SN Computer Science (2025) 6:983
https://doi.org/10.1007/s42979-025-04553-6

ORIGINAL RESEARCH

Examining Metaverse Intention to Use Among Computer Science and Engineering Students Via UTAUT2, DOI Through PLS-SEM, ML & Network Analysis

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Received: 30 October 2023 / Accepted: 15 November 2025

Abstract
This study explores Engineering and Computer Science students' inclination to adopt Metaverse systems by integrating the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) and the Diffusion of Innovations (DOI) models. To gain complementary insights authors employed a multi-analytical approach combining Partial Least Squares Structural Equation Modeling (PLS-SEM), Machine Learning (ML), and Network Analysis. The PLS-SEM analysis found "Facilitating Conditions" as significant predictor of Behavioral Intention (BI), while found "Price Value" have a minimal impact. Additionally, Compatibility, Complexity, and Observability unfold as key factors in Metaverse adoption. ML analysis found that Linear Discriminant Analysis outperforms other classifiers, showing high predictive accuracy (0. 882) for Behavioral Intention. Network analysis highlights the centrality of Behavioral Intention within the adoption network, confirming its crucial role and showing strong alignment with PLS-SEM findings. All these results together offer a comprehensive understanding of factors influencing Metaverse adoption, supporting aimed interventions and future research to enhance student engagement with Metaverse technologies.

Keywords Metaverse · UTAUT2 · DOI · PLS-SEM · Machine learning · Network analysis

Introduction

The Metaverse, an interactive virtual environment that facilitates the integration of physical and digital areas, presents a potentially fruitful path for the implementation of novel pedagogical approaches in the fields of engineering and computer science. This environment addresses specific educational challenges faced by students, such as limited access to specialized equipment, lack of immersive remote learning options, and reduced engagement in traditional settings. A system such as this makes available a plethora of interactive exercises which provide for learning spaces as well as virtual labs [1]. For instance, students overcome the barriers of physical resource constraints through collating and interacting with complex data structures in 3D settings or by virtually simulating the process of disassembly and reassembly of gears at a workstation. For sectors such as robotics and software development, simulations help recreate costly, resource-intensive laboratory settings, allowing for a more practical application of theoretical knowledge [2].

The collaborative practices taking place in the context of Metaverse are crucial for understanding the processes of joint work and communication, since students participate in shared activities such as coding, debugging or prototyping [3]. Apart from the conventional classroom aspects, metaverse provides unique networking opportunities that narrow the gap caused by geographical in professional networking for most engineering and computer science students [4]. Virtual meetings and conferences provide opportunities for individuals to engage in interactive sessions with experts, mentors, and professionals hailing from diverse

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Published online: 28 November 2025

geographical locations. Career-oriented platforms offer valuable industry insights, enabling students to actively explore various career trajectories and establish meaningful connections with professionals within their desired industries [5].

Another interesting feature about the Metaverse is that it allows students to participate in competitive activities like coding contests, hackathon, engineering and so forth, which can add a fun element into what has often been a highly tasking process of learning as it arouses interest in students when learning objectives can be approached in a game format [6]. There exist opportunities within the Metaverse for rethinking conventional approaches to teaching and instead fostering the development of more exciting educational experiences. Virtual tutorials and virtual lectures have scope for interactivity which allows students to be more actively involved during the learning process [7].

Other tools that are valued towards enhancing the educational experience include data visualization tools and personalized leaning pathways. Adaptive learning pathways may support each specific learner in mastering complex engineering and computer science concepts at his with his preferred pace [8]. The utilization of three-dimensional data visualization techniques can facilitate comprehension of complex designs and analyses. Moreover, the use of analytical tools incorporated in Metaverse enables immediate appraisals and feedback, which means that the teachers can closely track how the students are doing and fill in the gaps in their learning more effectively [9].

Nevertheless, integration of Metaverse into the realm of education presents certain obstacles. Ethical considerations, make sure resource accessibility for all of students, and addressing security and privacy concerns in metaverse, where its crucial factors that demand attention and solution [4]. The achievement of successful implementation necessitates careful strategic planning, significant allocation of resources towards technological advancements, and continuous faculty development [10]. In general, potential of the Metaverse is significant in terms of renewing pedagogical approaches, enhance of student involvement, cultivating creativity, and equipping students for professions in the swiftly progressing domains such as engineering and computer science.

Literature Review and Hypothesis Development

The term "metaverse," originating from science fiction, represents a shared virtual realm created by the convergence of persistent virtual and enhanced physical realities. Studies on Metaverse adoption in education have primarily used established models like the Technology Acceptance Model (TAM) or the Unified Theory of Acceptance and Use of Technology (UTAUT/UTAUT2) [11]. However, a gap exists in studies applying a combined framework that leverages both UTAUT2 and Diffusion of Innovations (DOI) to specifically understand the Behavioral Intention (BI) of students toward Metaverse adoption. This study aims to address this gap by applying a novel combined model of UTAUT2 and DOI theories to examine the factors influencing Metaverse adoption within this demographic, providing a unique perspective that integrates technology acceptance and diffusion principles.

Utaut2 Theory for Metaverse Systems

The UTAUT2 model by Venkatesh et al. [12], an expansion of the original UTAUT model, has been extensively utilized to comprehend user acceptance of various forms of technology. It includes the following seven constructs: price value, habit, hedonic motivation, social influence, performance expectancy, and effort expectancy.

In the context of Metaverse systems for computer science and engineering students, the model provides a relevant framework to understand usage intention. The students may anticipate improving their performance (performance expectancy) in their coursework or assignments. These systems' usability (effort expectation) and cost-effectiveness (price value) may be important determinants of how widely they are adopted. Additionally, students are frequently influenced by their instructors and peers (social influence), and supportive conditions like support, infrastructure, and access can have a significant impact on how willingly they use such systems.

Doi Theory for Metaverse Systems

To comprehend how, why, and how quickly new ideas and technologies spread, it is helpful to grasp the Diffusion of Innovations (DOI) theory, which Rogers, 1995 [13] first articulated. Relative advantage, compatibility, complexity, trialability, and observability are the five components of the DOI theory.

The relative advantage of Metaverse system for engineering and computer science students can come in the form of cutting-edge techniques for collaboration, learning, or problem-solving. The degree to which these systems accord with students' requirements, current norms, and ideals is referred to as compatibility. It's crucial to maintain user-friendliness because the complexity of utilizing such technologies could be a barrier. These solutions can be tried out by students, which might motivate them to do so without making a long-term commitment. Finally, more students may embrace these approaches if the advantages can be seen, as in successful case studies or peer demonstration.

Behavioral Intention to Use the Metaverse Systems

Both UTAUT2 and DOI theories heavily emphasize the concept of behavioral intention. It is thought to be a highly reliable indicator of real use behavior. Students studying engineering and computer science may have different influences on their behavioral intention to use Metaverse systems, as noted by UTAUT2 and DOI theories. Combining them could provide a holistic perspective that takes into consideration technological qualities as well as social, institutional, and individual issues. By ensuring that these systems satisfy the requirements and expectations of students and increasing their acceptance rates, this analysis can direct their design and implementation.

The concept of Metaverse and its implications have been widely discussed in literature. Riva and Wiederhold [14] emphasize that Metaverse is a transformative technology that can modify people's perception of reality. They highlight the importance of understanding the cognitive mechanisms involved in Metaverse, such as the experience of being in a virtual place and body, brain-to-brain attunement, and emotional experiences. This transformative nature of Metaverse sets it apart from previous technologies.

Trust in Metaverse is an important factor influencing usage intention. Ren et al. [15] found that trust in Metaverse positively affects usage intention through factors like technology readiness and the Technology Acceptance Model (TAM). The perceived usefulness and ease of use of Metaverse also play a significant role in shaping behavioral intention [16–18]. Additionally, factors like social influence, facilitating conditions, hedonic motivation, price value, relative advantage, compatibility, trialability, and observability have been identified as influencing behavioral intention to use Metaverse systems [18, 19].

