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

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Abstract

The evolving Metaverse in Higher Education (HE) in Mexico can enrich pedagogy, facilitate skills development, and improve students' learning experience. This research aimed to identify the factors guiding the adoption of the Metaverse in a Business School 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 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: *Adoption, higher education, metaverse, virtual reality, UTAUT Model.*

Introduction

The adoption of virtual and augmented reality technology is a major trend in higher education. It is driven by the need for interactive and personalized learning experiences and the increasing demand to align disciplinary student profiles with labor market needs (Van der Vlies, 2020). According to Statista's Metaverse in Education market report (2023), the global market for Metaverse should reach $24 billion by 2030, with a compound annual growth rate (CAGR) of

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45.52% from 2023 to 2030. Furthermore, the number of users should increase to 1.7 million by 2030.

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

According to Chen (2022), the Metaverse attracts HEIs because it provides immersive, multisensory, authentic, and practical learning experiences. Consequently, the Metaverse is a feasible method of achieving educational opportunities by breaking space, time, and cost barriers to solve complex, real-life issues.

Our study selected the VirBela metaverse platform as the preferred choice to host 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 own 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 Tecnologico de Monterrey. In addition, our students enjoy unrestricted access to this technology.

VirBela has established itself as the pioneer enterprise metaverse, enabling 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 (VirBela, 2012).

Examining the attitudes and intentions of students and faculty members with varying levels of learning motivation toward the metaverse (Arpaci & Bahari, 2023; Chang et al., 2022) is crucial. The UTAUT model has been used to analyze the willingness to adopt mobile learning in universities (Alowayr & Al-Azawei, 2021; Alyoussef, 2021; Botero, 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 (Altahi, 2021; Li, 2022; Padhi, 2018; Park

2021) and, the adoption of blended learning in the educational landscape (Martín,2014). To determine the factors influencing higher education stakeholders to adopt the Metaverse, this research used the UTAUT model as its theoretical framework and performed a quantitative analysis using structural equation modeling (SEM).

This study aimed to raise awareness about the factors that influence the adoption of the Metaverse in a higher education business school in Mexico. This research contributes to the literature in three significant ways: a) identifying the impact on the attitudes of the HE stakeholders adopting the Metaverse; b) analyzing functional practices and applications of the Metaverse and their impact on the higher education private universities; and c) specifying how the attitudes and behavioral intentions of the stakeholders in a business school context could influence the adoption of the Metaverse.

This article's structure continues 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 from the critical discoveries made during this research and general recommendations to Higher Education authorities.

Research Questions

The study has the following research questions:

Q1: What antecedents impact the attitudes of the stakeholders of higher education business schools towards adopting the Metaverse?

Q2: How might Metaverse applications impact Mexico's higher educational system?

Q3: Do the attitudes of the stakeholders of higher education business schools influence Metaverse adoption?

Theoretical Background

Metaverse Contemporary Development

The term "Metaverse" was coined by Neal Stevenson in his science fiction novel *Snow Crash*, published in 1992 (Stephenson, 1992). According to Prakash et al. (2023, p. 2), Metaverse "*refers* *to a virtual space where users can engage with each other in a variety of 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 linked to the physical world (Tlili, 2022).

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), a mirror world (Lee et al., 2021), an embodied internet (Chayka, 2021), an integrated social technology (Ning et al., 2021), a post-reality universe and multiuser environment (Mystakidis, 2021), a venue of simulation and collaboration (Lee et al., 2021), and as lifelogging (Bruun & Stentoft, 2019).

The backbone of the Metaverse is a protocol called The Street, linking different locations, an analog to the information superhighway (Mystakidis, 2022). Metaverse comprises three key elements: Users materialize in this universe through configurable digital bodies called avatars that 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.

