RMSEA includes a penalty for model complexity. The lower bound for both indices is 0, indicating a perfect fit. Values deviating in the positive direction from 0 signal worsening fit. Regarding conventions for evaluating fit, Whittaker and Shumacker (2022) offer the following: RMSEA values of 0 to less than 0.05 meet the criteria of close fit. The RMSEA value for the model is 0.048.

In addition to examining the RMSEA, we can also examine the 90% confidence interval for this estimate. If the lower bound of the confidence interval falls below .05 and the upper bound falls below .10, this could be interpreted as evidence of a close model fit (Whittaker & Shumacker, 2022). Additionally, it can be examined the p-close test tests whether the computed RMSEA from the analysis is significantly different from the expected RMSEA under the assumption of close model fit (i.e., RMSEA < = .05). According to Pituch & Stevens (2016), if the p-value is no greater than 0.05 the model exhibits close fit to the data. The value in the model is 0.493 and meets the model fit criteria.

The CFI and TLI are both incremental fit indices. For the CFI, values of >0.9300 are a good fit (Hair et al., 2006). LTI values of 0.90 or above are considered evidence of acceptable fit (Pituch & Stevens, 2016). Finally, the Standardized root mean squared residual (SRMR) values up to 0.5 indicate a close-fitting model. Values between 0.05 to 0.10 suggest an acceptable fit (Pituch & Stevens, 2016). The value of the model is 0.055. According to these criteria, the model accomplished an acceptable fit.

Table 5: Path analysis with the estimation of R^2

Effect	**Path**	**Hypothesis**	**Sign**	**β-value**	**Significance Level**	**R^2**	**Remarks**
Effect on ATT						0.938	
By PE	PE -> ATT	H1	(+)	0.887	***(p < 0.001)		Supported
By EE	EE -> ATT	H2	(+)	0.475	***(p < 0.001)		Supported
By SI	SI -> ATT	H3	(+)	0.785	***(p < 0.001)		Supported
By FC	FC -> ATT	H4	(+)	0.538	***(p < 0.001)		Supported
By EX	EX ->ATT	H6	(+)	0.151	NS		Not supported
By A	A ->ATT	H5a	(-)	0.044	NS		Not supported
By G	G -> ATT	H5b	(-)	0.005	NS		Not supported
By BI	BI -> ATT	H8	(+)	0.968	***(p < 0.001)		Supported
Effect on AD						0.94	
By BI	BI -> AD	H9	(-)	0.311	NS		Not supported
By ATT	ATT-> AD	H7	(+)	1.251	*(p < 0.05)		Supported

Note: Structural Model with Path Weights and Significance Level ns p > 0.05; *p < 0.05; **p < 0.01; ***p < 0.001.

Source: Own work.

Results and Discussion of the Study

The results are shown in Table 4 and demonstrate nine hypotheses: H1, H2, H3, H4, H5a-b, H6, H7, H8, and H9. From the analysis, it appears that there are insignificant effects of Gender (G), Age (A), and Experience (EX) on Attitude toward Adoption (AD). This is because the concerned path coefficients are as low as 0.005, 0.044, and 0.151, respectively, with a significance level of p>0.05 (NS). In other words, male and female, younger adults, and previous experience did not represent an obstacle to adopting the Metaverse. Therefore, H5a, H5b, and H6 have not been supported. The findings about age and gender coincide with the study of (Bellaj et al., 2015).

PE significantly and positively affected ATT, with a coefficient path of 0.887. This result is aligned with several studies suggesting that performance expectancy positively correlates with individuals' intention to use new technology (Mhina et al., 2018). Chatterjee and Bhattacharjee (2020) also found a positive relationship between PE as an external factor and the stakeholders' ATT. The study reveals that performance expectancy is the strongest predictor of the attitude of the stakeholders.