Extensive research has been conducted to examine the effects of Metaverse on several sectors such as education, healthcare, and entertainment. According to Alfaisal et al. [20] in their recent study, undertook a comprehensive analysis of existing scholarly works pertaining to the integration of Metaverse in educational settings. Their findings indicate that the Technology Acceptance Model (TAM) is commonly employed as a predictive framework to assess users' inclination towards adopting Metaverse system. In study conducted by Choi et al. [21], researchers examined the influence of Metaverse on mood regulation and overall life satisfaction. Findings of the study emphasized a beneficial outcome of engaging in social metaverse activities, which were found to positively impact the well-being of users.

Furthermore, the role of avatar customization in Metaverse has been studied. Jang and Kim [22], examined the impact of avatar customization on task engagement and expectancy-value beliefs for fashion education, emphasizing the importance of educational compatibility and the unique sensory, cognitive, and emotional experiences offered by Metaverse.

Performance Expectancy

The concept of Metaverse and its implications for various domains, including education, sustainability, and healthcare, have been extensively discussed in literature. Park and Kim [23] highlight that education using Metaverse can overcome limitations of traditional online education were providing a participatory and graceful experience, free from constraints of time and space. Emphasize potential of Metaverse to create innovative educational environments and contribute to achieving sustainable education goals [23, 24].

In terms of performance expectancy, studies have examined the factors influencing learners' adoption of educational Metaverse platforms. Teng et al. [25] conducted an empirical study using an extended (UTAUT) model and found that performance expectancy, along with other factors like effort expectancy, social influence, and facilitating conditions, positively influenced learners' satisfaction and continued usage intention. However, perceived risks were found to reduce learners' intention to use Metaverse platform.

Literature reveals some variability in the role of performance expectancy across contexts, despite its demonstrated significance in the adoption of other technological innovations like a food delivery apps [26] and mobile learning tools [27]. where Yang et al. [28], study found no significant correlation between performance expectancy and the behavioral intention to utilize metaverse systems for the purpose of basketball learning. Similarly, data revealed no significant relationship between performance expectancy and intention to use E-Government services [29]. In contrast, previous studies conducted by Khalil et al. [30] and Teng et al. [25] have showed a favorable correlation between performance expectancy and the adoption rates of educational metaverse platforms.

Effort Expectancy

Effort expectancy refers to the perceived ease of using new technology or product [12]. This concept is closely related to "perceived ease of use" variable in the Technology Acceptance Model (TAM) and the "complexity" construct in the Diffusion of Innovations theory. Effort expectancy and performance expectancy are important factors for understanding technology adoption behaviors and intentions [31].

The construct includes three main aspects: perceived ease of use, ease of use, and complexity. Perceived ease of use, as defined by Venkatesh et al. [12] measures how effortless individuals perceive use of technology to be. Ease of use, on the other hand, evaluates whether a technology is seen as challenging or simple to operate [32]. According to Rogers et al. [33] describe complexity as the degree to which a technology is considered difficult to understand and use, which can negatively impact its adoption rate. Empirical studies had demonstrated that effort expectancy significantly influences consumer attitudes toward both mandatory and voluntary technology use [34, 35].

The existing body of literature offers contrasting viewpoints regarding the significance of effort expectancy across different technical fields. Previous research conducted by Lee et al. [26] in the field of food delivery applications and Yang et al. [28] in the domain of basketball learning utilizing metaverse technology, yielded results indicating that effort expectancy did not exert a substantial influence on individuals' behavioral intentions. In contrast, the significance of effort expectancy has been demonstrated in various domains, including mobile learning tools [27], Internet of Things (IoT) [36], and educational metaverse platforms [25, 30]. In the context of educational metaverse platforms, Khalil et al. [30] and Teng et al. [25] have independently observed a favorable correlation between effort expectancy and the behavioral intention to adopt such systems. The observed variability in patterns across various technological contexts implies that the influence of effort anticipation may vary depending on the specific situation.

Social Influence

Researchers have widely investigated the principles of social influence and demonstrated the effects of social influence on altering users' actions. According to Rogers [33] stated that the social concept influences consumers' decision to accept an innovative technology beyond an individual's decision thinking. Social influence is generally categorized into two main types: social norms and critical mass. There are two types of effects in social norms: informational influences and normative influences. The term "informational influence" describes how people learn things from other people. The normative impact occurs when a user complies with social expectations to receive a reward or stay out of trouble [37]. According to Venkatesh [12], social influence is the level of significance that is accorded to using an innovative technology by other people. The social influence construct comprises three key components: subjective norm, social factor, and image. (1) The subjective norm, the social factor, and the image are the three components that make up the social influence construct. Subjective norm: the perceived social pressure to do or refrain from performing the activity [38]. The subjective norm in this study is the perceived social pressure to use Phablets. (2) The social component is an individual's internalization of the subjective culture of the social system and specific interpersonal agreements that the individual has established with others in a specific social circumstance [39]. (3) Image: the degree to which an individual recognizes that the use of an innovative technology can improve an individual's position in his or her social structure [40]. Based on the preceding literature analysis, the behavioral intention can predict the use of an innovative product.

The extant body of literature indicates that the role of social influence varies across many technological environments. The significance of social influence has been demonstrated in the adoption of various technologies, such as mobile learning tools [27], food delivery apps [26], and educational metaverse platforms [25, 30]. However, in the specific context of basketball learning through metaverse technology and the teachers use E-Government services with social influence was found to be insignificant [28, 29]. Significantly, the studies conducted by Khalil et al. [30] and Teng et al. [25] provide support for the beneficial impact of social influence on promoting the utilization of educational metaverse platforms.

Facilitating Conditions

The degree to which a person thinks that an organization and a technological infrastructure exist to enable the use of a system is known as the enabling conditions construct. According to Venkatesh et al. [12], is described as "the extent to which an individual believes that an organization and technical infrastructure exists to support the use of the system." The concept of facilitating conditions combines elements from several foundational theories, including Theory of Planned Behavior (TPB), Combined TAM and TPB (CTAMTPB), Model of PC Utilization (MPCU), and Innovation Diffusion Theory (IDT). These theories incorporate constructs such as compatibility, perceived behavioral control, and facilitating conditions to shape the overarching facilitating conditions construct. The intention to use is directly positively influenced by facilitating situations, although the impact is marginal after the initial usage. As a result, according to the paradigm [12], enabling factors directly and significantly affect usage behavior.

The available literature presents varying perspectives. The influence of facilitating conditions on the adoption of mobile learning tools [27] and educational metaverse platforms [25] has been observed. However, their significance has not been established in the context of food delivery apps [26] or basketball learning through metaverse technology

[28] or teachers utilize mobile internet for educational uses [41]. In their study, Teng et al. [25] observed a favorable relationship between conducive conditions and the behavioral intention to utilize educational metaverse systems. The divergent outcomes observed in various technological industries underscore the possible influence of contextual factors on facilitating settings.

Hedonic Motivation

Venkatesh et al. [12] defined Hedonic Motivation as the joy experienced following the adoption of a technology. According to Syed and Kabir [27], it illustrates how learners view cell phones as interesting and appealing for instructional purposes. According to motivation theory, Hedonic Motivation is essential in influencing consumers' adoption of technology [42]. In addition, Numerous previous empirical studies have demonstrated that hedonic experiences and qualities will affect the acceptability of consumer technology from both individual and organizational settings, comparable to the flow theory [38] In other words, adopting a technological product like a Phablet increases a person's likelihood of engaging in exploratory activities.

The current body of research presents a varied perspective on the influence of hedonic motivation in relation to various technologies. The impact of hedonic motivation on the inclination to utilize mobile internet in the teaching profession [41] and mobile learning tools [27] has been observed to be significant. However, it has been determined that hedonic motivation does not play a critical role in the domain of basketball learning through metaverse technology [28] or food delivery applications [26]. The observed variance indicates that hedonic motives, which encompass the delight or pleasure obtained from the technology, can have a context-dependent influence on behavioral intention.

Price Value

The pricing value is the other component in the UTAUT2 theory that is utilized to describe the behavioral intention to use. Price value describes how consumers make cognitive trade-offs between the costs associated with utilizing a certain technology and the advantages they believe it will provide. According to the UTAUT2 theory, the price value includes the quality, cost, and price that are most likely to have an impact on a user's decision to employ a certain technology [43]. As a result, in the study of the adoption of massive open online course (MOOC) usage, the user's intention to use would be impacted by their assessment of the quality of learning achieved through the programs in comparison to the cost of supporting infrastructure, such as the internet, computers, and cost of the education programs [44]. Due to the significance of learning outcomes in young people's assessments of the quality of life, these elements are crucial when making personal educational decisions and learning goals [45].

