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Statistical SEM-ANN Approaches for Metaverse Adoption in Education

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Abstract: The emergence of immersive virtual environments, such as the metaverse, presents promising opportunities to enhance and transform higher education. However, the effective integration of these technologies requires a nuanced understanding of the factors that influence user adoption. This study investigates the key determinants affecting the adoption of metaverse technology within higher education institutions in Jordan. The study uses a hybrid model that combines the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) and the Information Culture Theory(ICT). Data were collected using structured questionnaires from a stratified sample of 383 students at two Jordanian universities. Data were analyzed using a two-stage analytical framework: structural equation modelling (SEM) via SmartPLS 4 and artificial neural networks (ANN). The results showed that Performance Expectancy, Hedonic Motivation, Cultural Attitudes, Information Integrity, Personal Innovativeness, and Perceived Privacy had medium-sized, statistically significant positive effects on behavioral intention to adopt Metaverse technology. In contrast, perceived risks have emerged as notable inhibitors of behavioral intention to use, underscoring the urgent need to alleviate users' concerns about data security and the potential negative consequences of adopting this technology. Furthermore, the study emphasized the importance of social and cultural structures, as cultural attitudes towards change and innovation significantly influence adoption behavior.

Keywords: (UTAUT2), Metaverse, technology adoption, information culture theory.

1. Introduction

The integration of UTAUT2 and information culture theory

The successful implementation of Metaverse technology in higher education is contingent upon a multitude of factors that shape students', educators,' and institutions' perceptions of and engagement with it. To create more successful plans for incorporating Metaverse technologies into educational settings, educators, legislators, and technological developers should consider these elements. It is essential to recognize that various variables that fluctuate over time can impact users' intentions and the actual usage of Metaverse platforms.

These factors include performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, perceived risk, perceived privacy, personal innovativeness, user satisfaction, information integrity, information proactiveness, and cultural attitudes (individualism and collectivism), among others. Every element influences users' perceptions, interactions, and eventual adoption of the Metaverse, particularly in culturally and educationally environments, such as Jordanian higher education. The integration of various technological, individual institutional, and cultural factors provides a holistic framework for understanding and facilitating the adoption of Metaverse technology in higher education. These factors interact dynamically to shape users' intention to use and the actual use of Metaverse platforms.

One of the research gaps in this study is the notable deficiency in the literature regarding the use of the Metaverse, especially in higher education in Jordan. Additionally, there is a lack of knowledge about the elements that influence the adoption of Metaverse technologies in educational settings, which has been identified as a key research gap. Despite studies on frameworks such as the Unified Theory of Acceptance and Use of Technology (UTAUT), there remains an absence of comprehensive models that address the unique challenges and opportunities of the virtual world. Furthermore, there is a significant lack of empirical research examining the long-term impact of Metaverse interactions on educational outcomes and user behavior. Limited research has addressed the institutional and cultural barriers faced by Middle Eastern HEIs.

Integrating the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) with information culture theories offers

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a robust, comprehensive framework for understanding how organizational culture affects technology acceptance and use. UTAUT2 strengthens the explanatory power of the model. The primary contribution lies in creating a hybrid model that combines elements of technology acceptance frameworks, specifically UTAUT2, with information culture theory. An SEM-ANN hybrid methodology was used to capture both linear and non-linear relationships among variables.

Table 1: comparisonTheories between UTAUT2 and ICT

Aspect	**UTAUT2 (Venkatesh et al., 2012)**	**Information Culture Theory (Marchand et al., 2001)**
Focus	Individual behavioral intention to adopt technology	Organizational values, norms, and practices regarding information use
Core Constructs	- Performance Expectancy - Effort Expectancy - Social Influence - Hedonic Motivation - Habit	- Information Sharing - Proactiveness in Information Use - Information Integrity - Information Control
Unit of Analysis	Individuals (students, instructors)	Institutions (universities, academic departments)
Relevance to Metaverse	Explains why users accept or resist immersive tools like VR/AR and the Metaverse	Assesses institutional readiness and cultural openness to adopting innovative technologies
Strengths	Captures psychological and social predictors of adoption	Captures leadership, communication, and cultural enablers of adoption
Limitations	Limited attention to organizational influence	Not originally designed for technology-specific evaluation
Why Combine?	To understand both **user motivation** and **institutional support** for Metaverse adoption	Ensures a **comprehensive framework** capturing micro (user) and macro (organizational) levels
Contribution to Model	Enhances prediction of **individual behavior** in immersive learning contexts	Enriches understanding of **institutional dynamics** and readiness for change

Studies have shown that cultural variation influences the importance and strength of interactions within the UTAUT2 framework. For example, research has demonstrated that the adoption of technology is more strongly influenced by social influence in collectivist societies than in individualistic ones, where the importance of personal gains may be greater. The UTAUT2 theory reveals that behavioral intention to use is the strongest path for understanding consumer technology adoption, with Performance expectancy being the most utilized path and trust, personal innovativeness, perceived risk, attitude, and self-efficacy being key extensions.(Dwivedi et al., 2022; Tamilmani et al., 2021)

The following hypotheses are therefore proposed

1- H1: Performance Expectancy (PE) has a positive impact on behavioral intention to use (BI)
2- H2: Effort Expectancy (EE) has a positive impact on behavioral intention to use (BI)
3- H3: Facilitating Condition (FC) has a positive impact on behavioral intention to use (BI)
4- H4: Social Influence (SI) has a positive impact on behavioral intention to use (BI)
5- H5: Hedonic Motivation (HM) has a positive impact on behavioral intention to use (BI)
6- H6: Perceive Risek (PR) has a negative impact on behavioral intention to use (BI)
7- H7: Perceive Privacy (PP) has a positive impact on behavioral intention to use (BI)
8- H8: Personal Innovativeness (PI) has a positive impact on behavioral intention to use (BI)
9- H9: User Satisfaction (US) has a positive impact on behavioral intention to use (BI)
10- H10: Information Integrity (II) has a positive impact on behavioral intention to use (BI)
11- H11: Information Proactiveness (IP) has a positive impact on behavioral intention to use (BI)
12- H12: Culture, Attitudes Towards Change, and Innovation (CATCI) have a positive impact on behavioral intention to use (BI)
13- H13: Individualism vs. Collectivism (IC) has a positive impact on behavioral intention to use (BI)

Why are these factors important to the adoption of Metaverse technology and intentions to use

Performance Expectancy (PE) refers to the degree to which individuals believe that using a system or innovation, such as the Metaverse, will improve their job performance or overall effectiveness. Camilleri, (2024). This is a critical factor in technology adoption, as users are more likely to adopt technology if they perceive significant benefits such as enhanced virtual experiences or work efficiency. Research (e.g., Venkatesh et al., 2021; Marikyan & Papagiannidisis, 2023) consistently identifies PE as a strong predictor of **Behavioral Intention (BI)** to use technology, with studies showing a strong correlation between the two.