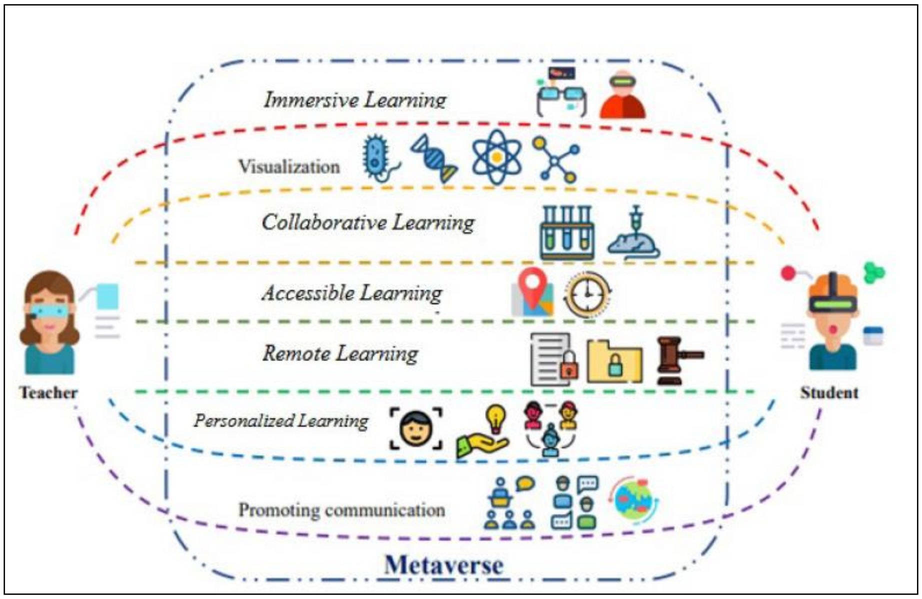

Figure 1: Lin et al.'s (2022) model presents seven ways Metaverse changes education.
Note: This model presents seven ways in which Metaverse is changing education. Lin et al.'s (2022) model was presented at the IEEE International Conference on Big Data. Source: Lin, H., Wan, S., Gan, W., Chen, J., & 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 educational systems: creating connections, evolving the immersive study, personalizing learning, exploring any geography at any time and place, disrupting thinking, and playing for life learning. Figure 2 depicts these components.

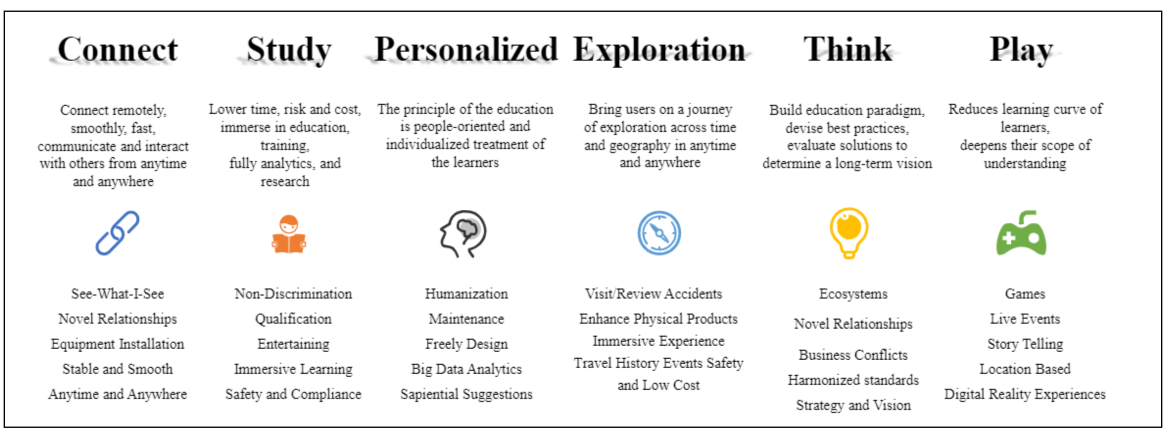

Figure 2: Revolution of Metaverse in Education
Note: Six components of the Metaverse change education. Source: Lin, H., Wan, S., Gan, W., Chen, J., & Chao, H. C. (2022, December). Metaverse in education: Vision, opportunities, and challenges. In 2022 IEEE International Conference on Big Data (Big Data) (pp. 2857-2866). IEEE.

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 come to an end." (Dewey, 1938, p-25)*

According to this principle, knowledge acquisition should be based on real-life experiences, providing a context for processing 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 to 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 produce an engineering education class on a metaverse platform called VoRtex. The findings indicated that students who 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 platform's features facilitated internal dialogue and the dissemination of knowledge among the participants.

