International Journal of Innovative Research and Scientific Studies, 8(6) 2025, pages: 2650-2658

IJIRSS
International Journal of Innovative Research & Scientific Studies

ISSN: 2617-6548

URL: www.ijirss.com

The metaverse technology adoption process using UTAUT in digital business education

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Abstract

The metaverse, a digital space where users interact through virtual and augmented reality, is set to transform business education in higher learning. This study explores the adoption of metaverse technologies in universities, utilizing the Unified Theory of Acceptance and Use of Technology (UTAUT). The UTAUT model, which includes performance expectancy, effort expectancy, social influence, and facilitating conditions, is used to examine the factors influencing adoption, with moderating variables such as Gender, Age, Experience, and Voluntariness of Use. The research targets undergraduates from the Faculties of Economics at State University of Jakarta and State University of Makassar. Data were gathered through surveys and analyzed using Partial Least Square-Structural Equation Modeling (PLS-SEM) with Variance Based (VB) SEM. The results indicate that performance expectancy and social influence significantly impact students' behavioral intention and usage behavior, particularly among different genders. Facilitating conditions also critically affect technology adoption. The study underscores the metaverse's potential to enrich educational experiences by offering immersive learning environments. However, the success of these technologies hinges on students' readiness and willingness to engage. The findings suggest that younger students, especially those influenced by social factors, are more likely to adopt metaverse technologies, guiding institutions in enhancing digital learning tools.

Keywords: Education, Metaverse, UTAUT Model adoption technology.

DOI: 10.53894/ijirss.v8i6.10190
Funding: This study received no specific financial support.
History: Received: 18 July 2025 / **Revised:** 20 August 2025 / **Accepted:** 22 August 2025 / **Published:** 24 September 2025
Copyright: © 2025 by the authors. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/).
Competing Interests: The authors declare that they have no competing interests.
Authors' Contributions: All authors contributed equally to the conception and design of the study. All authors have read and agreed to the published version of the manuscript.
Transparency: The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.
Publisher: Innovative Research Publishing

1. Introduction

1.1. Background

The Metaverse, a digital environment enabling interactions through virtual and augmented reality, has emerged as a significant innovation in response to the challenges posed by the COVID-19 pandemic [1]. The educational sector, facing unprecedented disruptions, has had to swiftly adapt, with many universities turning to platforms such as WhatsApp, Google Meet, and Zoom for instructional purposes [2]. These platforms, while functional, often lack the immersive and interactive qualities that the Metaverse can offer. By facilitating more engaging and human-like digital interactions, the Metaverse presents a promising avenue for enhancing digital teaching and learning experiences [3]. Although the technology is still evolving, its potential to transform eLearning, particularly during a global health crisis, is becoming increasingly evident. However, despite its efficiency, eLearning in its current form remains inadequate in fully addressing the complexities of modern education [4].

The absence of the 'tangible' elements inherent in face-to-face learning has posed challenges for some students in effectively engaging with lessons [5]. Virtual Reality (VR) can enhance students' confidence in applying acquired knowledge tenfold compared to traditional training methods. This improvement is at least 40% higher than in-class learning and over 35% greater than [6]. The integration of VR and Augmented Reality (AR) into the educational process can substantially enhance students' ability to assimilate information, as the immersive experiences provided by these technologies create a sense of realism. Engaging with the concept of 'reality' within the Metaverse allows students to develop personalized interpretations of the material. Ultimately, the goal is to optimize learning efficiency, which remains the primary objective [7]. With the advent of the Metaverse, driven by leading technology companies, the education sector must proactively adapt to this emerging technology. If successfully developed, the Metaverse could have a transformative impact on education, similar to the Internet's profound influence on the sector [8].

Beyond education, the Metaverse is expected to drive growth in various industries, including gaming, live streaming, cloud computing, and virtual/augmented reality. Additionally, the Metaverse could accelerate scientific advancements in hardware, network infrastructure, visualization, and artificial intelligence [9]. As this technology evolves, educational institutions must recognize its potential impact, not merely as a tool for branding, but as a transformative force in teaching and learning. However, it is essential to acknowledge that, regardless of technological advancements, the fundamental essence of education cannot be replaced. While the Metaverse has garnered interest from major corporations, there remains a degree of uncertainty regarding its future impact. Nevertheless, the growing acceptance of cyberspace socialization, particularly through gaming and educational platforms, is promising. By promoting more immersive online interactions, the Metaverse can make online education more engaging without compromising the traditional collegiate experience [3].