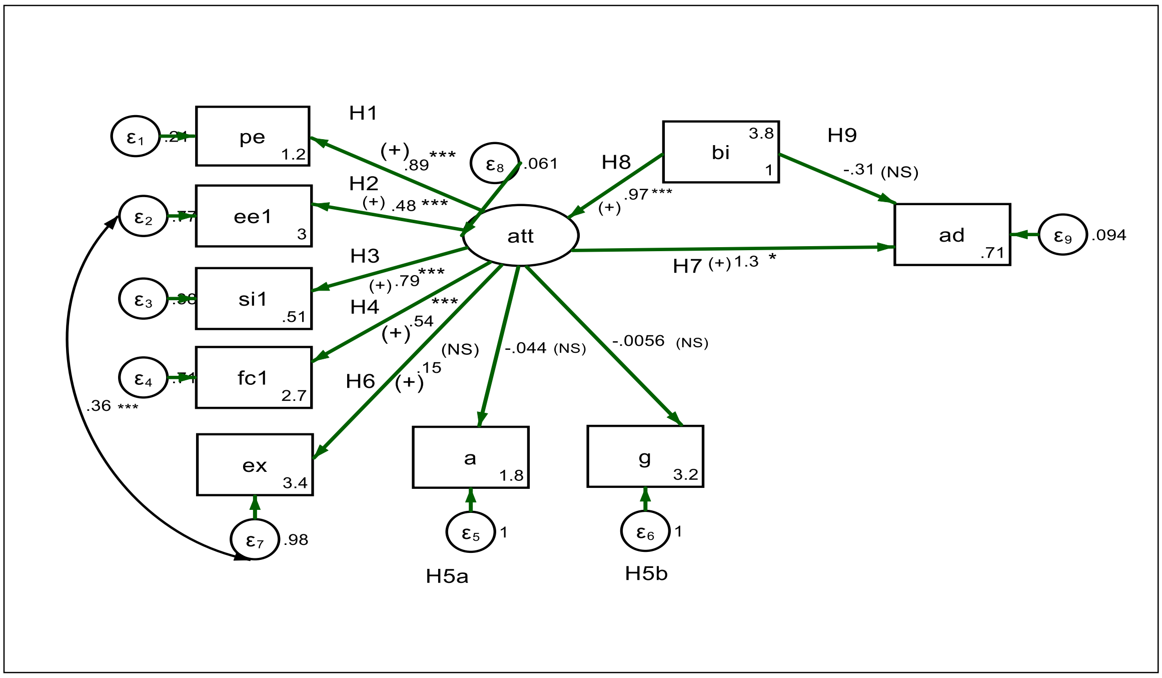
EE also positively and significantly affected ATT with a 0.474 coefficient path and SI with 0.785, respectively. According to Yakubu and Dasuki (2019), EE becomes less significant with the increased use of technology.

H4 was also supported, and the effect of FC is positive and significant on ATT, with a coefficient path of 0.538. Martin et al. (2014) and Oliveira et al. (2016) assumed that facilitating conditions positively affected the user's behavior in adopting new technology. Additionally, Raymond and Augier (2020) found that FC conditions combined with intrinsic variables explained that BI uses a learning system that integrates social media technology to predict the use behavior.

Moreover, it can be observed from the results that BI had a significant effect on ATT, with the highest coefficient path of 0.968. Hypotheses H1, H2, H3, H4, and H8 were supported with an explained power of 93.8%. It is essential to highlight that the covariance between Effort Expectancy EE and Experience EX is r=0.3556 and is significant ***(p < 0.001). Rahi & Abd (2018), Venkatesh et al. (2003), and Lee & Hyekyung (2022) revealed that PE, EE, SI, and FC had a significant influence on user intention to adopt the technology. The findings of this model are consistent with these inquiries.

Following the analysis, the results showed that BI did not have a relevant effect on AD, with a significance level of p>0.05 (NS). This result contradicts Chatterjee and Bhattacharjee's (2020) model and Nasrallah's (2014) research. Hence, H9 was not supported. Finally, the moderator effect of ATT had a positive and significant influence on AD of the Metaverse in Higher Education, with the most robust coefficient path of 1.251 and a *p < 0.05. This result is aligned with the previous work of Aboelmaged (2010) and Cox (2012). The power of explanation is provided by the R^2 coefficient of 94%. The structural model with path weights and significance levels are shown in Figure 8.

Figure 8: Structural Model with Path Weights



Note: Significance Level ns p > 0.05; *p < 0.05; **p < 0.01; ***p < 0.001 . *Source: Own work.*

This study proposed the model as a basic model helpful for the authorities to implement the adoption and engagement of Metaverse that would improve knowledge acquisition performance in Higher Education Institutions in Mexico. The results highlighted the following findings:

- Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC) have a significant impact on the Attitude (ATT) of the stakeholders toward the adoption (AD) of the Metaverse in Higher Education.
- Age (A), Gender (G), and Experience (EX) have no impact on the Attitude (ATT) for adoption (AD).
- Behavioral Intention (BI) positively and significantly influences the Attitude (ATT) of stakeholders rather than directly affecting the Adoption (AD).

The model under examination in this research has demonstrated a high explanatory power. In Mexico, the use of AI in higher education is in a developing stage. The ability of the respondents to adopt new technologies is another element to be considered. 81% of inputs obtained were from students who could be considered as actual adopters of new technology, such as the Metaverse, in Higher Education. The result cannot be generalized, and other constructs, such as "actual use" or "different levels or stages of experience," need to be validated with the inputs of adopters and non-adopters. Future research might use moderators in the UTAUT model (Venkatesh et al., 2003) to analyze the complete effect.