Effort Expectancy (EE) refers to the perceived ease of using a system, such as the Metaverse. If users find the technology simple and intuitive, they are more likely to adopt it (Nosica et al., 2024; Venkatesh et al., 2021). A difficult learning curve can hinder adoption; therefore, ensuring user-friendly design is crucial. Research shows a strong correlation between **EE** and **Behavioral Intention (BI)** to use technology, making it a key factor in technology acceptance. Malaysia's higher learning institutions had jump-started the **open and distance learning** (ODL) practices when education was disrupted during the COVID-19 pandemic. Soon ODL became an emergingtrend for students to access education and for universities to provide a conducive learning environment fortheir communities. Via ODL (Shanthi A., Xavierine J. ,2023).

Facilitating Conditions (FC) refer to the perceived availability of organizational and technical support (e.g., infrastructure, training, and resources) needed to use a system like the Metaverse effectively (Sewandono et al., 2022; Nosica et al., 2024). Key factors include access to technology, compatibility with existing systems, and reliable support (Venkatesh et al., 2021). Without proper infrastructure, such as high-speed internet and compatible devices, user adoption may be hindered. FC is thus critical for ensuring a seamless Metaverse experience and is hypothesized to influence technology usage.

Social Influence (SI) refers to the extent to which individuals perceive that important others (e.g., peers, family, or colleagues) expect them to use a technology, such as the Metaverse (Camilleri, 2024). Positive recommendations and social pressure can significantly motivate adoption (Rahmi and Frinaldi, 2019; Venkatesh et al., 2021). As the Metaverse thrives on shared experiences, social influence plays a key role in encouraging users to explore and adopt it.

Hedonic Motivation (HM) refers to the enjoyment or pleasure users derive from interacting with a technology, such as the Metaverse (Camilleri, 2024). This factor is particularly influential in voluntary adoption contexts, where user engagement is driven by fun and entertainment rather than necessity (Venkatesh et al., 2021). As the Metaverse thrives on immersive and entertaining experiences, its adoption is likely to increase if users perceive it as enjoyable (Marikyan & Papagiannidisis, 2023). Thus, HM is a key predictor of technology use in entertainment-driven platforms, such as social media and virtual environments.

Perceived Risk (PR) refers to a user's belief that using technology (like the Metaverse) may lead to negative consequences, such as financial loss, privacy breaches, or performance failures (Camilleri, 2024; Featherman & Pavlou, 2003). These concerns, particularly regarding data security and misuse, can deter adoption if risks outweigh the perceived benefits (Nosica et al., 2024; Feng et al., 2022). To gain acceptance, institutions must mitigate these risks through robust data protection measures and transparent security practices (Feng et al., 2022). Thus, PR is a critical barrier that can negatively influence both intention to use and actual adoption.

Perceived Privacy (PP) refers to a user's belief that a technology (e.g., the Metaverse) will effectively protect their personal data, ensuring security and confidentiality (Camilleri, 2024; Xu et al., 2012). Strong privacy safeguards enhance trust and encourage adoption, particularly in sensitive contexts such as healthcare or finance (Alsharo et al., 2022). Conversely, privacy concerns can deter usage if users fear a data breach or misuse (Xu et al., 2011). Thus, ensuring robust data protection and transparent privacy measures are critical for fostering user confidence and driving technology adoption. **Personal Innovativeness (PI)** refers to an individual's willingness to experiment with and adopt new technologies (Camilleri 2024). Those with high PI tend to be early adopters of emerging technologies, such as the Metaverse, driven by curiosity and enjoyment rather than immediate benefits (Jarrah et al., 2022; Venkatesh et al., 2012). This proactive attitude toward innovation moderately influences both behavioral intention and actual technology use (Musadieq et al., 2021). Thus, PI serves as a key differentiator in technology adoption, particularly for novel systems where advantages may not yet be fully established.

User Satisfaction (US) refers to the extent to which users are content with technology's performance and features, based on their expectations and experiences (Sewandono et al., 2022; DeLone & McLean, 2003). High satisfaction drives continued usage, positive recommendations, and broader adoption (Zhao and Zhang, 2022). For Metaverse platforms, ensuring user satisfaction is critical; feedback can refine the technology to better meet academic needs (DeLone & McLean, 2003).

Information Integrity (II) refers to the accuracy, completeness, and reliability of data within a technological system, serving as a cornerstone for user trust (Camilleri, 2024). In contexts such as the Metaverse, where students and faculty depend on credible content, II directly influences adoption by ensuring confidence in the system's outputs (Wang et al., 2022). A high II fosters both intentions to use and actual usage, particularly in data-sensitive applications (e.g., academic or financial platforms), where inaccuracies can undermine credibility.

Information Proactiveness (IP) refers to a system's ability to anticipate user needs and deliver relevant information proactively without explicit requests (Camilleri, 2024; Gregg & Scott, 2006). In Metaverse environments, particularly virtual learning, IP enhances engagement by providing timely resources, guidance, and feedback during complex tasks (Smith &

Gregor, 2022).

Culture, attitudes towards change, and innovation: The cultural values and attitudes of individuals influence their willingness to adopt new technologies. Camilleri (2024). This construction refers to the collective mindset and openness of a society or organization toward adopting new ideas and technologies. Cultures with a positive attitude toward change are more likely to embrace innovation and experimentation (Shraim, 2021).