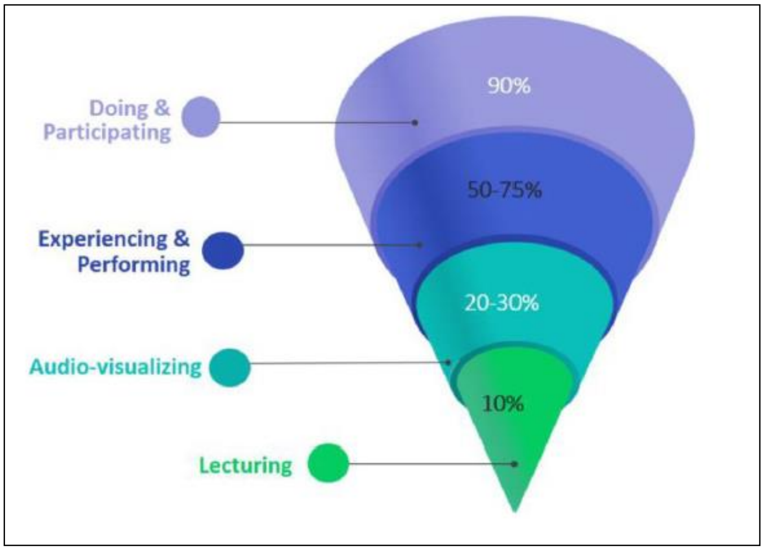

Figure 3: Cone of Metaverses learning model by Hwang et al. (2023)

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.

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 vital to identify the factors that affect the Higher Education community's acceptance of immersive experiential learning, such as the metaverse. For a clear perception of learning users' needs and requirements, many models have examined their acceptance of and intention to use new technology.

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). Modern society demands professionals with new competencies and skills to advance digital transformation (Morze & Strutynska, 2021).

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 (Alowayr & Al-Azawei, 2021; Alyoussef, 2021; García Botero, 2018; Chand, 2022); the acceptance of the Internet of Things (IoT) (Jain, 2022; Yang 2019); the continued intention to use online courses in universities (Altahi, 2021; Li, 2022; Padhi 2018; 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) and 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 interpretations of 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 and 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 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 that also affect 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), we chose the constructs of Performance Expectancy (PE), Effort Expectancy (EE), Social Intention (SI), Facilitating Condition (FC), Attitude (ATT), and Behavioral Intention (BI) 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.

Conceptual Model and Hypotheses

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). Vankatesh 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, Hypothesis 1 (H1) follows:

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

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). 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 adopting 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).

Social Influence (SI)

Social Influence (SI) is defined as the social 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). 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).

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. Vankatesh et al. (2003) reported that 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). Hence, the following hypothesis is:

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

The Moderating Role of Age, Gender, and Experience

Demographic variables such as age (A) and gender (G) have significant effects on social-factor studies (Mazman, 2011), modifying the individual's attitude (ATT). According to Morris and Vankatesh (2000), older individuals tend to be more cautious when making decisions but are also more susceptible to social influences. The findings of Dabaj's (2009) study showed that older students prefer attending face-to-face classes, and 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 roles 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 adopting the Metaverse in Higher Education (AD).

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

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 to interpret 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 hypothesis is proposed:

H7: Attitude (ATT) has a positive and significant impact on adopting the Metaverse in Higher Education (AD).

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 hypotheses are 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: The Behavioral Intention (BI) of stakeholders has a positive and significant impact on the adoption of the Metaverse in Higher Education (AD).