2. Literature Review

2.1. Unified Theory of Acceptance and Use of Technology (UTAUT)

Venkatesh, et al. [10] developed the Unified Theory of Acceptance and Use of Technology (UTAUT) to offer a comprehensive framework for understanding technology acceptance. UTAUT integrates elements from eight established theoretical models into a unified approach, focusing on four core determinants that influence technology acceptance: Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions. Additionally, the model incorporates four moderating variables, such as Gender, Age, Experience, and Voluntariness of Use. Those variables affect the strength and direction of these relationships.

- Performance Expectancy refers to the degree to which an individual believes that using the technology will enhance their job performance. This construct includes components from several models, such as perceived usefulness from the Technology Acceptance Model (TAM), relative advantage from the Innovation Diffusion Theory, and expected outcomes from Social Cognitive Theory [11].
- Effort Expectancy denotes the perceived ease of using the technology. It encompasses factors like perceived ease of use from TAM, complexity from the PC Utilization Model, and overall usability [12].
- Social Influence represents the degree to which individuals perceive that important others believe they should use the technology. This concept draws from the Theory of Reasoned Action (TRA), Theory of Planned Behavior (TPB), and related theories [13]
- Facilitating Conditions involve the resources and support available to use the technology effectively. This includes infrastructure and resources that facilitate technology use [14]

The UTAUT model also highlights how these determinants are moderated by variables such as Gender, Age, Experience, and Voluntariness of Use, which influence the relationships between the core determinants and technology acceptance [15]. Overall, UTAUT synthesizes insights from information systems theory, psychology, and sociology, offering a robust framework for examining technology adoption. This theoretical foundation is crucial for analyzing new technological environments, such as the metaverse. Applying UTAUT to the metaverse will provide valuable insights into user acceptance and usage patterns within this emerging digital space. Figure 1 is a description of the UTAUT technology acceptance paradigm [10].

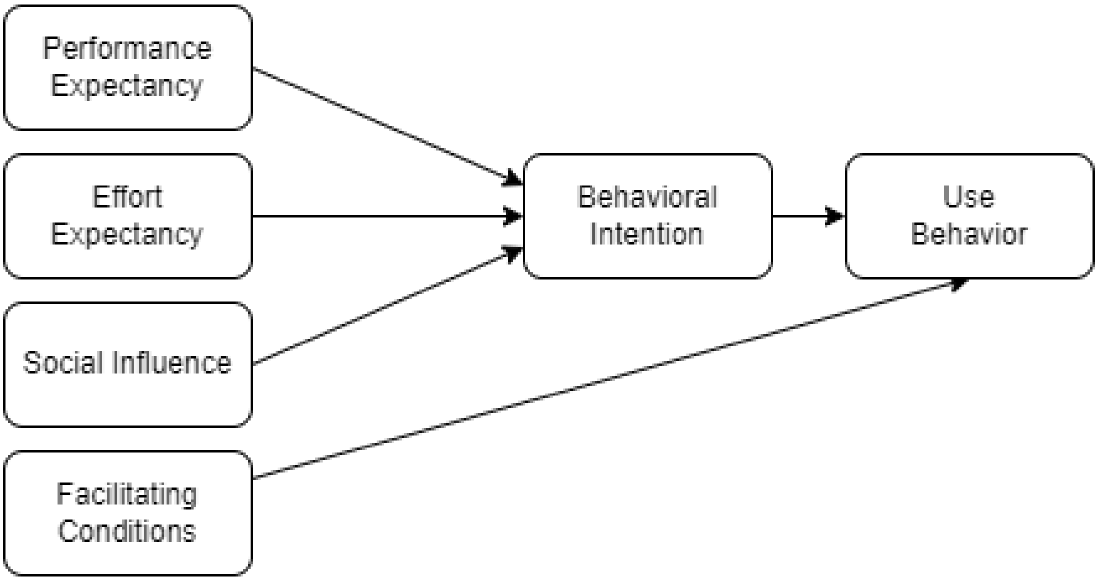

Figure 1.
Model of Unified Theory of Acceptance and Use of Technology (UTAUT).