Cultural attitudes towards change. It is more likely that cultures that value innovation and are individualistic will adopt the Metaverse more quickly, as they emphasize personal exploration and technological progress, which affects their willingness to adopt it. (Nosica et al.,2024; Shraim, 2021) Cultural perspectives on innovation reveal how receptive a community or organization is to embracing novel concepts and advancements in technology. Cultural attitudes in Jordan have the potential to help or impede the adoption of cutting-edge technology, such as the Metaverse. (Shraim, 2021)

Individualism vs. Collectivism: The extent to which individuals in a culture prioritize their interests versus the group's. This influences attitudes towards change and innovation. Camilleri (2024). Individualism refers to societies in which the connections between individuals are not strong, and everyone is expected to take care of themselves and their immediate family. On the other hand, collectivism refers to societies in which people are part of strong, united groups from birth, often extended families, who protect themselves in return for unwavering loyalty (Cheng et al., 2022; Hofstede, 2001). **The behavioral intention (BI)** in this research refers to the intent of learners to employ and adopt Metaverse technology and its applications in HEIs, which involves persistent use from the present to the future. From the above hypothesis, based on the hybrid model (UTAUT2 and information culture theory)

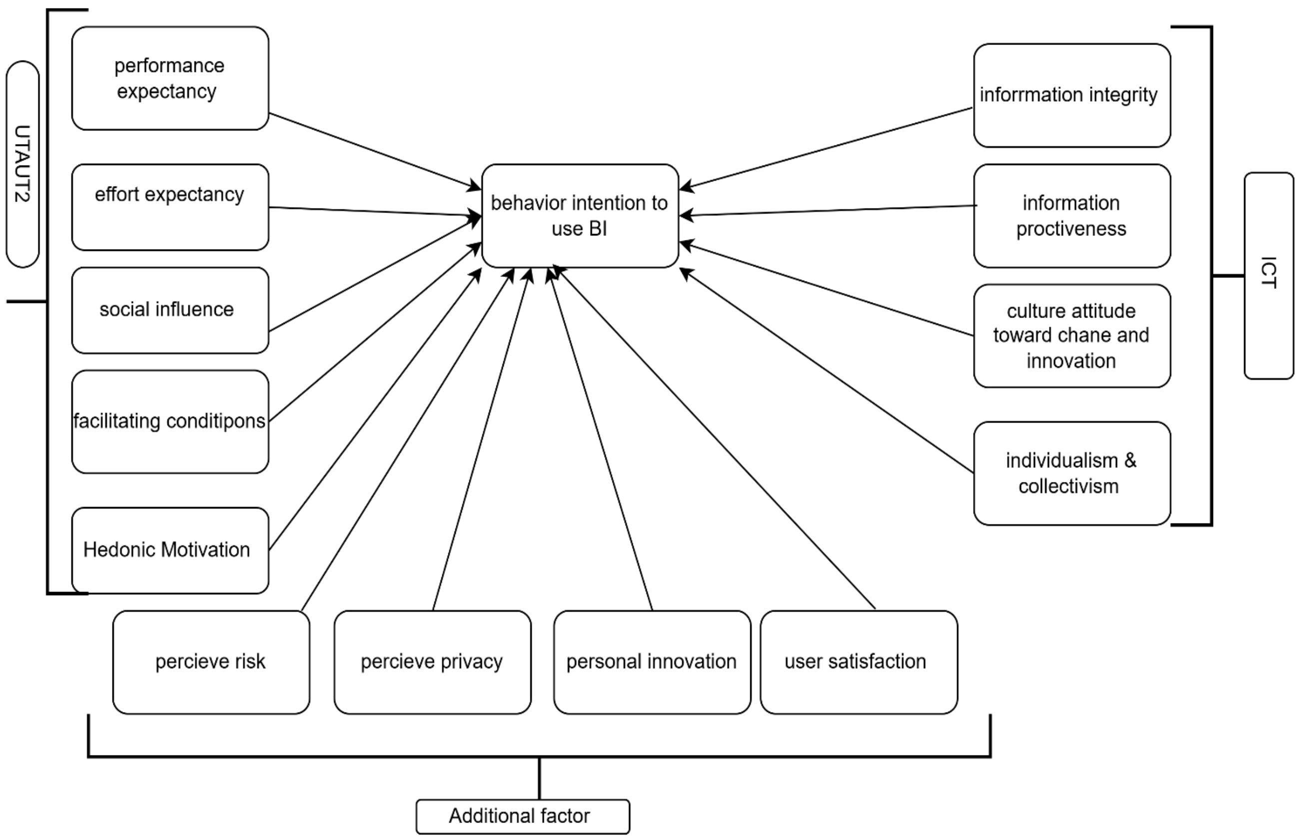

Fig. 1: -The proposed conceptual framework

H14: **Behavioral intention (BI**) has a positive impact on the actual use of Metaverse technology. When all variables are considered holistically, they create a supportive atmosphere that encourages both the intention and actual use of the Metaverse. Users are confident in the technology's potential to improve their learning or teaching results (performance expectation), find it simple and fun to use (effort expectancy and hedonic motivation), and perceive peer and institutional support (social influence and facilitating conditions). Addressing privacy concerns and offering a safe and user-friendly experience promote increased adoption.

Data Analysis

This study employed various analytical techniques to examine the collected data. Descriptive statistics were first conducted using SPSS to determine key measures, such as mean, standard deviation, and data distribution. The validity and reliability of the measurement instruments were assessed using Smart PLS 4. To test the research hypotheses, a hybrid SEM-ANN approach was applied, combining the explanatory power of structural equation modelling (SEM) with the predictive capability of artificial neural networks (ANN). This method is particularly effective for small samples and non-normal data distributions. Given the low response rate, the SEM-ANN was suitable for analysing complex linear and non-linear relationships. The approach enabled the exploration of the direct and indirect effects of factors such as performance expectancy, effort expectancy, and social influence on Metaverse adoption in Jordanian universities.