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

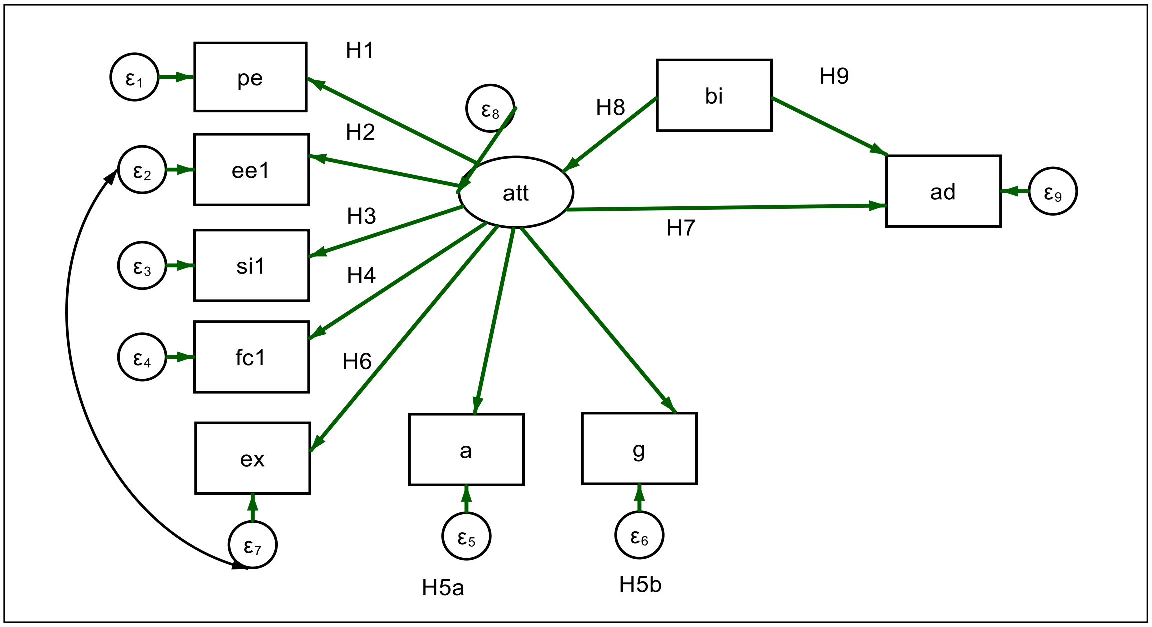

Figure 4: Research Model for the Adoption of Metaverse in Higher Education

Note: This model was produced by Chatterjee and Bhattacharjee (2020), summarizing 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.

Method

Research Design

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, we followed the methodology of Carpenter (2018) and experts' opinions. Figure 4 depicts the methodology. The final questionnaire contained 21 items in the form of statements, including three initial questions identifying relevant characteristics of the sample (i.e., Age, Gender, Status).

The questions addressed different aspects of the Metaverse for the Higher Education sector. Some of the questions concerned how the Metaverse could improve the teaching-learning process. A few questions covered the need to create more educational content to understand climate change and sustainability in business thoroughly. The questionnaire also covered the level of experience and effort stakeholders require to meet their individual needs. The summary of the questions in statements and the answers collected are presented in Appendix Table 7 and Figure 9, respectively.

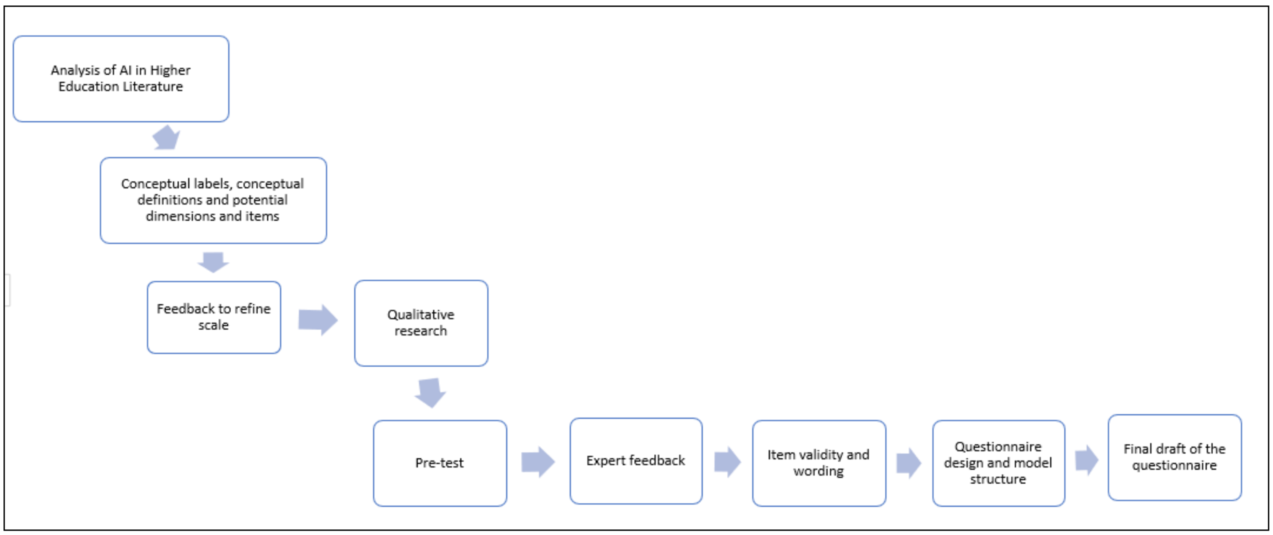

Figure 5: Carpenter's methodology (2018): Step-by-step scale of development.
Source: Carpenter, S. (2018). Ten steps in scale development and reporting: A guide for researchers. Communication methods and measures, 12(1), 25-44.

Study Sample

For the selection of the respondents, this research focused on three main stakeholders: students, staff, and professors from the Accounting and Finance academic department of the Business School of Tecnologico de Monterrey. The students were enrolled in 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 respond within three days. Their e-mails and consents were collected in 12 days, from May 26th to June 6th. Table 1 shows the demographic profile of the 117 respondents 1.

Table 1

Profile of respondents

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

Source: Own work

Study Instrument

A five-point Likert scale questionnaire was administered to 120 users. One hundred seventeen users answered the questionnaire without bias and incomplete responses. According to Deb and David (2014), this is within the acceptable range of 1:4 to 1:10 (ratio of number of questionaries to number of responses). The survey work occurred during June and July 2023, excluding the time of feedback collection. The instrument reliability was verified using Cronbach's Alpha. The test results showed that the study's total Cronbach's Alpha coefficient was 0.9531. The Data Analysis section details the results of the Exploratory Factor Analysis to validate the questionnaire.