3. Research Methods

This study tests the impact of various factors on behavioral intention and technology use in the metaverse, based on the UTAUT model. The proposed hypotheses aim to assess these relationships and their effects on technology use:

$H_{1:}$ Performance Expectancy has a positive significant effect on Behavioral Intention

$H_{2:}$ Effort Expectancy has a positive significant effect on Behavioral Intention

$H_{3:}$ Social Influence has a positive significant influence on Behavioral Intention

$H_{4:}$ Facilitating Conditions have a positive significant influence on Use Behavior

$H_{5:}$ Behavioral Intention has a positive significant influence on Use Behavior

$H_{6:}$ The influence of Effort Expectancy on Behavioral Intention is mediated by Behavioral Intention and affects Use Behavior

$H_{7:}$ The influence of Social Influence on Use Behavior is mediated by Behavioral Intention

$H_{8:}$ The influence of Performance Expectancy on Use Behavior is mediated by Behavioral Intention

This study uses the Partial Least Squares (PLS) method to analyze the proposed hypotheses, taking advantage of its ability to handle multiple factors and intervening variables. Causal modeling, specifically path analysis, was used to examine relationships and influences within the proposed framework, with data analysis conducted using Structural Equation Modeling (SEM) in the SMARTPLS 3.0 software.

3.1. Place and Time of Research

The research was conducted over a six-month period, from March to August 2024, at the Faculty of Economics and Business, State University of Jakarta, and the Faculty of Economics and Business, State University of Makassar.

3.2. Population and Sample

The study population consists of 1000 undergraduate students enrolled in the Faculty of Economics and Business for the academic year before 2023. A purposive sampling method was used to select participants based on predetermined criteria, focusing specifically on this cohort.

3.3. Data Collection and Analysis

The research was conducted in three stages:

- Literature Review: An extensive review of relevant theories and prior research was performed to develop the theoretical framework and formulate hypotheses.
- Data Collection: Survey questionnaires were distributed to the selected participants to gather the necessary data.
- Data Analysis: The collected data were analyzed using the Partial Least Squares Structural Equation Modeling (PLS-SEM) method. Variance Based SEM's capability to model complex relationships, including interactions and nonlinearity, was utilized to provide a comprehensive analysis of the data.

4. Results and Discussion

4.1. Validity Test Results

This section presents the results of the construct validity test. The validity test in the initial stages focuses on two main aspects: convergent validity and discriminant validity. These aspects are essential to ensure that the research instruments accurately measure the intended constructs and can be distinguished from one another. The results of the validity test analysis conducted can be seen in Table 1.

Table 1.
Variable Validity Test Result.

	Outer loadings
BIX1 <- BIX*	0.848
BIX2 <- BIX*	0.847
BIX3 <- BIX*	0.832
BIX4 <- BIX*	0.851
EEX1 <- EEX*	0.842
EEX2 <- EEX*	0.848
EEX3 <- EEX*	0.856
EEX4 <- EEX*	0.871
FCX1 <- FCX*	0.864
FCX2 <- FCX*	0.857
FCX3 <- FCX*	0.880
PEX1 <- PEX*	0.834
PEX2 <- PEX*	0.847
PEX3 <- PEX*	0.827
PEX4 <- PEX*	0.842
PEX5 <- PEX*	0.837
SIX1 <- SIX*	0.831
SIX2 <- SIX*	0.854
SIX3 <- SIX*	0.854
SIX4 <- SIX*	0.849
USEX1 <- USEX*	0.858
USEX2 <- USEX*	0.830
USEX3 <- USEX*	0.852
USEX4 <- USEX*	0.841

4.2. Convergent Validity

Convergent validity was assessed to ensure that the indicators used in this study accurately represent the constructs they are intended to measure. One of the key criteria for evaluating convergent validity is the loading factor of each indicator on its respective construct. Based on the results of the analysis, all indicators in the model have a fairly high loading factor value, which is above 0.70, which is the minimum limit value [16].

- BIX (Behavioral Intention to Use):
  The indicators for BIX (BIX1, BIX2, BIX3, BIX4) have outer loadings ranging from 0.832 to 0.851. These values are above the commonly accepted threshold of 0.70, indicating that these indicators have a strong relationship with the BIX construct.
- EEX (Effort Expectancy):
  The outer loadings for EEX indicators (EEX1, EEX2, EEX3, EEX4) range from 0.842 to 0.871, also exceeding the threshold of 0.70. This shows that the indicators are reliably measuring the EEX construct.
- FCX (Facilitating Conditions):
  The FCX indicators (FCX1, FCX2, FCX3) have loadings from 0.857 to 0.880. These values suggest good convergent validity for the FCX construct.
- PEX (Performance Expectancy):
  The PEX indicators (PEX1, PEX2, PEX3, PEX4, PEX5) show outer loadings between 0.827 and 0.847, which are above the 0.70 threshold, indicating that these indicators are valid measures of the PEX construct.
- SIX (Social Influence):
  The SIX indicators (SIX1, SIX2, SIX3, SIX4) have loadings from 0.831 to 0.854, suggesting that the indicators are well-aligned with the SIX construct.
- USEX (Use Experience):
  The USEX indicators (USEX1, USEX2, USEX3, USEX4) range from 0.830 to 0.858, indicating strong convergent validity for the USEX construct.