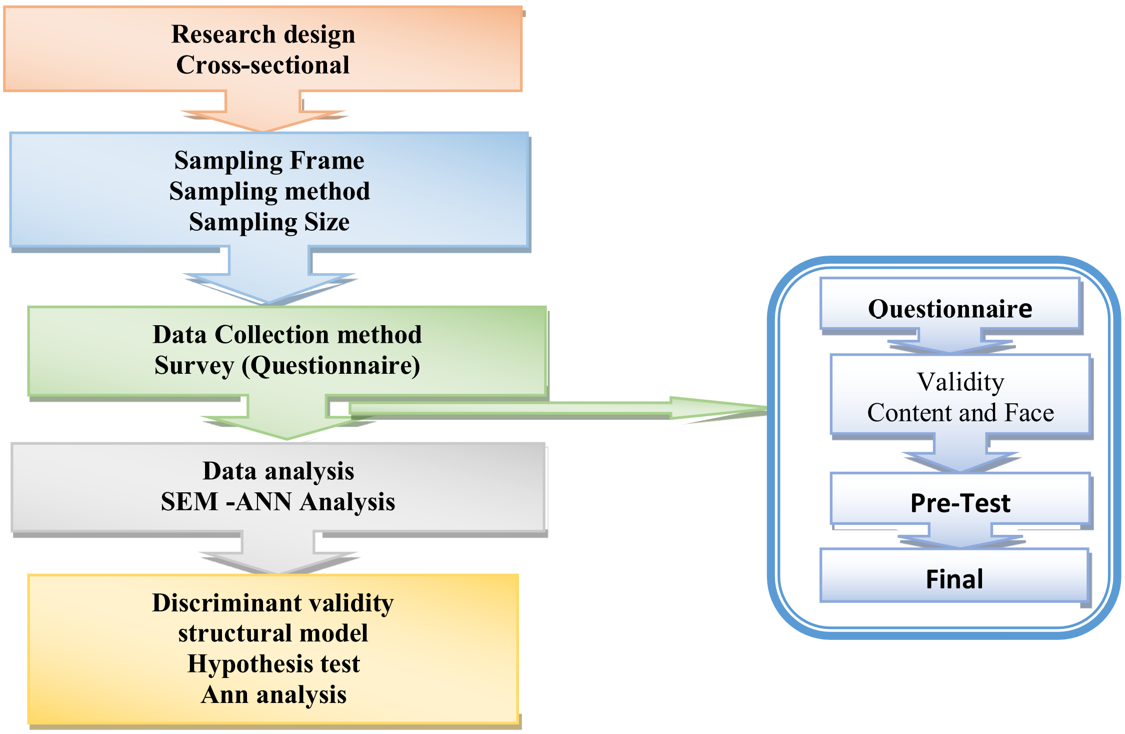

Fig. 2: research design

2. Methodology

Quantitative techniques were employed to ensure comprehensive data analysis. Advanced statistical tools were used to enhance the accuracy and depth of the findings. The Likert-scale data were interpreted based on the category length criteria defined by Norman (2010), classifying responses into poor, fair, good, or excellent levels. This classification aided in evaluating participants' perceptions clearly and systematically. The hybrid SEM-ANN analysis enabled the identification of both linear and non-linear relationships, offering robust insights into the factors influencing behavioural intention toward Metaverse adoption. SEM is good for theory testing and confirming relationships, whereas ANN excels at handling nonlinear relationships and prediction without strict assumptions about data distribution.

2.1 Population and Sample

A representative sample is essential to obtain reliable research results. Following Hair et al. (2016), the study employed key sampling steps, including defining the population, selecting a sampling frame, choosing a technique, determining the sample size to be 383 participants, and implementing the process. This research focuses on Metaverse adoption in Jordanian higher education, targeting students and faculty members from two universities known for their emphasis on technology: Princess Sumaya University for Technology and Tafila Technical University. A structured sampling approach ensures representation of diverse perspectives. Faculty members provide insights into integration challenges and benefits, while students share experiences on usability and learning engagement. This balanced sample enhances the validity of the study and ensures meaningful conclusions. The final sample size was calculated using statistical guidelines to maintain accuracy and representativeness in analyzing Metaverse technology adoption in education.

Table 2: Total Number of Students in Selected Jordanian Universities

	Students (population)			Students (sample)		
University	Males	Females	Total	Males	Females	Total
Princess Sumaya University for Technology	800	572	1,372	9	7	16
Tafila Technical University	18,000	14,767	32,767	201	163	364
total	18,800	15,339	34,139	210	170	380

2.2 Data Collection

Once the sample was finalized, data collection commenced. Surveys were used as the primary data collection methods. Surveys were distributed to both faculty and students at the selected universities, whereas interviews were conducted with a smaller subset of participants to gain more in-depth insights. The quantitative method provides a richer understanding of Metaverse adoption. By following these multi-stage cluster sampling procedures, the study ensured that the sample was both representative and manageable, facilitating meaningful insights that could be generalized to other universities and contexts within Jordan. Furthermore, this method ensures a robust data-collection process that is efficient, cost-effective, and reliable.

2.3 Study Instrument

This study used a structured questionnaire as the main data collection tool, incorporating established measurement scales adapted from prior technology adoption research (Sim, 2023; Rosli, 2024). Each construct was measured using Likert-scale items (1 = Strongly Disagree to 5 = Strongly Agree), allowing for easy quantification and analysis. To enhance contextual relevance, local studies on Metaverse adoption (Al-Adwan et al., 2024; AL Faisal et al., 2024) are included, along with cultural considerations such as individualism vs. collectivism (Bouzaki, 2023). Data analysis involves descriptive statistics and SEM-ANN analysis, which integrate structural equation modeling and artificial neural networks to examine complex relationships. This combined approach provides insights into how various factors influence behavioral intentions to adopt Metaverse technology in Jordanian higher education, offering both theoretical and practical contributions. The category length was calculated. According to Norman (2010), mean scores from 1.0 to 1.50 are considered poor, from 1.51 to 3.50 are at. fair, from 3.51 to 4.50 are at. good, and from 4.51 to 5.0 are at. excellent.

3. Results

This section outlines the results obtained from analysing the study data using SPSS 28 and SmartPLS4 software. The initial part presents the descriptive statistics for the demographic details of the respondents, while the subsequent part tests the study hypotheses through Structural Equation Modeling (SEM).

3.1 Demographic data for respondents

The following table presents descriptive statistics for the respondents' demographic data, including the frequency and percentage for each category, providing essential information about the characteristics of the sample in the study, which aids in the accurate interpretation of the results

Table 3: Descriptive statistics of demographic data for respondents

Table (3) presents the demographic characteristics of the 383 respondents. The sample consisted of 201 males (52.5%) and 182 females (47.5%). The majority of respondents (54.8%) were aged between 18 and 29 years, followed by those aged 40–49 years (31.6%), 30–39 years (9.4%), and a smaller proportion aged 50–59 years (4.2%). Regarding educational level, most held a bachelor's degree (79.4%), while 12% had a master's degree, 7% a doctorate, and only 1.6% a diploma. Participants came from various colleges, with the College of Information Technology being the most represented (54.6%), followed by the College of Engineering (15.4%), and the College of Arts and Design (7.8%). Other colleges had smaller representation, thus ensuring a diverse sample across disciplines.