Data Collection

The present study involved acquiring data through administering a questionnaire after the participants' engagement in a Metaverse experience. The data collection was conducted per the pre-determined research objectives and aimed at gathering insights into the users' experience, perceptions, and attitudes towards the Metaverse concept. The data collected through this process will be analyzed to provide valuable insights into the users' perspective on Metaverse and guide the development of future Metaverse experiences. The following section presents the data analysis.

Metaverse engagement was tested in the "Financial Management and Controllership CF302B" course in the summer of 2023. The ten-week course involved integrating sustainability reporting and data analytics. It aimed to assess the financial impact of financial and non-financial decisions for an international cement company located in Mexico. Based on creative problem-solving tasks with divergent thinking (creative, disruptive, design, lateral), students participated in relevant Metaverse conferences and guided visits to Mostla Lab as part of Tecnologico de Monterrey facilities. The VirBela platform hosted the Metaverse conferences.

VirBela is a virtual 3D university campus that connects students, companies, and professors in a 3D world for expert collaboration (Mora-Beltrán et al., 2020). It also offers three specific advantages: 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).

The students had a conference call on "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 knowledge retention increased. The speaker shared a video, conducted web browsing, and provided links during the conference, which resulted in high participation and satisfaction from the students and staff.

Figure 6: VirBela 3D Tecnologico de Monterrey Campus

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

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

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

Data Analysis

Mean values are reported with standard deviations (SDs). Data management and confirmatory factor analysis were carried out in Stata 18. Shaphiro-Wilk test of normality testing on item scores showed significant deviation from the normal distribution ($p < 0.001$, see Table 2), indicating that the data were not normally distributed. As established before, the data were screened for assumptions or normality, outliers, and missing values. Examination of frequency data on each item indicated that scores on the 5-point Likert-type scale were ordinal; thus, all subsequent analysis utilized non-parametric tests.

Table 2

Descriptive Statistics

Item	Mean	SD	Skewness	Kurtosis	Shaphiro-Wilk z	*p*
PE1	3.786325	1.097246	-0.82797	3.014441	3.320	0.00045
PE2	3.230769	1.302416	-0.36313	2.095132	3.884	0.00005
PE3	4.162393	0.89015	-0.91178	3.443204	4.421	0.00000
PE4	4.145299	0.976137	-1.01963	3.511001	4.981	0.00000
EE1	4.222222	0.891639	-0.88872	2.848602	3.479	0.00025
FC1	4.205128	0.905333	-0.76444	2.453326	3.213	0.00066
SI1	3.700855	1.100666	-0.59573	2.706413	2.207	0.01366
BI1	3.675214	1.112849	-0.72882	2.976648	2.581	0.00492
BI2	3.803419	1.100465	-0.73582	2.912159	2.972	0.00148
BI3	3.675214	1.120568	-0.59111	2.579204	2.129	0.01662
BI4	3.965812	0.982007	-0.64474	2.632688	2.934	0.00167
BI5	3.982906	1.082644	-0.86665	3.082643	3.883	0.00005
AD1	3.803419	1.092603	-0.64017	2.702133	2.797	0.00258
AD2	3.846154	1.134228	-0.76362	2.792592	3.111	0.00093
AD3	3.760684	1.08794	-0.6846	2.898237	2.717	0.00329
AD4	3.777778	1.239515	-0.74513	2.553478	2.652	0.00400
AD5	3.512821	1.310537	-0.43191	2.068866	3.121	0.00080

Source: Own work.

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 adequacy of sample size. In this study, one of the first steps was to test if the questionnaire's constructs were reliable. Ten factors were retained following the Eigen-values-greater-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 and 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 good, 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). Thus, according to this principle, this study considered both constructs. Appendix Table 3 shows the entire results.

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 the items had good internal stability and consistency.

We computed Ordinary Least Square (OLS) linear regression 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 was 2.06, which is considered acceptable, and the model did not present multicollinearity (Johnston, Jones, and Manley, 2018).

Discriminant analysis "is a statistical technique which allows the researcher to study the differences between two or more groups or objects with respect to 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 larger than any correlation coefficient among any pair of latent constructs (Gefen and 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 position, and these values are greater than the corresponding correlation coefficients shown in off-diagonal places of the matrix. This confirms the discriminant validity test (Fornell & Lacker, 1981). Table 4 shows the study results.