The current collection of literature presents diverse viewpoints regarding the significance of pricing value within various technological contexts. The influence of perceived price value on the adoption of e-Government services [29] and mobile learning tools [27] has been extensively studied. However, its significance as a primary factor has not been identified in relation to metaverse prospects [46], teachers' utilization of mobile internet [41], or the usage of food delivery apps [26]. The presence of this contradiction implies that the assessment of value in relation to cost, also known as price value, might vary in its impact depending on the particular technology and its intended use.

Relative Advantage

According to Rogers [33] definition of relative advantage, it "is the extent to which an individual considers an innovative technology to be preferable than the precedent to that innovation" [47]. According to Chen et al. [48], the most important element influencing current users' acceptance of mobile payments is relative advantage. Accessibility, availability, and quickness are all advantages that mobile payment services have over other conventional payment methods [49].

The extant of literature across various sectors strongly supports the idea that perceived relative advantage influences technology adoption. Various studies have examined a range of topics, including Islamic credit cards [50], Islamic banks [51], halal meat supply chains [52], e-paper products [53], and social media marketing [54]. These studies have consistently demonstrated that the perception of a relative advantage, characterized by factors such as enhanced convenience, improved features, or more favorable outcomes, exerts a significant influence on individuals' behavioral intentions to adopt a particular technology. The concept presents a tempting avenue for future research in the field of Metaverse systems, as it highlights the consistent positive impact of relative advantage across different domains.

Compatibility

According to Nadile et al. [55], comfort is defined as the degree of ease students feel around their peers, instructors, and course materials. The concept of comfortability has been expanded to include using a specific system as well [56, 57], as well as with environmental changes [58]. For instance, Silva et al. [59] studied whether people would revert to previous behavior's after COVID-19. This featured the concept of online education, including whether it is a long-term answer to student learning or whether people will switch back to conventional means of learning because of its unique features. According to Arain et al. [60], people are more likely to continue utilizing technology if they feel comfortable doing so. Accordingly, the current study makes the case that students' BI will probably grow after COVID-19 when they resume face-to-face mode of study based on the amount of comfort they experienced with the system during the epidemic.

The existing literature overwhelmingly corroborates the significance of compatibility in shaping the adoption of technology across many sectors. Previous research has examined various topics such as Islamic credit cards [50], IoT [61], halal meat supply chains [52], Islamic banks [51], and social media marketing [54]. These studies have consistently demonstrated that the level of compatibility between technology and individuals' existing practices, values, or needs plays a crucial role in shaping their behavioral intentions to adopt the technology. However, a study conducted by Sholahuddin et al. [53] did not identify compatibility as a significant issue in relation to e-paper products.

Complexity

The existing field of research presents varied perspectives on the influence of complexity in technology adoption. Complexity, defined as the perceived level of difficulty in understanding and using a new technology, has been shown to impact behavioral intention differently across various sectors. For instance, studies in Islamic banking [51], Islamic credit cards [50], and e-paper products [53] have indicated that complexity may not significantly affect users' intentions to adopt these technologies. In contrast, research by Qader et al. [52] on halal meat supply chains and Farajnezhad et al. [54] on social media marketing found that complexity can indeed serve as a barrier, with higher perceived complexity detrimentally impacting the intention to use the technology.

These mixed findings suggest that the impact of complexity on adoption may be context dependent. In the case of Metaverse technologies, which often involve complex interfaces and novel interaction methods, understanding how complexity influences user intention is crucial. Our study examines whether complexity similarly hinders behavioral intention in Metaverse adoption among students, particularly in contexts where the technology may initially feel unfamiliar or challenging to navigate.

Trialability

According to the trialability construct, innovations are absorbed and assimilated more readily the more a customer may test them out in small doses [62]. Adopters are more likely to use and be inspired to adopt new technology during the early stages if they feel that they can experiment with and investigate it individually [63]. However, prior technological studies have demonstrated that trialability has a favorable impact on adoption.

Scholarly literature presents varying outcomes concerning the significance of trialability, which refers to the degree to which a technology may be tested prior to making a commitment, in the process of technology adoption. Previous research conducted by Jamshidi and Kazemi [50] examined the impact of Islamic credit cards on consumer behavior, while Sholahuddin et al. [53] investigated the adoption of e-paper products. Additionally, Yang Lu [61] explored the adoption of Internet of Things (IoT) technologies, while Ouaddi Rachid et al. [51] examined the behavior of customers towards Islamic banks. However, none of these studies found trialability to have a significant effect on behavioral intentions. On the other hand, a study conducted by Farajnezhad et al. [54] in the field of social media marketing provided evidence in support of the idea that trialability does really exert a favorable influence on the adoption process.

Observability

Observability refers to the extent to which the outcomes of an innovation are discernible to those who adopt it. The adoptability of an innovation is enhanced when there are discernible beneficial outcomes resulting from its deployment [64].

The existing studies offer a rather divergent perspective regarding the significance of observability in the process of technological adoption. The concept of observability, which refers to the degree to which the outcomes of utilizing a particular technology are discernible to external observers, has been identified as a noteworthy determinant in various domains, including e-paper products [53], Islamic banks [51], and social media marketing [54]. In contrast, recent scholarly investigation conducted by Jamshidi and Kazemi [50] revealed that observability not identified as a significant determinant in shaping behavioral intention within the context of Islamic credit cards.

Research Hypotheses

Based on reviewed literature, a set of hypotheses is proposed by Author's to explore the factors influencing the intention to use Metaverse systems:

H1 Performance expectancy will positively influence behavioral intention to use Metaverse systems.

H2 Effort expectancy will positively influence behavioral intention to use Metaverse systems.

H3 Social influence will positively influence behavioral intention to use Metaverse systems.

H4 Facilitating conditions will positively influence behavioral intention to use Metaverse systems.

H5 Hedonic motivation will positively influence behavioral intention to use Metaverse systems.

H6 Price value will positively influence behavioral intention to use Metaverse systems.

H7 Relative advantage will positively influence behavioral intention to use Metaverse systems.

H8 Compatibility will positively influence behavioral intention to use Metaverse systems.

H9 Complexity will negatively influence behavioral intention to use Metaverse systems.

H10 Trialability will positively influence behavioral intention to use Metaverse systems.

H11 Observability will positively influence behavioral intention to use Metaverse systems.

Each hypothesis proposed offers a unique opportunity to advance understanding of factors that influence adoption and use of Metaverse systems. By examining elements like performance expectancy, effort expectancy, social influence, and facilitating conditions, this study aims to shed light on diverse aspects that impact users' intentions and actual behaviors. Hypotheses addressing hedonic motivation, price value, and habit further contribute to identifying motivational and contextual factors that enhance user engagement with Metaverse technologies. Additionally, insights from behavioral intention and actual use will deepen comprehension of how these variables interact within educational and professional domains. Exploring these hypotheses collectively allows for a comprehensive view of Metaverse adoption, fostering a foundation for future research to build upon and adapt to the evolving technological landscape.

Related Work

Table 1 presents a comprehensive summary of prior scholarly investigations pertaining to diverse independent variables that influence adoption of technology. Table 1 categorizes studies based on their examination of independent variables like Performance Expectancy, Effort Expectancy, and Social Influence, among other factors. Table 1 provides additional details regarding the specific domains of application, encompassing a wide range of areas such as educational settings utilizing metaverse technology, Islamic finance, and social media marketing. In addition, it provides an overview of whether the independent factors were determined to have a substantial impact on Behavioral Intention (BI) in each respective scenario.

Research Method

Objective

The main aim of this study is to investigate the willingness of Engineering and Computer Science students to use Metaverse systems through a proposed model that uniquely combines constructs from the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) and the Diffusion of Innovations (DOI), an integration not previously explored in studies on Metaverse adoption [11]. This research employs a multi-analytical approach, conducted in three phases: validating the model using Partial Least Squares Structural Equation Modeling (PLS-SEM) [16, 65], developing a predictive model using machine learning to estimate Behavioral Intention (BI) for new students, and conducting Network Analysis to uncover relational patterns.