3.2 Description of Study Variables

This section presents a descriptive analysis of the study variables, focusing on the mean, standard deviation, and relative importance of each construct. These statistical indicators provide insights into the central tendencies and variability in respondents' perceptions. The analysis helps identify how key factors, such as job commitment, strategic entrepreneurship, and leadership support, are perceived and prioritized by employees within Jordanian information technology companies. The ranking of variables emphasizes which dimensions are viewed as the most significant by participants, while the standard deviation reflects the consistency of their responses. This descriptive overview is essential for understanding the relative importance and variability of the study's constructs, laying the groundwork for a deeper inferential analysis in subsequent sections.

Table 3: Results of Measurement Model Assessment

Sub- Construct	Items	Factor Loading >0.6	Cronbach's Alpha >0.7	CR > 0.6	Average Variance Extracted AVE > 0.5	Item(s) deleted due to low loadings
Behavioral intention	BI1	0.688	0.784	0.876	0.705	
	BI2	0.926				
	BI3	0.886				
Cultural Attitudes	CA1	0.885	0.788	0.903	0.823	**CA3**
	CA2	0.929				
Effort Expectancy	EE1	0.647	0.696	0.828	0.620	
	EE2	0.826				
	EE3	0.871				
Facilitating Conditions	FC1	0.859	0.870	0.919	0.790	
	FC2	0.918				
	FC3	0.889				
Hedonic Motivation	HM1	0.891	0.912	0.944	0.850	
	HM2	0.941				
	HM3	0.933				
Information Integrity	II1	0.862	0.824	0.895	0.739	
	II2	0.822				
	II3	0.893				
Information Proactiveness	IP1	0.816	0.722	0.842	0.641	
	IP2	0.847				
	IP3	0.735				
Performance Expectancy	PE1	0.873	0.866	0.918	0.789	
	PE2	0.916				
	PE3	0.874				
Personal Innovativeness	PI1	0.819	0.768	0.866	0.684	
	PI2	0.775				
	PI3	0.883				
Perceived Risk	PR2	0.679	0.839	0.838	0.729	**PR1**
	PR3	0.998				
Social Influence	SI1	0.800	0.793	0.878	0.706	
	SI2	0.822				
	SI3	0.895				
User Satisfaction	US1	0.908	0.888	0.931	0.817	
	US2	0.916				
	US3	0.888				
Perceived Privacy	PP1	0.814	0.854	0.884	0.74	
	PP2	0.988				
	PP3	0.859				
Individualism and Collectivism	IC1					**Deleted All**

Table (4) displays the mean scores, standard deviations, and the perceived importance of the study variables. The highest-rated construct was *Performance Expectancy* with a mean of 3.86 (SD = 0.657), indicating a strong perception of the usefulness of Metaverse technology. *Hedonic Motivation* (M = 3.83), *Personal Innovativeness* (M = 3.77), and *User Satisfaction* (M = 3.666) also received "good" importance ratings. Similarly, *Effort Expectancy* (M = 3.624), *cultural attitudes Towards change and innovation* (M = 3.697), and *Behavioral Intention to Use* (M = 3.611) were rated as "good," reflecting positive attitudes toward adoption. *Information Integrity* (M = 3.516) and *Information Proactiveness* (M = 3.53) also fell into the "good" category. In contrast, *Social Influence* and *Facilitating Conditions* had lower means of 3.034 with higher standard deviations (SD = 1.042), suggesting moderate and varied perceptions, thus rated as "fair." *Perceived Privacy* (M = 3.216) and *Individualism and Collectivism* (M = 3.455) also received "fair" ratings, indicating room for improvement in these areas.

Table 4: The mean, SD, and rank for study variable

Items	Mean	SD	importance
Performance Expectancy	3.86	0.657	good
Effort Expectancy	3.624	0.68	good
Social Influence	3.034	1.042	fair
Facilitating Conditions	3.034	1.042	fair
Hedonic Motivation	3.83	0.816	good
Perceived Privacy	3.216	0.687	fair
Personal Innovativeness	3.77	0.736	good
User Satisfaction	3.666	0.741	good
Information Integrity	3.516	0.73	good
Information Proactiveness	3.53	0.682	good
Cultural Attitudes Towards Change and Innovation	3.697	0.652	good
Individualism and Collectivism	3.455	0.649	fair
BI (Behavioral intention to use)	3.611	0.762	good

Table 5: Reliability and internal consistency results

	Frequency	%
Gender		
Female	182	47.5
Male	201	52.5
Age group		
18-29	210	54.8
30-39	36	9.4
40-49	121	31.6
50-59	16	4.2
Educational level		
Bachelor's	304	79.4
Diploma	6	1.6
Doctorate	27	7
Master's	46	12
College Names		
College of Arts and Humanities	29	7.6
College of Economics and Business Administration	12	3.1
College of Education	18	4.7
College of Sharia and Islamic Studies	8	2.1
College of Science	18	4.7
College of Arts and Design	30	7.8
College of Engineering	59	15.4
College of Information Technology	209	54.6
Total	**383**	**100**

3.3 Internal Consistency of Reliability

Internal consistency reliability refers to the extent to which the items within a scale work cohesively to measure the same underlying construct (Sun et al., 2007). In organizational research, common tools for assessing the reliability of multi-item scales include Cronbach's alpha and composite reliability coefficients (Peterson and Kim, 2013). Cronbach's alpha was used to evaluate the internal consistency of the adapted scale. However, Goetz et al.(2010) suggest that composite reliability coefficients offer a more accurate measure of reliability because they account for the varying contributions of each indicator to the construct, unlike Cronbach's alpha, which assumes that all items contribute equally. Composite reliability values above 0.70 are generally considered acceptable (Hair et al. [7], 2017), while a Cronbach's alpha value of 0.7 or higher is regarded as satisfactory (Sekaran & Bougie, [10], 2016). Convergent validity measures how well the indicators of a latent construct are related and how accurately they represent the construct. It is evaluated using the Average Variance Extracted (AVE). AVE reflects the average variance shared between the construct and its indicators. To confirm convergent validity, the AVE should exceed 0.5, according to the rule of thumb (Barclay et al. [3], 1995). The results shown in Table 3 confirm that all AVE values exceed the 0.5 threshold, validating the convergent validity of all constructs. Additionally, the results in Table 3 and Figure 1 indicate that the composite reliability coefficients for the constructs exceeded the required threshold of 0.70, further confirming the reliability and validity of the adapted measurement scales used in this study.