The Metaverse in HE could unlock learning activities for learners that enable them to perceive, explore, and create knowledge. Adopting this technology could open some potential applications in education. The first one is blended learning during the lessons. Learners can be encouraged to participate in various activities virtually and remotely, such as small group panels, quizzes, and creating virtual spaces for discussion. This represents an opportunity to enhance the learning interest of students.

Additionally, the Metaverse could offer a potential solution for competency-based education (CBE). First, it allows HE stakeholders to easily transition between classroom and professional settings in a virtual environment, allowing them to gain functional knowledge. Second, it allows students to practice skills in a professional training environment. Finally, integrating the model may enable Higher Education authorities to embrace the Metaverse, potentially leading to enhanced performance metrics.

4.4 Limitations of the Study

Findings in this study were estimated using a quantitative research approach that could be limited in terms of providing deeper insights and understating the variables presented. Future studies must implement qualitative or mixed-methodology approaches to incorporate perceptions, ideas, and views of students and faculty members to deeply understand the factors that affect the adoption of the Metaverse in HE.

Additionally, the hypotheses presented in this model must be validated for the Accounting and Finance academic department and all areas of the business school, including staff at Tecnológico de Monterrey.

4.5 Recommendations for Future Research

Further research can include variables such as culture, language, nationality, and other contextual variables to enrich the study of the determinants of technology adoption, especially if universities receive international students. This study does not explore the moderating effect of voluntariness of use; therefore, examining this variable's role can help better understand the relationship between the adoption factors of the Metaverse in Higher Education.

5. Conclusions

Metaverse has opened a new horizon of teaching, learning, and administrative work opportunities in HE in México. The Metaverse's full use is still in the incubation stage. This study explored the possibilities of adopting Metaverse in Higher Education, considering that education is a human-based endeavor and is not dependent only on technology. As Chatterjee & Bhattacharjee (2020, p. 3456) stated: *“the sole reliance on technology in education would not fetch expected results.”*

Educational Institutions struggle with effectively incorporating the Metaverse into their teaching and learning processes, primarily because they use these technologies by digitizing traditional methodologies, content, and hierarchical structures. Such approaches tend to be technologically driven rather than pedagogically informed (Sife et al., 2007). According to Mystakidis (2021), Metaverse allows wider deployment of learning methods, including playful design, gamification, and complex simulation games to foster a relaxed and creative learning culture of inclusion, initiative, and experimentation without the gravity of the consequences or errors in the physical world (Pellas et al., 2021).

Sife et al. (2007) state that genuine technology integration calls for a transformative undertaking in which all stakeholders come together to reassess and rethink current practices and systems. Rather than minor modifications, a full-scale revolution in attitudes toward teaching and learning is necessary for technology to be effectively utilized. This revolutionary shift also entails reorganizing how Higher Education Institutions are designed, governed, and structured.

Metaverse in Higher Education enables professors and faculty members to assume a more prominent and legitimate role in students' learning process while liberating them from the tedium of knowledge dissemination. Metaverse can leverage technology environments to facilitate students' autonomy in customizing students' engaging learning experiences and personalizing knowledge. This leads to a more personalized acquisition and application of knowledge in the virtual realm.

Modern society demands professionals with new competencies and skills to take forward digital transformation (Morze & Strutynska, 2021). Higher Education authorities must address and accurately provide the essential requirements of the stakeholders. This research aimed to establish the factors that affect the adoption of Metaverse to enhance the student experience in higher education. The model of this research showed a positive and significant impact on the attitude of the stakeholders adopting Metaverse.

The Metaverse, when applied and developed, has positively impacted the learning experiences of students pursuing a bachelor’s degree in Accounting and Finance in business school at Tecnológico de Monterrey. Authorities can assist users -professors, students, and staff- by raising awareness and creating favorable conditions for using the Metaverse in Higher Education, helping them express their acceptance and approval and fostering lifelong learning.