Each method offers distinct advantages and complements the other phases. PLS-SEM was chosen for its strength in validating complex models and measuring relationships between latent variables, which is essential for testing the proposed theoretical constructs [66]. Machine learning is utilized to develop a predictive model that can estimate Behavioral Intention for future student populations without reapplying PLS-SEM, making it practical and scalable [67]. Finally, Network Analysis is applied to explore relational patterns among variables, revealing interconnected structures that might not be evident through traditional statistical methods [68]. Together, these methods provide a multi-faceted analysis, enhancing the depth and robustness of the findings, and offering valuable insights into students' behavioral intention toward Metaverse adoption [16, 65, 69].

Table 1 Summarizes some of the previous studies' results for independent variables

No.	Independent	Domains	Support-BI	Reference	Advantages / Disadvantages
1.	Performance Expectancy	Metaverse technology for basketball learning	Not supported	[28]	Limited in contexts requiring physical interaction
		Food Delivery Apps	Supported	[26]	Useful in convenience and service-oriented apps
		Mobile Learning Tool	Supported	[27]	Promotes quick adoption and ease of use
		E-Government Services	Not supported	[29]	Limited effectiveness in highly structured environments
		Educational Metaverse	Supported	[30]	Enhances user engagement in educational applications
		Educational Metaverse	Supported	[25]	Effective in learning environments with interactivity
2.	Effort Expectancy	metaverse technology for basketball learning	Not supported	[28]	Limited in complex, skill-based applications
		Food Delivery Apps	Not supported	[26]	Effectiveness decreases in convenience-driven domains
		Mobile Learning Tool	Supported	[27]	Facilitates easy adoption in tech-based education
		E-Government Services	Supported	[29]	Helpful in tech adoption for straightforward applications
		IoT	Supported	[61]	Significant for ease of use in smart tech
		Educational Metaverse	Supported	[30]	Effective in educational applications for easy access
		Educational Metaverse	Supported	[25]	Works well in accessible, interactive learning settings
3.	Social Influence	metaverse technology for basketball learning	Not supported	[28]	Limited in individual-focused domains
		E-Government Services	Not supported	[29]	Low influence on individual government service adoption
		Mobile Learning Tool	Supported	[27]	Helps promote adoption in social or peer-driven platforms
		Food Delivery Apps	Supported	[26]	Strong effect in collaborative, tech-enhanced education
		Educational Metaverse	Supported	[30]	High relevance in social-based learning environments
		Educational Metaverse	Supported	[25]	Beneficial for environments with supportive infrastructure
4.	Facilitating Conditions	metaverse technology for basketball learning	Not supported	[28]	Limited where infrastructure is lacking
		E-Government Services	Not supported	[29]	Low effectiveness without adequate resources
		Teachers Use Mobile Internet	Not supported	[41]	Limited impact in constrained teaching environments
		Food Delivery Apps	Not supported	[26]	Low impact where limited technical support is available
		Mobile Learning Tool	Supported	[27]	Helps with easy tech adoption if resources available
		Educational Metaverse	Supported	[25]	Enhances adoption in resource-supported learning
5.	Hedonic Motivation	metaverse technology for basketball learning	Not supported	[28]	Limited in purely functional applications
		Teachers Use Mobile Internet	Supported	[41]	High effectiveness in engaging users through fun elements
		Mobile Learning Tool	Supported	[27]	Enhances motivation in gamified learning tools
		Food Delivery Apps	Not supported	[26]	Low influence on adoption in service-oriented apps
6.	Price Value	Metaverse Prospects	Not supported	[46]	Limited impact when cost is not a primary concern
		E-Government Services	Supported	[29]	Relevant for value-driven government services
		Teachers Use Mobile Internet	Not supported	[41]	Low impact where pricing is not a decisive factor
		Mobile Learning Tool	Supported	[27]	Promotes adoption when perceived value is high
		Food Delivery Apps	Not supported	[26]	Limited relevance in low-cost applications
7.	Relative Advantage	Islamic credit card	supported	[50]	Promotes adoption in finance, convenience-driven sectors
		Islamic bank	Supported	[51]	Highly effective in financial services
		halal meat supply chain	Supported	[52]	Effective in supply chain efficiency improvements
		E-Paper Product	Supported	[53]	High relevance in tech-based product adoption
		Social media marketing	Supported	[54]	Promotes advantages in fast-paced, interactive platforms

Table 1 (continued)

No.	Independent	Domains	Support-BI	Reference	Advantages / Disadvantages
8.	Compatibility	Islamic credit card	Supported	[50]	Encourages adoption in aligned technology applications
		E-Paper Product	Not supported	[53]	Low compatibility perception limits adoption
		IoT	Supported	[61]	High relevance in technology-driven ecosystems
		halal meat supply chain	Supported	[52]	Promotes alignment in supply chain applications
		Islamic bank	Supported	[51]	Enhances alignment in finance sector adoption
		Social media marketing	Supported	[54]	Effective in marketing, aligns with user tech preferences
9.	Complexity	Islamic credit card	Not supported	[50]	High complexity may hinder adoption
		Islamic bank	Not supported	[51]	Complexity limits appeal in finance-related tech
		halal meat supply chain	Supported	[52]	Effective when complexity is manageable
		E-Paper Product	Not supported	[53]	High complexity reduces product appeal
		Social media marketing	Supported	[54]	Works in fast-paced, adaptive platforms
10.	Trialability	Islamic credit card	Not supported	[50]	Limited impact if trialability is not feasible
		E-Paper Product	Not supported	[53]	Low trialability may reduce adoption
		IoT	Not supported	[61]	Complex systems may limit trialability
		Islamic bank	Not supported	[51]	Not effective where trials are impractical
		Social media marketing	Supported	[54]	Effective in low-risk, trial-based services
11.	Observability	Islamic credit card	Not supported	[50]	Low impact if tech benefits are not visible
		E-Paper Product	Supported	[53]	High observability aids in promoting tech awareness
		Islamic bank	Supported	[51]	Effective in services where results are visible
		Social media marketing	Supported	[54]	Helps boost adoption by making benefits observable

Theoretical Framework

A study combines between Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) and Diffusion of Innovations (DOI) theoretical frameworks to examine the Behavioral Intention (BI) of students toward Metaverse systems. The independent variables under UTAUT2 framework are (Performance Expectancy (UTPE), Effort Expectancy (UTEE), Social Influence (UTSI), Facilitating Conditions (UTFC), Hedonic Motivation (UTHM), and Price Value (UTPV)). However, DOI model includes also independent variables like: Relative Advantage (DORA), Compatibility (DOCB), Complexity (DOCP), Trialability (DOTB), and Observability (DOOB). These constructs work together as independent predictors whereas the study's dependent variable is Behavioral Intention (BI). The theoretical framework is depicted graphically in Fig. 1, which shows variables' interrelationships.

Data Collection

From 1-May to 30-August 2023, data collection was conducted among students enrolled in Engineering and Computer Science programs at two private universities in the United Arab Emirates (UAE). The sampling approach utilized a class-based recruitment strategy, leveraging the cooperation of lecturers in the relevant fields to ensure direct access to the target demographic through online survey (Limesurvey). This method enhanced the precision of the model and aligned with the study's emphasis on fields characterized by a high adoption rate of emerging technologies.

The survey instrument comprised 42 questions designed to gather comprehensive demographic data (age, gender, education level, and area of specialization) and technology-related attributes. Constructs from the UTAUT2 and DOI models were operationalized using three questions per construct to ensure a multidimensional exploration of participant responses. Following expert recommendations, "Habit" was excluded from the UTAUT2 construct suite, and specific equations were refined to enhance the survey's methodological rigor and clarity.

To standardize participant understanding of the Metaverse and its educational applications, an introductory video was shown to all respondents before they engaged with the survey. Participation was voluntary, with strict anonymity protocols in place to protect respondent privacy, and individuals were given the option to withdraw at any point without penalty.

A total of 420 responses were initially gathered. A rigorous data cleaning process—focused on identifying and addressing missing data, inconsistencies, and outliers—resulted in the validation of 380 complete and high-quality responses for subsequent analysis. This structured and methodical approach ensured the reliability and robustness of the dataset used for the study.