3.4 Discriminant Validity

Discriminant validity measures how well a construct is separated from others, ensuring its uniqueness and avoiding excessive overlap (Fornell and Larcker 1981). In Smart PLS 4, several methods are used to evaluate discriminant validity, with the Fornell-Larcker criterion being one of the most common. This method compares the square root of the Average Variance Extracted (AVE) for each construct with the correlations between constructs. To confirm discriminant validity, the square root of the AVE for each construct must be greater than its correlation with any other construct in the model. This method is explained in more detail in the next section.

3.5 Variable correlation using the Fornell-Larcker criterion.

Table (6) presents the results of the multivariable correlation analysis using the Fornell-Larcker criterion to evaluate the discriminant validity of the measurement model. According to Fornell and Bookstein [13] (1982), discriminant validity is confirmed when the square root of the Average Variance Extracted (AVE) for each construct exceeds the correlation values between the constructs.

In other words, the AVE values should be larger than the off-diagonal correlations in the corresponding rows and columns of the correlation matrix, as demonstrated in this study. This condition ensures that the predictor variables exhibit discriminant validity, meaning each construct is sufficiently distinct from the others and accurately represents its intended measure. Therefore, this method confirms that the dimensions used in the study are adequately distinct from each other and provide an accurate representation of the measured variables.

Table 6: Reliability and internal consistency results

		1	2	3	4	5	6	7	8	9	10	11	12	13
1	Behavioral intention	**0.840**												
2	Cultural Attitudes	0.621	**0.907**											
3	Effort Expectancy	0.477	0.351	**0.787**										
4	Facilitating Conditions	0.278	0.240	0.442	**0.889**									
5	Hedonic Motivation	0.637	0.554	0.556	0.250	**0.922**								
6	Information Integrity	0.563	0.487	0.308	0.472	0.462	**0.860**							
7	Information Proactiveness	0.601	0.569	0.501	0.551	0.557	0.744	**0.801**						
8	Perceived Risk	0.310	0.102	0.107	0.018	0.105	0.076	0.093	**0.854**					
9	Performance Expectancy	0.589	0.485	0.540	0.328	0.611	0.438	0.501	0.228	**0.888**				
10	Personal Innovativeness	0.605	0.568	0.543	0.239	0.623	0.408	0.542	0.088	0.526	**0.827**			
11	Social Influence	0.471	0.581	0.393	0.540	0.448	0.489	0.607	0.114	0.467	0.340	**0.840**		
12	User Satisfaction	0.655	0.663	0.604	0.404	0.684	0.660	0.680	0.368	0.575	0.623	0.521	**0.904**	
13	Perceived Privacy	0.547	0.621	0.638	0.451	0.487	0.587	0.589	0.356	0.521	0.354	0.542	**0.621**	**0.86**

3.6 Hypothesis Testing (Path Coefficient)

Table 7 presents the results of the direct path analysis used to examine the hypothesized relationships between various independent variables and the dependent variable *Behavioural Intention to Use Metaverse Technology*. The analysis was conducted using structural equation modeling (SEM) to evaluate the strength, direction, and

the significance of each path. The table includes standardized path coefficients (β), means, standard deviations (SD), t-statistics, and p-values for each relationship. These results help determine which factors have a statistically significant influence on behavioural intention, thereby identifying the key drivers of Metaverse adoption among students and faculty in Jordanian universities. The findings provide valuable insights for understanding the direct effects of psychological, technological, and contextual variables on users' intentions to engage with Metaverse-based educational platforms.

Table 7: The Test Result of Direct Hypotheses

Path	β	mean	SD	T statistics	P values
Cultural Attitudes -> Behavioral intention	**0.195**	**0.193**	**0.076**	**2.557**	**0.011**
Effort Expectancy -> Behavioral intention	0.065	0.071	0.053	1.239	0.215
Facilitating Conditions -> Behavioral intention	-0.082	-0.075	0.046	1.798	0.072
Hedonic Motivation -> Behavioral intention	**0.154**	**0.163**	**0.074**	**2.068**	**0.039**
Information Integrity -> Behavioral intention	**0.194**	**0.182**	**0.055**	**3.556**	**0.000**
Information Proactiveness -> Behavioral intention	0.068	0.076	0.059	1.155	0.248
Perceived Risk -> Behavioral intention	0.033	0.013	0.068	0.483	0.629
Performance Expectancy -> Behavioral intention	**0.162**	**0.154**	**0.051**	**3.204**	**0.001**
Personal Innovativeness -> Behavioral intention	**0.144**	**0.135**	**0.071**	**2.035**	**0.042**
Social Influence -> Behavioral intention	0.019	0.011	0.064	0.301	0.763
User Satisfaction -> Behavioral intention	0.045	0.054	0.091	0.496	0.620
Perceived Privacy -> Behavioral intention	**0.146**	**0.144**	**0.052**	**2.810**	**0.005**

Table 4.28 presents the results of the direct effects of the study variables on *Behavioral Intention to Use Metaverse Technology*. Several variables showed statistically significant positive relationships. *Cultural attitudes Towards change and innovation* (β = 0.195, p = 0.011), *Hedonic Motivation* (β = 0.154, p = 0.039), *Information Integrity* (β = 0.194, p = 0.000), *Performance Expectancy* (β = 0.162, p = 0.001), *Personal Innovativeness* (β = 0.144, p = 0.042), and *Perceived Privacy* (β = 0.146, p = 0.005) had significant positive effects on behavioral intention, indicating that these factors play a critical role in influencing the intention to use Metaverse technology in educational settings. However, variables such as *Effort Expectancy*, *Facilitating Conditions*, *Information Proactiveness*, *Perceived Risk*, *Social Influence*, and *User Satisfaction* did not show statistically significant effects (p > 0.05), suggesting that their influence on behavioral intention is limited or indirect in this context. Notably, *Facilitating Conditions* showed a negative but marginally non-significant effect (β = -0.082, p = 0.072). Overall, the findings highlight the importance of technological perceptions, user readiness, and cultural openness in driving Metaverse adoption in Jordanian universities.