Table 4

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.

Structural Equation Modeling (SEM)

Structural equation modeling (SEM) is a collection of statistical techniques that examine a set of relationships between one or more independent variables (IVs) and one or more dependent variables (DVs) (Ullman and 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, we obtained 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.

Table 5 shows that all these parameters are within standard acceptable limits, establishing the adequacy of the model fit. Figure 8 presents the path analysis showing the relationships in the model. The coefficient of the determinant known as R2 was computed to estimate the portion of the variance in the dependent variable, which can be predicted from the independent variable.

Table 5

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 test of "badness of fit." The chi-square goodness of fit test is not significant, $\chi^2(25)=31.623$, $p>.169$, 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 a 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 in our study was 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 0.10, this could be interpreted as evidence of a close model fit (Whittaker & Shumacker, 2022). Additionally, the p-close test can be examined, testing 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 and 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 was 0.493, meeting the model fit criteria.

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

Table 6

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

Table 6 shows the results for the nine hypotheses, H1, H2, H3, H4, H5a-b, H6, H7, H8, and H9. The analysis indicates insignificant effects of Gender (G), Age (A), and Experience (EX) on Attitude toward Adoption (AD) because the concerned path coefficients are low as 0.005, 0.044, and 0.151, respectively, with a significance level $p>0.05$ (NS). Therefore, H5a, H5b, and H6 were not supported. These 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 aligns 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 in PE as an external factor toward the ATT of the stakeholders.

EE also positively and significantly affected ATT with a 0.474 coefficient path and SI with 0.785, respectively. H4 was also supported, and the effect of FC was 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 combined with intrinsic variables explained the BI use of a learning system that integrates social media technology to predict the use behavior.

Moreover, the results show that BI significantly affected ATT, with the highest coefficient path, 0.968. Thus, Hypotheses H1, H2, H3, H4, and H8 were supported with an explanatory percentage of 93.8%. It is essential to highlight that the covariance between Effort Expectancy EE and Experience EX was $r=0.3556$ and was significant ***($p < 0.001$). Rahi and 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 due to a significance level of $p>0.05$ (NS). This result contradicts Chatterjee and Bhattacharjee's (2020) model and Nasrallah's research (2014). Hence, H9 was not supported. Finally, the moderator effect of ATT had a positive and significant influence on the AD of the Metaverse in Higher Education, with the strongest coefficient path of 1.251 and a *$p < 0.05$. This result aligns with the previous work of Aboelmaged (2010) and Cox (2012). The R2 coefficient of 94% provides the power of explanation. Figure 8 shows the structural model with path weights and significance levels.