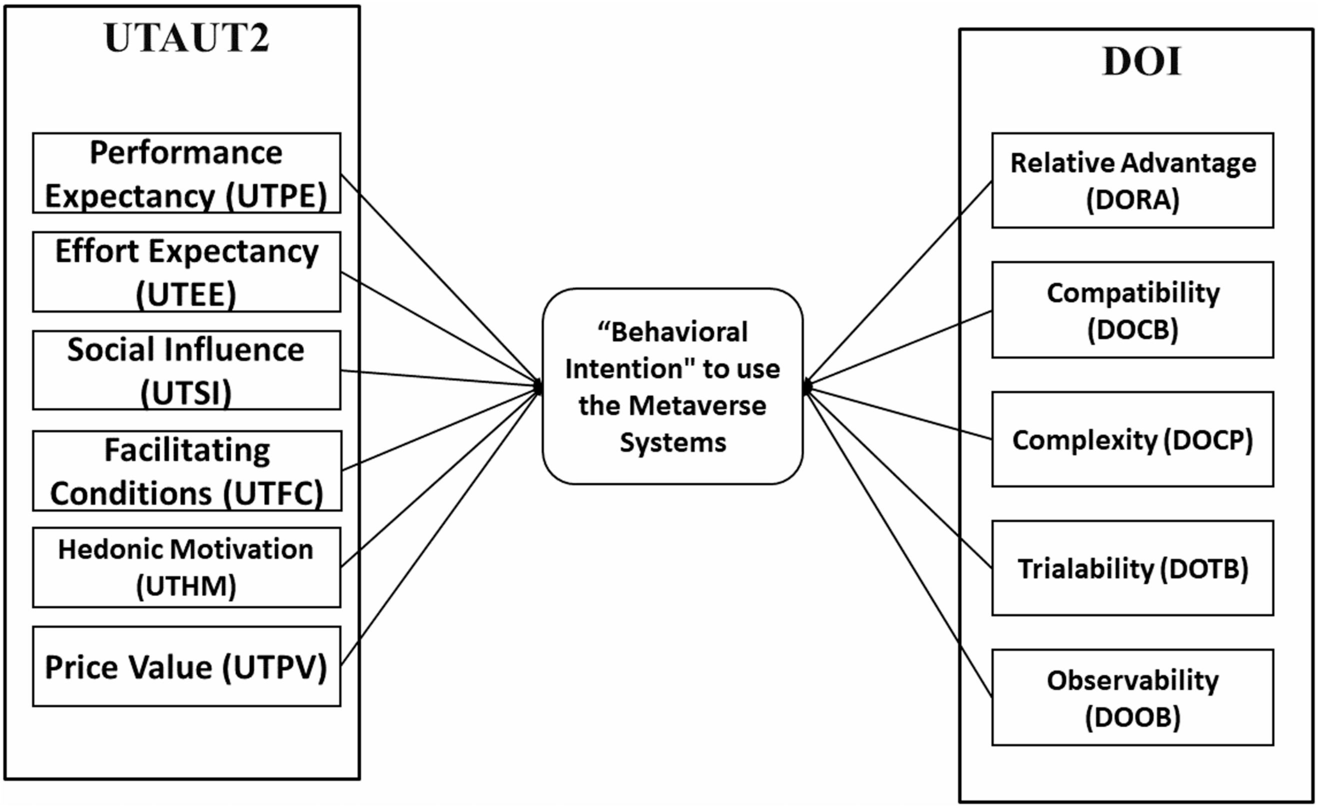


Fig. 1 Theoretical Framework

Experimental Setup and Control Variables

To control the factors and ensure the reliability of the responses, the study designed certain conditions. First, only Engineering and Computer Science students were recruited for the survey to keep academic background as uniform as possible. Second, each student was exposed to the same set of introductory videos about the notion of the Metaverse prior to the survey, which served to ensure that all the respondents had the same level of initial knowledge of the theme of the questionnaire and that there was no considerable interference due to the varying levels of initial knowledge.

Data Processing and Analysis

The responses to the survey questionnaires were scrutinized for missing information, consistency and outliers. If responses were flagged as incomplete, they were deleted to optimize the quality of the analysis. The first phase of analysis utilized PLS-SEM to validate the relationships between UTAUT2 and DOI constructs and their impact on Behavioral Intention. This in turn helped ascertain whether the developed and proposed model had the structural validity to effectively predict the BI toward the use of Metaverse by students.

Following PLS-SEM validation, a machine learning model was developed to enable BI prediction for new student responses. This model allows for practical application by making predictions based on new students survey data, eliminating the need to reapply PLS-SEM. Various classifiers, like (Linear Discriminant Analysis, Logistic Regression, Naive Bayes, Support Vector Machines, Decision Trees, AdaBoost, Gradient Boosting, Extra Trees, Random Forest, K-Nearest Neighbors, and a baseline Dummy classifier), were evaluated to determine a best classifier fit for predicting BI. Each classifier's performance was assessed using metrics like Accuracy, Precision, Recall, F-Measure, and ROC AUC to ensure reliable BI prediction.

In addition to PLS-SEM and machine learning, Network Analysis was employed to explore a relational dynamic among a study variable. Network Analysis uses graph theory to map the structural relationships between independent variables and dependent variable, allowing for the visualization and examination of interactions that may not be evident through traditional statistical or machine learning approaches. This analysis identifies clusters and influential nodes within the network that could impact Behavioral Intention, providing valuable insights into complex system dynamics and revealing relational structures beyond what PLS-SEM and ML methods alone can achieve. Together, PLS-SEM provides structural validation, machine learning facilitates BI prediction, and Network Analysis illuminates underlying network relationships.

Data Analysis

This study integrates three analytical approaches to examine Behavioral Intention (BI) toward Metaverse Systems:

- PLS-SEM: Conducted with SmartPLS software (version 4.0.5.9), PLS-SEM validates the structural relationships among UTAUT2 and DOI constructs, confirming the model's predictive integrity for BI.
- Machine Learning: Multiple classifiers were implemented in Python to predict BI in new student responses. Classifier performance was assessed through metrics like Accuracy, Precision, and ROC AUC, ensuring reliable predictions without reapplying PLS-SEM.
- Network Analysis: Using NetworkX in Python, network analysis explores hidden relationships among variables, revealing patterns and influential nodes that enrich understanding of factors shaping BI.

A multi-method approach combines structural validation, predictive modeling, and relational analysis to provide a robust, comprehensive view of student engagement with Metaverse Systems.

Demographic Analysis and Relevance

It can be inferred from Fig. 2 that the greatest percentage of respondents to the survey were male (71.3%) aged between 20 and 24 years (64.2%) with the majority enrolled in bachelor's degree programs (85.3%). A large portion of the subjects (66.6%) described themselves as a beginner user of comparable virtual technologies, though a significant proportion (85.26%) had some degree of prior knowledge with such technologies. These distributions are represented in visual forms like bar charts to provide a contextual framework for understanding the predictive relevance of the models in a sample that is both novice-leaning and tech-affiliated. This specific demographic profile enables a deeper understanding of the importance and possible use