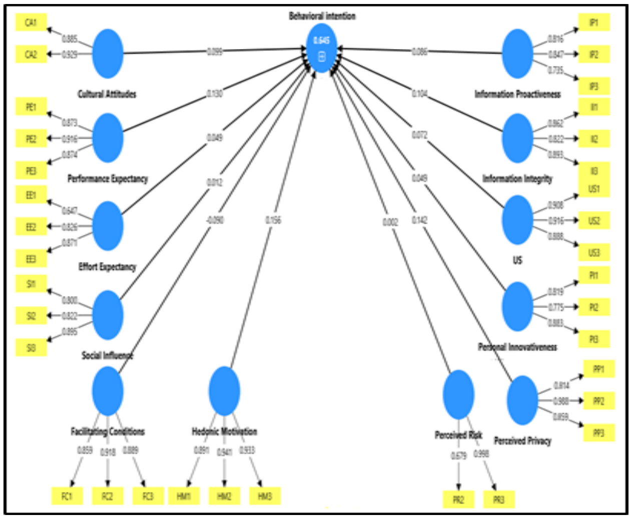

Fig. 3: ANN Artificial Neural Network (ANN)

Artificial Neural Networks (ANNs) are computational models inspired by the human brain's structure, designed to recognize patterns and make decisions through interconnected nodes with adjustable weights. They learn from data to improve performance and are widely used in AI applications, such as image recognition and medical diagnosis. The structure model

Table 8: Case Processing Summary

Category	**N**	**Percent**
Training Sample	277	72.3%
Testing Sample	106	27.7%
Valid Total	**383**	**100.0%**
Excluded Cases	0	—

In Table (8), out of 383 valid cases, 72.3% were used for training the neural network model, while 27.7% served as the testing sample to assess its accuracy and generalizability. No data were excluded to ensure a complete dataset. This balanced division supported effective model training and reliable validation.

Table 9: Model Summary

Metric	**Training**	**Testing**
Sum of Squares Error	24.360	11.133
Relative Error	0.177	0.237
Stopping Rule Used	1 consecutive step with no decrease in error	
Training Time	0:00:00.02	

Note: Error calculations are based on the testing sample.

The neural network model demonstrated good predictive performance for behavioral intention. The relative error for the training sample was low (0.177), and the error for the testing sample remained acceptable (0.237), indicating that the model generalizes well and is not overfitted. These results suggest that the selected input variables meaningfully contribute to predicting behavioral intention in this context.

Table 10: Parameter Estimates

Predictor		Predicted			
		Hidden Layer 1			Output Layer
		H(1:1)	H(1:2)	H(1:3)	BI
Input Layer	(Bias)	-.361	-.700	1.201	
	PE	.132	-.541	.300	
	EE	.236	-.135	-.228	
	SI	.004	-.039	-.392	
	FC	.128	.293	.051	
	HM	-.193	.097	.920	
	PR	-.161	-.094	-.531	
	PP	.379	.129	.050	
	PI	.344	.585	.507	
	US	.168	-.717	-.052	
	II	.130	-.545	.208	
	IP	.435	-.014	-.334	
	CA	.746	.819	.672	
	IC	-.273	-.112	.588	
Hidden Layer 1	(Bias)				-.439
	H(1:1)				.516
	H(1:2)				-.495
	H(1:3)				.677

Table (10) summarizes the parameter estimates of the Multilayer Perceptron neural network, highlighting how input variables influence the hidden layer neurons and, ultimately, the output variable—Behavioral Intention (BI). Cultural Attitudes showed consistently strong positive weights across all hidden neurons, indicating a major impact on network processing. Personal Innovativeness and Perceived Privacy also had notable positive contributions. In contrast, Perceived Risk and User Satisfaction had mostly negative weights, suggesting that they reduce neuron activation. The hidden-to-output layer weights revealed mixed effects, with two neurons positively influencing behavioral intention and one negatively influencing behavioral intention. Bias terms helped adjust activation baselines for better model performance. Overall, these estimates reveal the varying importance and influence of each predictor in shaping the neural network's prediction of behavioral intention.

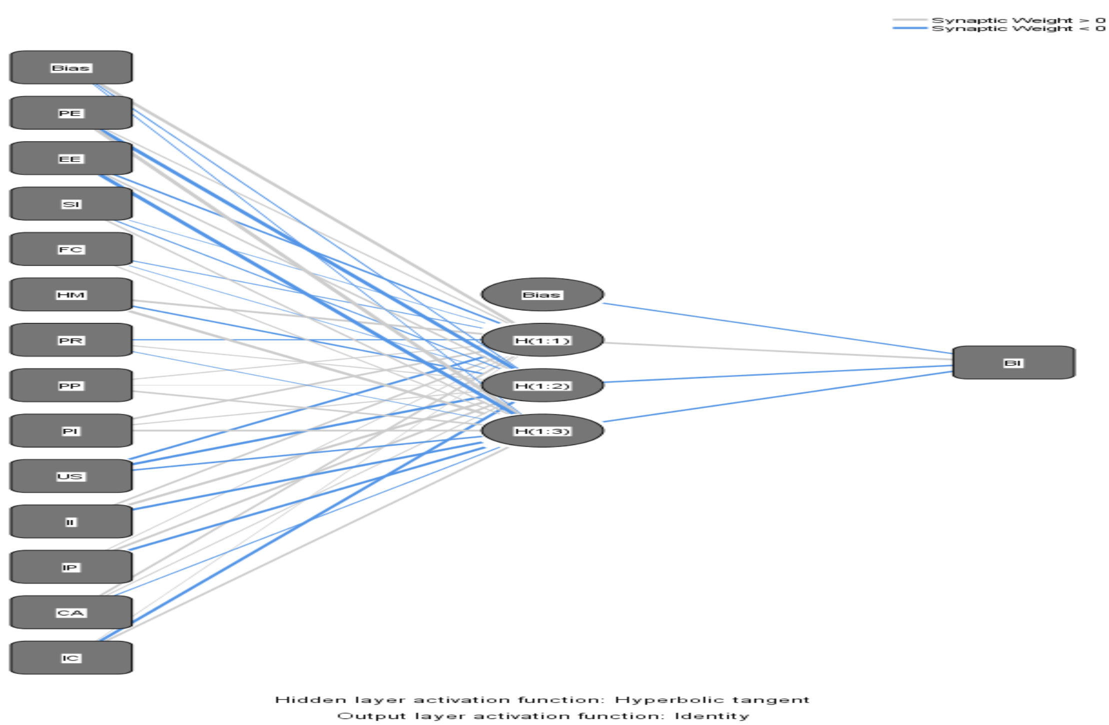

Fig. 4: Structure of the Artificial Neural Network (ANN) Model

4. Discussion

The findings from this study shed light on what drives students and faculty in Jordanian universities to embrace Metaverse technology for learning, blending insights from the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) and information culture theory. The results confirm that certain factors play a pivotal role in shaping users' intentions to adopt immersive technology, whereas others have less direct influence, offering practical clues for educators and university leaders.