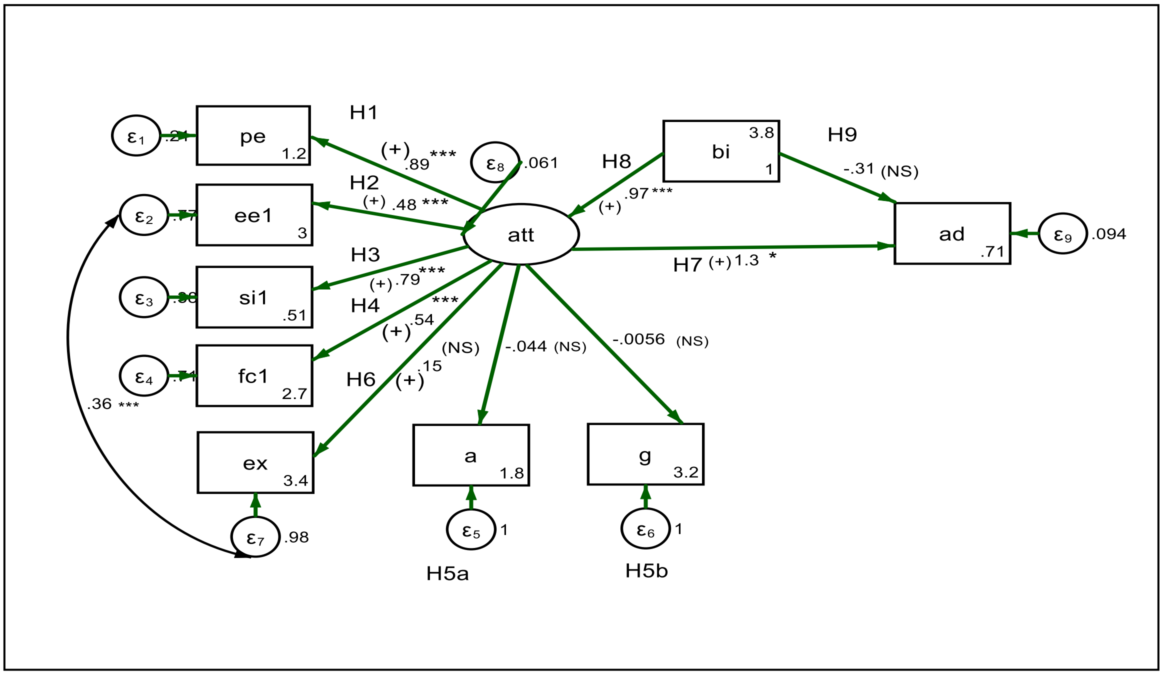

Figure 8: Structural Model with Path Weights

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 educational authorities to implement the adoption and engagement of Metaverse to improve knowledge acquisition in Higher Education Institutions in Mexico. The results highlighted the following findings related to the research questions:

Q1: What antecedents impact the attitudes of the stakeholders of higher education business schools towards adopting the Metaverse?

- Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC) have a significant impact and act as antecedents of the Attitude (ATT) of the stakeholders toward the adoption (AD) of the Metaverse in Higher Education. Therefore, hypotheses H1, H2, H3 and H4 were accepted.

- Age (A), Gender (G), and Experience (EX) have no impact on the Attitude (ATT) for adoption (AD). Hypotheses H5a, H5b, and H6 were rejected.

- Behavioral Intention (BI) positively and significantly influences the Attitude (ATT) of stakeholders rather than directly affecting the Adoption (AD). Hypotheses H8 and H9 were accepted and Hypothesis H7 was rejected.

Q2: How do Metaverse applications impact Mexico's higher education system?

The applications of the Metaverse could modernize the assessment system and the evolution of students' capabilities. The Metaverse has the potential to transform traditional learning methods and provide innovative approaches to measuring students' skills. Hence, there is a need to analyze how to effectively adopt it in higher education, specifically in the context of a business school in Mexico. This study focused on interactive learning experience as one of many Metaverse applications that can facilitate a more efficient and effective learning experience.

Q3: Do the attitudes of stakeholders of higher education business schools influence the adoption of the Metaverse?

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 to utilize technology effectively. This revolutionary shift also entails reorganizing Higher Education Institutions' designs, governance, and structures.

The model under examination in this research demonstrated a high explanatory power of 94%. Hence, to answer the third research question, the attitude of the stakeholders of higher education positively influences the adoption of the Metaverse in a business school context. The novelty of this study lies in revealing that Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions are antecedents of stakeholders' Attitudes toward adopting the Metaverse. Higher education authorities can use this information to model the behavior of students and professors in embracing the adoption of new technology. Age and gender did not play a vital role in adopting the Metaverse. 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.

The research findings provide theoretical implications within the Unified Theory of Acceptance and Use of Technology (UTAUT) framework, reshaping the understanding of the metaverse adoption in Higher Education. The study determined that there is no significant relationship between age, gender, and experience of stakeholders' attitudes toward adopting new technology. This suggests that other factors, such as perceived enjoyment (Sarosa, 2019), should be considered to determine the degree of positive perception and comfort towards metaverse technology. Additionally, the study highlights the significance of facilitating conditions such as regulatory dynamics and institutional support in significantly shaping technology adoption.

On the other hand, the research findings also provide policy and practical implications. Policymakers and academia need to work together to create regulatory frameworks that can be adapted to the rapid pace of technological advancement without compromising the student's learning performance. Also, it is recommended that Higher Education institutions develop digital literacy initiatives and faculty programs that promote innovation and pedagogical excellence. This research confirms that a collaborative effort among stakeholders, including policymakers and faculty, is key to ensuring the integration of the metaverse into Higher Education.

Conclusions

The Metaverse has opened a new horizon of opportunities in Mexican HEIs for teaching, learning, and administrative work. The Metaverse's full potential is still in the incubation stage. This study explored the possibilities of adopting a metaverse in Higher Education, considering that education is a human-based endeavor and not dependent only on technology.

Educational institutions struggle with effectively incorporating the Metaverse into their teaching and learning processes primarily because they use these technologies by simply digitalizing traditional methodologies, content, and hierarchical structures. In other words, the implementation tends to be technologically driven rather than pedagogically approached. The benefits of the Metaverse in higher education lie in the potential to prepare students for digital future job markets and provide unique opportunities for hands-on, experiential learning.