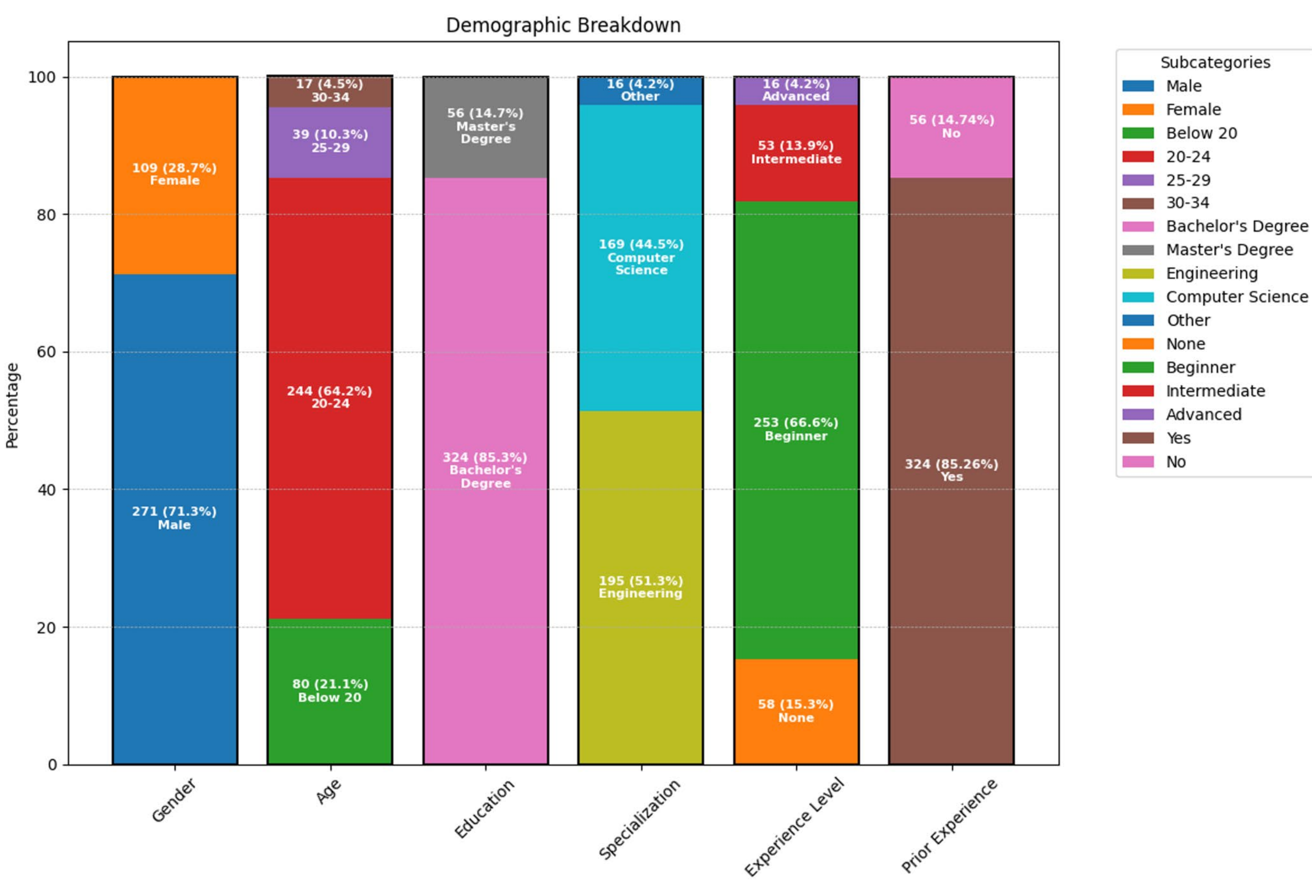


Fig. 2 Demographic Data

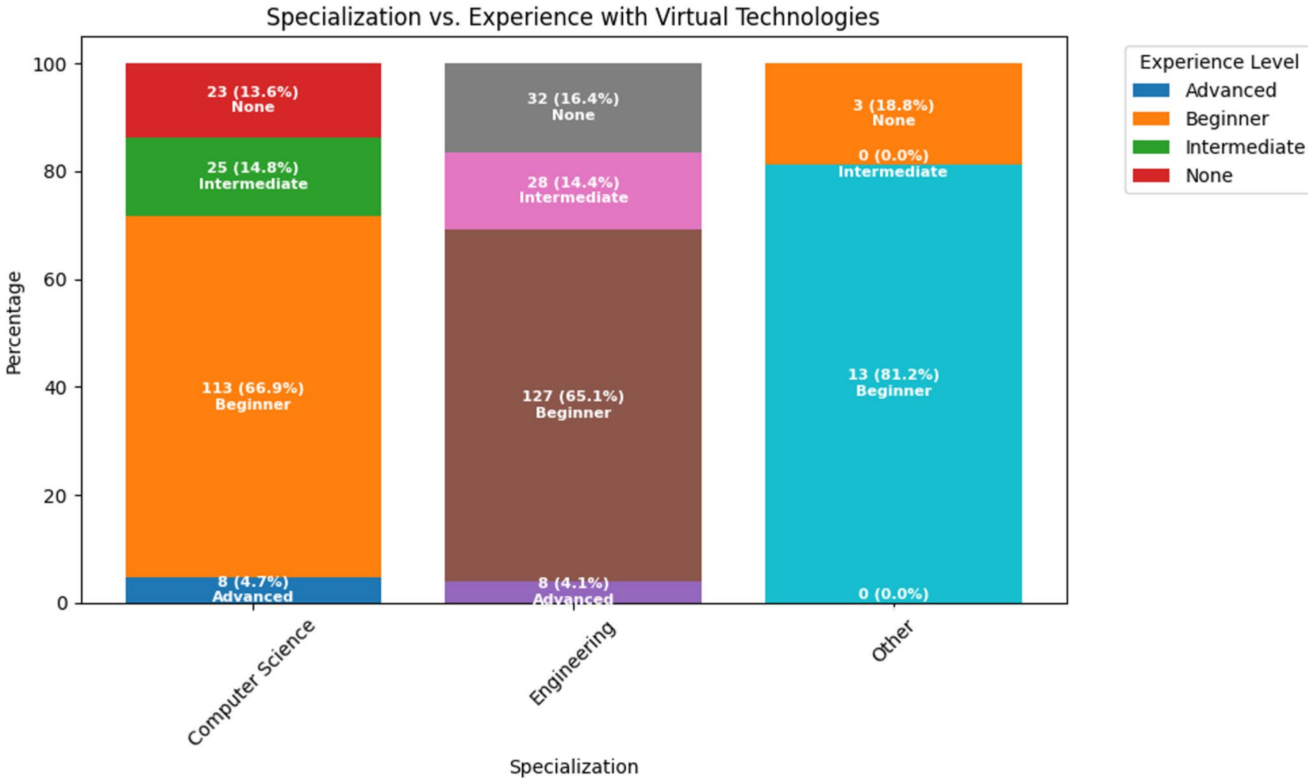


Fig. 3 Cross-Tabulation Analysis

cases of the study with respect to the adoption of the Metaverse for other similar student cohorts.

Cross-Tabulation Analysis

The Cross-Tabulation Analysis presented in Fig. 3 examines the relationship between specialization (Computer Science vs. Engineering) and experience with virtual technologies to identify potential differences in familiarity with virtual environments between these groups. The results reveal that both groups are predominantly beginners in virtual technologies, with 66.86% of Computer Science students and 65.13% of Engineering students falling into this category. However, Computer Science students show a slightly higher proportion in the "Intermediate" category (14.79%) compared to Engineering students (14.36%), and a lower percentage with no experience (13.61% vs. 16.41%). Advanced familiarity remains low in both groups (4.73% for Computer Science and 4.10% for Engineering). These patterns suggest a comparable familiarity with virtual environments across both specializations, but with a marginally higher exposure among Computer Science students. This insight contextualizes differences in Behavioral Intention, as students with more exposure may exhibit greater openness to Metaverse adoption, supporting the relevance of targeted strategies in the model for these demographics.

Table 2 Reliability and validity analysis

	Cronbach's alpha	(rho_a)	(rho_c)	(AVE)	F-Square
Behavioral Intention	0.943	0.943	0.963	0.897	
Compatibility	0.835	0.839	0.901	0.752	1.919
Complexity	0.74	0.744	0.852	0.658	0.915
Effort Expectancy	0.75	0.751	0.857	0.667	1.064
Facilitating Conditions	0.803	0.829	0.883	0.715	0.773
Hedonic Motivation	0.9	0.934	0.936	0.831	0.011
Observability	0.719	0.722	0.842	0.64	1.546
Performance Expectancy	0.805	0.847	0.883	0.716	1.172
Price Value	0.907	0.985	0.937	0.832	0.001
Relative Advantage	0.78	0.8	0.871	0.692	1.266
Social Influence	0.864	0.866	0.917	0.786	0.923
Trialability	0.909	0.992	0.93	0.817	0.000

Partial Least Squares-Structural Equation Modeling (PLS-SEM) Analysis

Reliability Analysis

Table 2 provides a comprehensive and up-to-date assessment of internal consistency and reliability across multiple dimensions, with particular emphasis on Behavioral Intention (BI). The revised study yielded Cronbach's Alpha values that varied among the constructs, with Observability exhibiting the lowest value of 0.719 and Behavioral Intention demonstrating the highest value of 0.943. The Cronbach's Alpha values for all constructs in the study surpass the commonly accepted criterion of 0.7, therefore confirming the internal consistency and reliability of the constructs [70, 71]. Furthermore, the study demonstrates a range of Composite Reliability (rho_a) values, varying from 0.722 for Observability to 0.985 for Price Value. It is worth noting that all these values surpass the widely acknowledged threshold of 0.7, which is usually accepted in the field. This provides evidence for the dependability of the structures and acts as an extra level of verification. The research paper also presents an additional aspect of composite reliability, referred to as rho_c, which exhibits a range of values from 0.842 for Observability to 0.963 for Behavioral Intention. The inclusion of this additional measure enhances the support for the internal consistency and reliability of the scale. When combined with the utilization of Cronbach's Alpha and rho_a, it provides a thorough assessment of the strength and stability of the constructs. It is worth mentioning that there is a notable tendency where the values of rho_c tend to be greater than the comparable values of rho_a for the majority of constructs. The citation references indicate that the scales employed possess qualities that demonstrate stability and reliability. Consequently, these findings provide more evidence in favor of the constructs' validity as dependable measures [72, 73].