Based on the results can be concluded that the outer loadings for all indicators exceed the 0.70 threshold, demonstrating strong convergent validity for the constructs in your model. This implies that the indicators are consistently reflecting their respective constructs.

4.3. Discriminant Validity

Discriminant validity was tested to ensure that each construct in the model can be distinctly differentiated from other constructs. In this study, discriminant validity was evaluated by examining the cross-loadings of each indicator. Ideally, an indicator should have a higher loading on its designated construct than on any other construct. In the context of evaluating discriminant validity, we typically compare the square root of the Average Variance Extracted (AVE) for each construct with the correlations between the constructs. A construct is considered to have discriminant validity if the square root of its AVE is higher than its correlations with other constructs. The AVE value for each construct will be calculated based on the outer loading data in the Table 1. The AVE value is calculated by the formula in Equation 1 as follows.

$$AVE = \frac{\sum(outer\ loading^2)}{number\ of\ indicators} \qquad (1)$$

The following is the Average Variance Extracted (AVE) value for each construct.

Table 2.
AVE of Construct.

Construct	***AVE***
BIX	0.713
EEX	0.730
FCX	0.752
PEX	0.701
SIX	0.717
USEX	0.715

All AVE values are above the 0.5 threshold, which indicates that the constructs have good convergent validity. This means that more than 50% of the variance of each construct is explained by its indicators [16].

4.4. Intervening Test
4.4.1. Direct Effect
In this section, we will discuss the results of the intervening test conducted to identify the direct effects between variables in the structural model that has been developed. The intervening test is an important step in path analysis because it helps determine whether the effect of a variable on another variable occurs directly or through a particular mediator. By understanding these direct effects, we can evaluate the strength and significance of the relationship between variables and gain deeper insight into the dynamics that occur in the research model.

Table 3.
Direct Effect.

	Original sample (O)	**Sample mean (M)**	**Standard deviation (STDEV)**	**T statistics (|O/STDEV|)**	**P values**	**Status**
BIX -> USEX	0.568	0.568	0.034	16.796	0.000	Accepted
EEX -> BIX	0.169	0.170	0.092	2.173	0.007	Accepted
FCX -> USEX	0.371	0.371	0.043	8.697	0.000	Accepted
PEX -> BIX	0.531	0.529	0.072	7.412	0.000	Accepted
SIX -> BIX	0.193	0.196	0.094	2.051	0.040	Accepted

BIX -> USEX

The positive coefficient of 0.568 indicates a strong and positive relationship between Behavioral Intention (BIX) and Use Experience (USEX). This effect is highly significant with a high t-value and a very low p-value.

The findings of this study are relevant to the claims made by Khan and Abideen [17] revealed that behavioral intention has a positive and significant impact on digital wallet use behavior. This finding strengthens the argument that strong behavioral intentions will encourage users to use digital wallet services more frequently and more intensively, which in turn enriches the use experience. This research is also relevant if digital wallet technology is replaced with Metaverse technology. Behavioral intention will still have a positive and significant impact on use behavior in the context of Metaverse. In other words, although the technology is different, the principles underlying the relationship between behavioral intention and use behavior still apply and have a significant impact.

The findings are also relevant to the claims made by Alshammari and Alrashidi [18] state that behavior intention is one of the factors that influence use experience. In conclusion, behavioral intention significantly influences the use experience within Metaverse technology, driving users to engage more deeply and actively with the virtual environment, thereby enhancing their overall experience.

EEX -> BIX

The positive coefficient of 0.169 indicates a positive effect of Expectancy (EEX) on Behavioral Intention (BIX). This effect is statistically significant with a p-value of 0.007, although not as large as some of the other relationships.

The findings are relevant to the claims made by Utomo, et al. [19] state that Effort expectancy significantly affects behavioral intention, because the perceived ease of use in a technology drives individuals' intention to adopt and use the technology. When users feel that technology is easy to learn and operate, they tend to have a stronger intention to use it consistently, including in the context of Metaverse technology.