The Metaverse in Higher Education enables professors and faculty members to assume a more prominent and legitimate role in students' learning processes while liberating them from the tedium of knowledge dissemination. The Metaverse can leverage technology environments to facilitate students' autonomy by customizing engaging learning experiences and personalizing knowledge. This leads to a more personalized acquisition and application of knowledge in the virtual realm. Nevertheless, some challenges are educators' technological readiness and content creation. Hence, there is a latent need for training programs and resources.

Higher Education authorities must address and accurately meet stakeholders' essential requirements. This research aimed to establish the factors that affect the adoption of Metaverse to enhance the student experience in higher education. The research model positively and significantly impacted the stakeholders' attitudes toward adopting Metaverse. In summary, this study emphasizes the crucial importance of Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions as factors that lead to the Attitude of stakeholders towards the Metaverse. Behavioral Intention also plays a role in shaping stakeholders' attitudes. However, Age, Gender, and previous Experience do not impact the adoption of this technology.

The Metaverse, when applied and developed, positively impacted the learning experiences of students pursuing a bachelor's degree in Accounting and Finance in the School of Business at Tecnologico de Monterrey. The most significant achievement of this research, driven by the results of this study, was the redesign of the curricula for the accounting program, integrating emerging technologies with the analysis of financial data.

This study, however, has some limitations. In Mexico, the use of the Metaverse in higher education is in a developmental stage. The ability of the respondents to adopt new technologies is another element to consider. Eighty-one percent of input came from students who could be considered actual adopters of new technology, such as the Metaverse, in Higher Education. The results cannot be generalized because other constructs, such as "actual use" and "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 to analyze the complete effect.

Additionally, 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.

In addition, 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. Finally, as a general suggestion, the hypotheses presented in this model must be validated not only for the Accounting and Finance academic department but also for all areas of the Business School, including staff at Tecnológico de Monterrey. Finally, integrating the model may enable higher education institutions' authorities to embrace the Metaverse, potentially leading to enhanced performance metrics.

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Appendix

Table 3

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		
Behavioral 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 7

Summary of questionary

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.

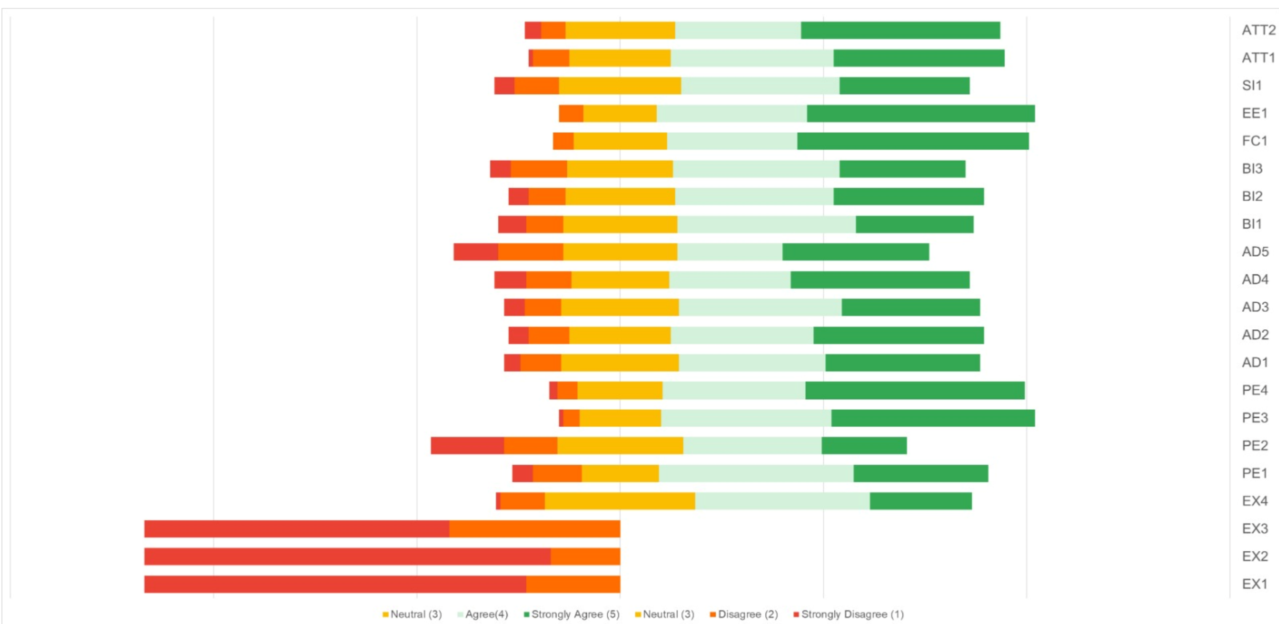

Figure 9: Collected answers matrix.

Source: Own work.