Convergent Validity Assessment

The Average Variance Extracted (AVE) is an essential diagnostic tool in the field of structural equation modeling. It serves as a crucial benchmark for evaluating the convergent validity of the constructs incorporated in the model. Convergent validity assesses the extent to which variables or constructs that are conceptually connected have strong correlations inside a specific model. In more accessible language, the Average Variance Extracted (AVE) is a metric used to assess the extent to which the observed variables accurately reflect the latent constructs they are intended to measure. A higher AVE value indicates a higher level of construct quality or reliability. To ensure robust convergent validity, it is advisable to have an Average Variance Extracted (AVE) value that is equal to or exceeds 0.5 [74]. This threshold indicates that a majority of the observed variance may be ascribed to the construct under consideration, rather than to random error. Remarkably, Table 2 presents an investigation that reveals that all structures surpass this standard. One example of note is the construct of Behavioral Intention (BI), which has a significantly high Average Variance Extracted (AVE) value of 0.897. This finding provides substantial evidence for the robust convergent validity of BI. The components derived from both the Diffusion of Innovations (DOI) and Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) frameworks have strong Average Variance Extracted (AVE) values. The observed values for the variables in the model exhibit a range, with Observability having the lowest value of 0.64 and Price Value having the highest value of 0.832. This range of values serves to emphasize the model's comprehensive reliability and validity. The substantial AVE values reported across the constructs provide strong evidence that the measured variables effectively capture the underlying latent constructs. The model's constant performance provides more evidence supporting its integrity and enhances the overall methodological rigor of the investigation.

Table 3 R-Square and Q^2 predict

	R-square	*R*-square adjusted	Q^2predict	RMSE	MAE
Behavioral Intention	0.906	0.904	0.899	0.319	0.263

Model Fit Assessment

The R-Square and Adjusted R-Square values presented in Table 3 demonstrate a high level of goodness-of-fit for the model, with values of 0.906 and 0.904, respectively. The R-Square value of 0.906 indicates that the model explains almost 90.6% of the variability in Behavioral Intention, demonstrating a high level of prediction accuracy [74]. The model's validity is further enhanced by the Adjusted R-Square score of 0.904, which incorporates the model's complexity by considering the number of predictors. The high degree of concordance between the R-Square and the Adjusted R-Square, differing by a mere 0.002, suggests that the incorporation of multiple predictors derived from both the UTAUT2, and DOI theories is well-founded. The strong alignment ensures that the model's intricacy improves its capacity for explanation without incurring the potential drawback of overfitting. The high and closely aligned values of R-Square and Adjusted R-Square provide convincing evidence for the model's robustness and appropriateness in investigating Behavioral Intention within the unique setting of this study.

The model's performance is further supported by the Q^2 Predict, RMSE, and MAE values, in addition to the high R-Square and Adjusted R-Square values. The high predictive ability under the Q^2 Predict value of 0.899 also confirms the claim of the model exhibiting strong out-of-sample predictive accuracy. A Q^2 value close to 1 signifies that the model reliably predicts Behavioral Intention even on new or unseen data, which enhances the robustness of the model beyond mere explanatory power.

The Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) provide further justification for the model's prediction accuracy. The low RMSE of 0.319 and 0.263 MAE suggest that the model's predictions are very close to the actual value due to lower error margins. Both RMSE which is the average value of deviations of the prediction from the actual values, and MAE which is the average of absolute values of the deviations further assure one of the accuracies of the model. All these values put together support the model's contention that it not only explains Behavioral Intention but also can predict it with accuracy making the model appropriate and useful in the context of the study.

Effect Size Estimation

The F-square values provide valuable insights into the extent of influence that each independent variable has on the dependent variable, Behavioral Intention. The F-square values presented in Table 2 exhibit a diverse range of influence across multiple parameters [75]. For example, the components of Compatibility (1.919), Effort Expectancy (1.064), and Performance Expectancy (1.172) exhibit significant influences on Behavioral Intention, suggesting that these variables should be prioritized in treatments or future research within the specific context. In contrast, the F-square values for Hedonic Motivation (0.011) and Price Value (0.001) are notably low, indicating that they may not hold significant importance influencing Behavioral Intention within strategic approaches. It is noteworthy that Trialability exhibits an F-square value of 0, suggesting that this variable may have minimal or insignificant influence on Behavioral Intention within the specified context. The aggregate range of these F-square values provides substantial evidence for the strength, dependability, and precision of the structural equation modeling (SEM) utilized in the study. The results of this study provide valuable insights into the diverse levels of influence that these elements exert on Behavioral Intention. Consequently, these findings can assist in determining the order of importance of variables for subsequent research endeavors and interventions.

Indicator Validity

The information pertaining to the Outer Loadings, which are a crucial indicator of the extent to which latent variables are associated with their observable indicators, is presented in Table 4. The findings of this research indicate that all Outer Loadings above the required threshold of 0.7, so confirming their statistical significance and strengthening the validity of the relationships between the latent constructs and their observed indicators [74]. For example, certain indicators, including DOCP2 and UTPV3, have significant Outer Loadings of 0.829 and 0.885, respectively, indicating a robust level of construct validity for these particular items. This implies that these indicators have a high level of effectiveness in capturing and quantifying the fundamental characteristics of their corresponding latent components. In a similar vein, additional indicators such as BI1, BI2, and BI3, which pertain to Behavioral Intention, demonstrate exceptional Outer Loadings that span from 0.937 to 0.955. This provides further support for the overall reliability and validity of the model. The presence of high and consistent Outer Loadings across all indicators serves to confirm the operational measurements of the latent variables and strengthens the credibility and interpretative capacity of the structural equation model utilized in the study.

Multicollinearity Check

In relation to the Variance Inflation Factor (VIF) values, the findings of the study in Table 5 indicate that all VIF metrics are considerably lower than the commonly acknowledged threshold of 5 [66] hence indicating that the presence of multicollinearity inside the model is not a substantial concern. This suggests that each predictor variable provides distinct information, allowing for the examination of the independent effects of each variable on the dependent variable. Although the VIF readings are below the threshold of 5.0, they do demonstrate a certain degree of variability. For example, the variables DOTB2 and UTPV2 exhibit the greatest Variance Inflation Factor (VIF) values, measuring at 3.304 and 3.342, respectively. At the lower end of

Table 4 Indicator validity

indicators	Outer loadings	indicators	Outer loadings	indicators	Outer loadings	indicators	Outer loadings
BI1	0.955	DOOB1	0.791	UTEE1	0.822	UTPE1	0.89
BI2	0.937	DOOB2	0.8	UTEE2	0.816	UTPE2	0.82
BI3	0.95	DOOB3	0.809	UTEE3	0.812	UTPE3	0.826
DOCB1	0.861	DORA1	0.799	UTFC1	0.888	UTPV1	0.953
DOCB2	0.875	DORA2	0.83	UTFC2	0.86	UTPV2	0.896
DOCB3	0.865	DORA3	0.865	UTFC3	0.786	UTPV3	0.885
DOCP1	0.821	DOTB1	0.916	UTHM1	0.934	UTSI1	0.881
DOCP2	0.829	DOTB2	0.96	UTHM2	0.914	UTSI2	0.891
DOCP3	0.782	DOTB3	0.831	UTHM3	0.886	UTSI3	0.888