Research by Rumangkit, et al. [20] also state that effort expectancy has an important influence on behavioral intention, because the perception that a technology is easy to use can increase an individual's desire to use it. When users feel that they will not face significant difficulties in using the technology, this will encourage their intention to adopt and interact with the technology more often, including in the context of Metaverse. These studies are relevant to the research findings.

FCX -> USEX

The positive coefficient of 0.371 indicates that Facilitating Conditions (FCX) has a strong positive influence on Use Experience (USEX). This effect is highly statistically significant.

Research conducted by Hossain, et al. [21] states that Facilitating Condition (FC) has a significant impact on Use Experience (USEX). Research shows that conditions that facilitate technology use have an important moderating effect in the relationship between behavioral intention (BI) and User Experience. In other words, although behavioral intentions do not always automatically translate into user experience, facilitating conditions can strengthen the relationship. This finding confirms that FC plays a crucial role in determining the extent to which behavioral intentions can be realized in the form of actual usage behavior.

Research conducted by Rumangkit, et al. [20] shows that facilitating conditions, such as resource availability and ease of access, contribute significantly to users' intention to utilize learning support media, which in turn affects their commitment to continue using such media. These findings emphasize that FC is a key factor in influencing the usage behavior of educational technology and suggest that improving the conditions that support usage can increase users' effectiveness and commitment. These studies are relevant to the research findings.

PEX -> BIX

The positive coefficient of 0.531 indicates that Performance Expectancy (PEX) has a strong positive influence on Behavioral Intention (BIX). This effect is statistically significant.

Research conducted by Fathonah and Nastiti [22] shows that gender affects behavioral intention in the context of pro-environmental behavior. Using an extended Theory of Planned Behavior (TPB) framework, this study shows that factors such as attitudes, subjective norms, perceived behavioral control, trust, and risk perception can vary by gender. These findings underscore that gender differences can influence pro-environmental intentions, and therefore, it is important to consider gender when designing interventions that aim to increase pro-environmental behavior among university students. Thus, gender not only moderates pro-environmental intentions but also plays a role in shaping and directing environmental actions based on existing gender differences.

Research conducted by Junita, et al. [23] shows that gender affects behavioral intention in the context of pro-environmental behavior. This research shows that personal and social factors have a direct and significant impact on pro-environmental behavior among university students, with an increase in social factors exerting a greater influence than personal factors. In this context, although the abstract does not directly mention gender, differences in responses based on personal and social factors may be influenced by gender differences. This suggests the importance of considering gender as a variable that moderates the relationship between these factors and pro-environmental behavioral intentions. As such, the influence of gender on pro-environmental behavior intentions may provide additional insights into how to more effectively increase college students' engagement in environmentally friendly behaviors. These studies are relevant to the research findings.

SIX -> BIX

The positive coefficient of 0.193 indicates a positive effect of Social Influence (SIX) on Behavioral Intention (BIX). This effect is statistically significant, although not as large as some of the other relationships.

Research conducted by Khatimah, et al. [24] shows that social influence affects behavioral intention. The research findings show that social influence significantly affects payment habits, which in turn affects the intention to use e-money. In other words, social influence not only has a direct impact on behavioral intentions but also influences those intentions through the mediating role of payment habits. These findings confirm the important role of social influence in shaping e-money usage intentions, suggesting that social factors such as the opinions and behaviors of others can significantly influence an individual's decision to use digital payment technology. These studies are relevant to the research findings.

4.5. Indirect Effect

In this section, we will discuss the results of the intervening tests conducted to identify indirect effects between variables in the developed structural model. Intervening tests for indirect effects are very important in path analysis because they help reveal the mechanism or path through which an independent variable affects the dependent variable through one or more mediators. By understanding these indirect effects, we can evaluate the complexity of the relationship between variables and gain a more comprehensive insight into the dynamics present in the research model. The findings will provide a more in-depth picture of how and through which pathways an independent variable affects the dependent variable.

Table 4.
Indirect Effect.

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Status
EEX -> BIX -> USEX	0.096	0.097	0.053	2.811	0.002	Accepted
SIX -> BIX -> USEX	0.110	0.111	0.054	2.036	0.042	Accepted
PEX -> BIX -> USEX	0.302	0.301	0.044	6.828	0.000	Accepted

EEX -> BIX -> USEX

The indirect effect of experience and expectancy (EEX) on Behavioral Intention (BIX) and then on Use Experience (USEX) is 0.096. The t-statistics (2.811) and p-value (0.002) show that this effect is significant. This indicates that EEX affects usage (USEX) through BIX significantly.