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Appendix

Table 2: Estimation of LV, AVE, and CR

Constructs/ Items	**LF**	**AVE**	**CR**
Performance Expectancy (PE)		0.540876	0.824517
PE1	0.7529		
PE2	0.7727		
PE3	0.7437		
PE4	0.6682		
Effort Expectancy (EE)		0.243345	0.243345
EE1	0.4933		
Facility Conditions (FC)		0.308025	0.308025
FC1	0.555		
Social Influence (SI)		0.623468	0.623468
SI1	0.7896		
Behavioural Intentions (BI)		0.74499	0.872303
BI1	0.845		
BI2	0.8604		
BI3	0.872		
BI4	0.3252		
BI5	0.8121		
Adoption of Metaverse in Higher Education (AD)		0.837126	0.910105
AD1	0.8539		
AD2	0.8048		
AD3	0.8508		
AD4	0.8036		
AD5	0.7759		

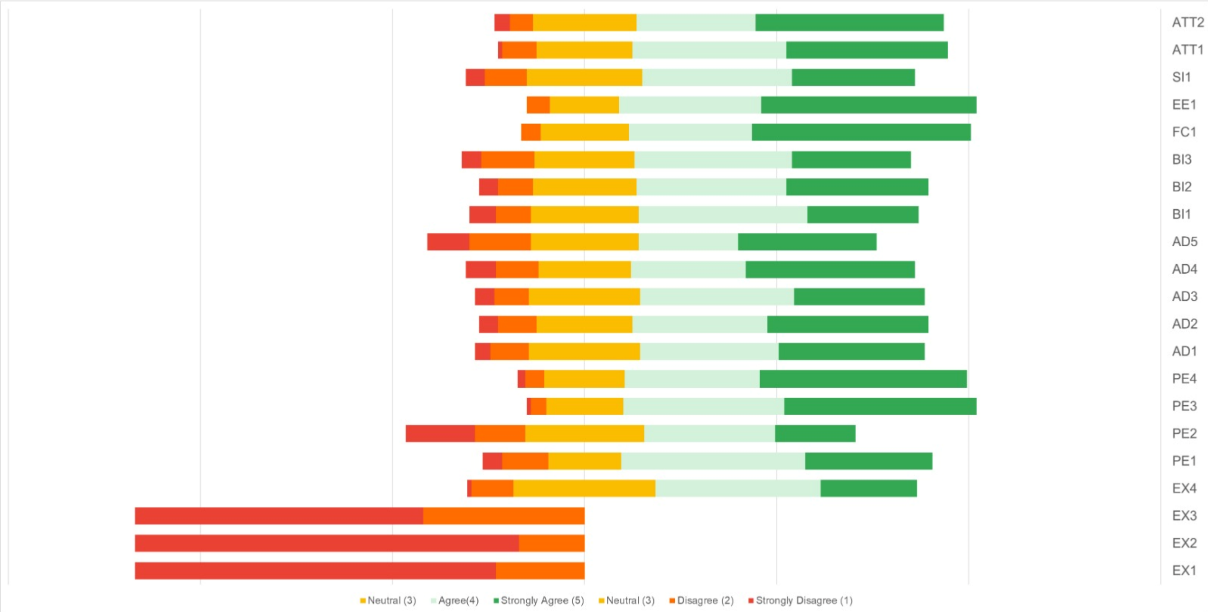
Source: Own work

Table 5: Summary of the questionnaire in Spanish

Item	**Statements**
PE1	I think the Metaverse can help to develop my learning experience.
PE2	I believe that using the Metaverse can help increase students' concentration in class.
PE3	I think the Metaverse can help to develop my IT skills.
PE4	I think the Metaverse can help to develop my creativity.
EE1	I have the ability to learn Metaverse technology quickly.
EX1	Do you have experience using the Metaverse or other technologies such as Artificial Intelligence?
EX2	Do you know what the Metaverse is?
EX3	Have you used the Virbela Virtual Campus?
EX4	Please, rate how competent you are using technology (any type: software, artificial intelligence, metaverse, apps, etc.)
FC1	My university encourages all its collaborators and users to embrace and learn new technologies.
FC2	My university promotes the use and learning of new technologies among all its collaborators and users.
SI1	I believe that developing more content in the Metaverse by Business School professors can result in more effective learning on sustainability and climate change issues.
BI1	I believe that using the Metaverse can enhance the teaching-learning process, ensuring student engagement.
BI2	I believe that the use of the Metaverse can help to increase the teaching-learning process and increase the students' interest in learning.
BI3	I believe that the use of the Metaverse can help to increase the teaching-learning process and increase student participation.
BI4	I believe that Metaverse technology is easy to learn at a beginner level.
BI5	Should Metaverse technology be explored by all users in the university education sector for learning purposes?
AD1	I believe that using the Metaverse can enhance the teaching and learning experience in Business School classes.
AD2	I believe that in order to meet market demands, Business School professors should focus on developing more content in the Metaverse.
AD3	I believe that the Metaverse has the potential to enhance my critical thinking skills.
AD4	I believe that utilizing the Metaverse can improve my ability to collaborate with others.
AD5	I believe that the Metaverse has the potential to enhance my communication skills.

Source: Own work.

Figure 9: Collected answers matrix



Source: Own work.