Key Drivers of Adoption: The structural equation modeling (SEM) results highlight that Performance Expectancy (β = 0.162, p = 0.001) and Information Integrity (β = 0.194, p = 0.000) are among the strongest predictors of behavioural intention to use Metaverse technology. This makes sense—students and faculty are more likely to dive into virtual learning spaces if they believe that these platforms will boost their academic performance and deliver reliable and trustworthy content. For instance, a dental student at the University of Jordan might be motivated to practice virtual simulations if they trust the accuracy of digital tools. Similarly, Cultural Attitudes Towards Change and Innovation (β = 0.195, p = 0.011) and Personal Innovativeness (β = 0.144, p = 0.042) showed significant positive effects. In Jordan, where education is deeply valued, cultural openness to innovation—especially among tech-savvy students at places like Princess Sumaya University for Technology—encourages early adoption. Hedonic Motivation (β = 0.154, p = 0.039) also matters, suggesting that the fun and engagement of virtual environments, such as collaborative engineering projects at Jordan University of Science and Technology, make the Metaverse appealing. Perceived Privacy (β = 0.146, p = 0.005) further boosts adoption, as users feel confident when their personal data are protected, a critical factor in a digital age where privacy concerns loom large.

Surprising Non-Significant Factors

Interestingly, Effort Expectancy, Social Influence, Facilitating Conditions, Information Proactiveness, Perceived Risk, and User Satisfaction did not show a direct significant impact on behavioural intention ($p > 0.05$). This is a bit unexpected, especially for Social Influence, given Jordan's collectivist culture, where peer opinions often sway decisions. The "fair" rating for Social Influence (M = 3.034) suggests students and faculty might not yet see their peers or mentors strongly advocating for the Metaverse, possibly due to its novelty in educational settings. Facilitating Conditions (β = -0.082, p = 0.072) even showed a slightly negative effect, hinting that infrastructure challenges— such as unreliable Internet or limited device access—might dampen enthusiasm, though not significantly. This aligns with the 'fair' rating for Facilitating Conditions (M = 3.034), indicating room for improvement in technical support.

Cultural Nuances: The role of individualism versus collectivism (M = 3.455, rated "fair") was less clear, as all related items were deleted due to low factor loadings. This suggests that cultural orientation might not be as straightforward as expected to influence Metaverse adoption in Jordan. While collectivist values could drive group-based learning in virtual spaces, the Metaverse's flexibility for self-paced learning might appeal to individualistic tendencies, creating a mixed effect that requires further exploration.

ANN Insights: Artificial neural network (ANN) analysis complements the SEM findings by capturing non-linear relationships. Cultural Attitudes and Personal Innovativeness showed strong positive weights across hidden neurons, reinforcing their importance. Perceived Risk, however, had negative weights, suggesting that lingering concerns about data security or system reliability could subtly undermine adoption, even if not significant in the SEM model. The low relative error in the ANN model (0.177 for training and 0.237 for testing) confirms that these factors collectively predict behavioural intention, offering a robust framework for understanding adoption dynamics.

Implications: These findings suggest that universities should focus on demonstrating the Metaverse's academic benefits, ensuring reliable content, and fostering a culture open to technological innovation. Privacy protections are non-negotiable because trust is a key driver. The weaker role of social influence and infrastructure points to the need for better advocacy and technical upgrades to make adoption smoother. Developers should emphasize collaborative features to leverage social influence in collectivist cultures

5. Recommendations

Based on the study's findings, there are actionable recommendations for Jordanian universities, educators, and policymakers to boost Metaverse adoption in higher education.

1. **Highlight Academic Benefits:** Since Performance Expectancy is a top driver, universities should showcase how the Metaverse enhances learning outcomes. For example, create demo sessions where students can experience virtual labs (e.g., engineering simulations at Tafila Technical University) to see tangible academic gains. Marketing campaigns should emphasize real-world examples, such as virtual clinics, to improve dental students' skills. Educators should focus on hands-on training to reduce effort expectancy

2. **Ensuring Content Reliability:** Information Integrity is critical. Universities should partner with trusted tech providers to ensure that Metaverse platforms deliver accurate, reliable educational content. Regular audits of virtual resources can build user confidence, especially for faculties relying on these tools for teaching.

3. **Foster a Culture of Innovation:** Given the significant role of cultural attitudes Towards change, universities should promote a tech-forward mindset. Workshops, innovation hubs, and guest lectures on emerging technologies can inspire students and faculty, particularly in tech-focused institutions such as Princess Sumaya University.

4. **Strengthening privacy protection:** Perceived privacy drives adoption, so universities must implement robust data security measures. Transparent policies on data handling, encryption, and user consent should be communicated to build trust. For example, a university-wide privacy campaign can reassure users about the safety of their personal information.

5. **Improved Infrastructure:** The marginal negative effect of Facilitating Conditions suggests infrastructure gaps. Universities should invest in high-speed Internet, and policymakers should invest in 5G infrastructure to improve facilitating conditions, compatible devices, and user-friendly platforms. Partnerships with tech companies can provide subsidized VR headsets or cloud-based access to reduce barriers.

6. **Leverage Fun and Engagement:** Hedonic Motivation matters; therefore, Metaverse platforms should include gamified elements or interactive features to make learning enjoyable. For instance, virtual group projects or immersive storytelling for arts students at the College of Arts and Design can boost engagement.

7. **Build Peer Advocacy:** Although Social Influence was not significant, its "fair" rating suggests potential. Universities can encourage early adopters (e.g., IT students) to share positive experiences through campus events or social media, thus amplifying peer influence in Jordan's collectivist culture.

8. **Support Early Innovators:** Personal Innovativeness drives adoption, so universities should identify and support tech-curious students and faculty. Innovation clubs or pilot programs for Metaverse projects can nurture early adopters, who can inspire others.

9. **Further Research:** The mixed findings on individualism vs. collectivism and non-significant factors such as Effort Expectancy suggest a need for deeper study. Future research could explore how specific cultural traits or improved infrastructure impacts adoption over time.

10. **Limitation:** Sample Specificity: The study focused on two universities in Jordan, limiting generalizability to other regions or countries with different educational systems or cultural contexts. This study used a cross-sectional Design, which limits the ability to infer causality or track changes in adoption over time. Future research should employ longitudinal studies. Self-reported Data, Reliance on self-reported questionnaire data might introduce common method bias.

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