Research conducted by Amenuvor, et al. [25] is in line with the findings, that Customer experience and expectations (EEX) significantly influence behavioral intention (BIX). Hedonic value acts as a mediator in the relationship between customer experience and behavioral intention, suggesting that a satisfying experience can increase the intention to use the service or product further. While utilitarian value is negatively but significantly related to behavioral intention, indicating that although functional benefits are important, emotional value is more dominating in influencing behavioral intention.

Research conducted by Hwang and Mulyana [26] is in line with the findings, that e-commerce habits contribute to the formation of behavioral intentions, which in turn drive e-commerce usage behavior. Similarly, strong social influence can increase behavioral intentions towards e-commerce, facilitating e-commerce usage behavior. These results suggest that user experience and expectations (EEX) play an important role in shaping behavioral intentions and usage behavior.

SIX -> BIX -> USEX

The indirect effect of Social Influence (SIX) on Behavioral Intention (BIX) then on Use Experience (USEX) is 0.110. The t-statistics (2.036) and p-value (0.042) show that this effect is significant. This means that SIX affects USEX through BIX.

Research conducted by Jeon, et al. [27] is in line with the findings, that Social influence plays a key role in shaping how customers interact with a b&b website and how strong their intention to use the service is. Understanding how social influence modifies the relationship between motivation, stream experience, and behavioral intentions can assist b&b managers in designing more effective marketing strategies that harness the power of social media to influence customer decisions and improve user experience.

Research conducted by Irani, et al. [28] is in line with the findings, that Social influence plays an important role in shaping behavioral intentions and usage experiences, but this influence varies depending on the source of feedback and the context. Understanding these dynamics can help in designing more effective interventions and marketing strategies, particularly in contexts involving target groups sensitive to social influence such as adolescents.

PEX -> BIX -> USEX

The indirect effect of Performance Expectancy (PEX) on Behavioral Intention (BIX) and then on Use Experience (USEX) is 0.302. The t-statistics (6.828) and p-value (0.000) show that this effect is highly significant. This indicates that PEX affects USEX through BIX significantly.

Research conducted by Tomić, et al. [29] is in line with the findings, that Performance expectancy plays an important role in shaping behavioral intentions and usage experience of electronic payment systems. Therefore, it is important to focus on how technology can improve performance and user benefits to improve their adoption and experience. Technology providers should ensure that the performance benefits promised by their systems are clearly conveyed to users to positively influence behavioral intentions and improve usage experience.

Research conducted by Utomo, et al. [19] is in line with the findings, although performance expectancy does not significantly influence behavioral intention to use the Sá and Serpa [3] application, it suggests a need to improve communication and emphasis on the performance benefits of this application. Increasing users' awareness of the specific benefits and advantages offered by this application can help increase users' intention to use it and, ultimately, create a more positive usage experience.

5. Conclusion

The validity analysis shows that all indicators used in this study have good convergent validity with outer loadings values above 0.70. In addition, discriminant validity is also achieved with an AVE above 0.5, which means that each construct can be clearly distinguished from other constructs. This indicates that the instruments used in this study consistently measure the intended constructs.

The results of testing direct effects show that there is a significant relationship between the variables in the research model. Behavioral Intention (BIX) has a strong and significant influence on Use Experience (USEX), while Performance Expectancy (PEX) and Facilitating Conditions (FCX) also show a significant influence on BIX and USEX. Social Influence (SIX) and Effort Expectancy (EEX) also have an effect on BIX, although the effect is smaller than the other variables.

Testing for indirect effects shows that Behavioral Intention (BIX) mediates the influence between Effort Expectancy (EEX), Social Influence (SIX), and Performance Expectancy (PEX) on Use Experience (USEX). This mediation effect is significant, which means that BIX plays an important role in bridging the influence of these variables on use experience.

These findings have important practical implications, especially in the context of technology adoption such as Metaverse. It is important to ensure that users perceive high performance benefits and ease of use, and pay attention to conditions that support the use of technology. In addition, social influence and users' behavioral intentions need to be considered in marketing strategies and product development to improve user experience.

In conclusion, this research validates the UTAUT model's applicability across diverse contexts and highlights the significance of individual and contextual factors in technology adoption. The findings offer valuable insights for enhancing Metaverse adoption strategies, aiming to boost user engagement and streamline the adoption process. This study deepens our understanding of the factors shaping behavioral intentions and usage experiences, providing a solid basis for developing more effective strategies to support the adoption of new technologies.

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