Table 5 Variance inflation factor (VIF)

indicators	VIF	indicators	VIF	indicators	VIF
DOCB1	1.887	DOTB1	2.776	UTPE1	1.796
DOCB2	1.918	DOTB2	3.304	UTPE2	1.811
DOCB3	2.036	DOTB3	3.06	UTPE3	1.646
DOCP1	1.51	UTEE1	1.507	UTPV1	2.748
DOCP2	1.492	UTEE2	1.475	UTPV2	3.342
DOCP3	1.418	UTEE3	1.525	UTPV3	2.967
DOOB1	1.459	UTFC1	1.947	UTSI1	2.139
DOOB2	1.408	UTFC2	1.719	UTSI2	2.386
DOOB3	1.374	UTFC3	1.631	UTSI3	2.189
DORA1	1.571	UTHM1	2.977		
DORA2	1.668	UTHM2	2.758		
DORA3	1.611	UTHM3	2.686		

the spectrum, the VIF values for DOOB3 and DOCP3 are 1.374 and 1.418, respectively. The observed range of values indicates that although there exists a certain degree of connection among some variables, the magnitudes of these correlations are not sufficiently high to undermine the integrity and consistency of the model. It is important to emphasize that the Variance Inflation Factor (VIF) values for all variables exceed 1, indicating a certain degree of correlation among these predictors. However, this correlation does not reach a level that would undermine the different nature of the variables. This finding verifies the lack of troublesome multicollinearity, hence enhancing the model's dependability and validity to a large extent. The results of the Variance Inflation Factor (VIF) analysis provide support for the appropriateness of the selected predictor variables in the research. The model's general dependability and validity are further supported, therefore bolstering the study's methodological rigor.

Discriminant Validity Assessment

The Heterotrait-Monotrait Ratio (HTMT) is a significant diagnostic tool used to examine the discriminant validity of latent variables in a structural equation model. This study serves as a tool for evaluating the uniqueness of constructs derived from the (UTAUT2) and (DOI) theories. Based on contemporary academic recommendations, Table 6 it has been established that an HTMT score that falls much below 0.85 provides strong evidence of discriminant validity, so affirming that the constructs under investigation effectively capture separate theoretical phenomena [28, 70].

Distinct patterns become apparent when examined from the perspective of their respective frameworks. As an illustration, it can be shown that in the UTAUT2 model, Behavioral Intention (BI) exhibits the most robust associations with Facilitating Conditions (0.244) and Effort Expectancy (0.312). This alignment is consistent with the arguments put out by UTAUT2, which emphasize the significance of both

Table 6 The Heterotrait-Monotrait ratio (HTMT)

	1	2	3	4	5	6	7	8	9	10	11	12
1 Behavioral Intention												
2 Compatibility	0.55											
3 Complexity	0.451	0.171										
4 Effort Expectancy	0.312	0.092	0.082									
5 Facilitating Conditions	0.244	0.057	0.049	0.145								
6 Hedonic Motivation	0.055	0.085	0.089	0.042	0.038							
7 Observability	0.458	0.047	0.058	0.078	0.047	0.066						
8 Performance Expectancy	0.365	0.058	0.078	0.066	0.066	0.03	0.054					
9 Price Value	0.036	0.073	0.047	0.049	0.098	0.057	0.075	0.052				
10 Relative Advantage	0.367	0.062	0.042	0.069	0.052	0.053	0.099	0.07	0.064			
11 Social Influence	0.275	0.079	0.053	0.104	0.056	0.048	0.043	0.071	0.048	0.056		
12 Trialability	0.036	0.048	0.066	0.064	0.077	0.124	0.061	0.117	0.061	0.056	0.066	

contextual factors and ease of use in influencing behavior. In contrast, within the DOI framework, Complexity (0.451) and Observability (0.458) have the most significant correlations with Behavioral Intention. This finding supports the idea that individuals' intentions to adopt a particular behavior are influenced by the simplicity of comprehending and the opportunity to observe the advantages associated with that behavior.

The research of HTMT also provides insights into fascinating interplay between different theoretical perspectives. For instance, even though both UTAUT2 and DOI components exhibit significant correlations with Behavioral Intention (BI), their relatively low HTMT values in comparison to one another, such as 0.07, indicate that they are measuring distinct aspects of behavioral intention. Further support for discriminant validity is seen in the presence of low cross-model heterotrait-monotrait (HTMT) values, such as the 0.082 value observed between Effort Expectancy (UTEE) and Complexity (DOCP). This highlights the observation that the dimensions derived from the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) and the Diffusion of Innovation (DOI) theories not only exhibit statistical significance but also provide distinct explanatory depth in enhancing our comprehension of Behavioral Intention. The research conducted on the HTMT (heterotrait-monotrait) ratio reveals that components derived from both the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) and the Diffusion of Innovation (DOI) theories make important contributions to the explanation of Behavioral Intention. Moreover, these constructs possess distinct explanatory capacities, hence reinforcing the argument for the use of these two theoretical frameworks in forthcoming studies.

Hypothesis Testing and Significance

Table 7 provides significant insights into the correlation between each independent variable and the dependent variable, Behavioral Intention (BI). The table comprises several metrics, including Original Sample Estimates (O), Sample Mean (M), Standard Deviation (SD), T-Statistics, and P-values. In general, when the P-values are below 0.05, it indicates a high level of statistical significance. This strengthens the belief that these variables have a significant impact on Behavioral Intention. In addition, it is worth noting that all the hypotheses that have received support have T-statistics that are beyond the traditional threshold of 1.96. This further enhances the statistical significance of these findings, lending them additional confidence.

Upon careful examination of the initial sample estimates (O) and sample means (M), it is observed that there exists a variation in coefficients ranging from 0.009 (Price Value -> BI) to 0.433 (Compatibility -> BI). The coefficients in this analysis serve to quantify the influence of each variable on business intelligence (BI), with greater coefficients indicating stronger effects. Among the predictors examined, Facilitating Conditions (0.273) emerges as the most influential, while Price Value (0.009) exhibits a rather weak impact. The strong correspondence seen between the original sample and sample mean estimations, along with the presence of minimal standard deviations, provides evidence for the dependability and uniformity of these results. This comprehensive analysis enhances our comprehension of the variables influencing Behavioral Intention and lays the groundwork for further focused investigations and practical implementations as shown in Fig. 4.

Machine Learning (Classifier Performance Assessment)

The current study employed a multi-analytical framework that integrates Partial Least Squares Structural Equation Modeling (PLS-SEM) with machine learning (ML) classification techniques. This combined approach enhances the depth of the analysis, offering both validation of structural relationships and predictive capabilities. PLS-SEM is instrumental in examining complex relationships among the UTAUT2 and DOI constructs, assessing their impact on

Table 7 Coefficients paths

H	Relationship	Original sample (O)	Sample mean (M)	SD	T statistics	*P*-values	Coefficients
H1	Performance Expectancy -> Behavioral Intention	0.335	0.333	0.022	15.119	0.00	Supported
H2	Effort Expectancy -> Behavioral Intention	0.32	0.318	0.021	15.512	0.00	Supported
H3	Social Influence -> Behavioral Intention	0.297	0.293	0.022	13.375	0.00	Supported
H4	Facilitating Conditions -> Behavioral Intention	0.273	0.27	0.02	13.907	0.00	Supported
H5	Hedonic Motivation -> Behavioral Intention	-0.032	-0.03	0.018	1.758	0.079	Not Supported
H6	Price Value -> Behavioral Intention	0.009	0.01	0.021	0.43	0.667	Not Supported
H7	Relative Advantage -> Behavioral Intention	0.347	0.343	0.022	15.775	0.00	Supported
H8	Compatibility -> Behavioral Intention	0.433	0.428	0.022	19.598	0.00	Supported
H9	Complexity -> Behavioral Intention	0.298	0.296	0.02	15.056	0.00	Supported
H10	Trialability -> Behavioral Intention	-0.002	-0.001	0.018	0.116	0.907	Not Supported
H11	Observability -> Behavioral Intention	0.383	0.38	0.024	16.029	0.00	Supported

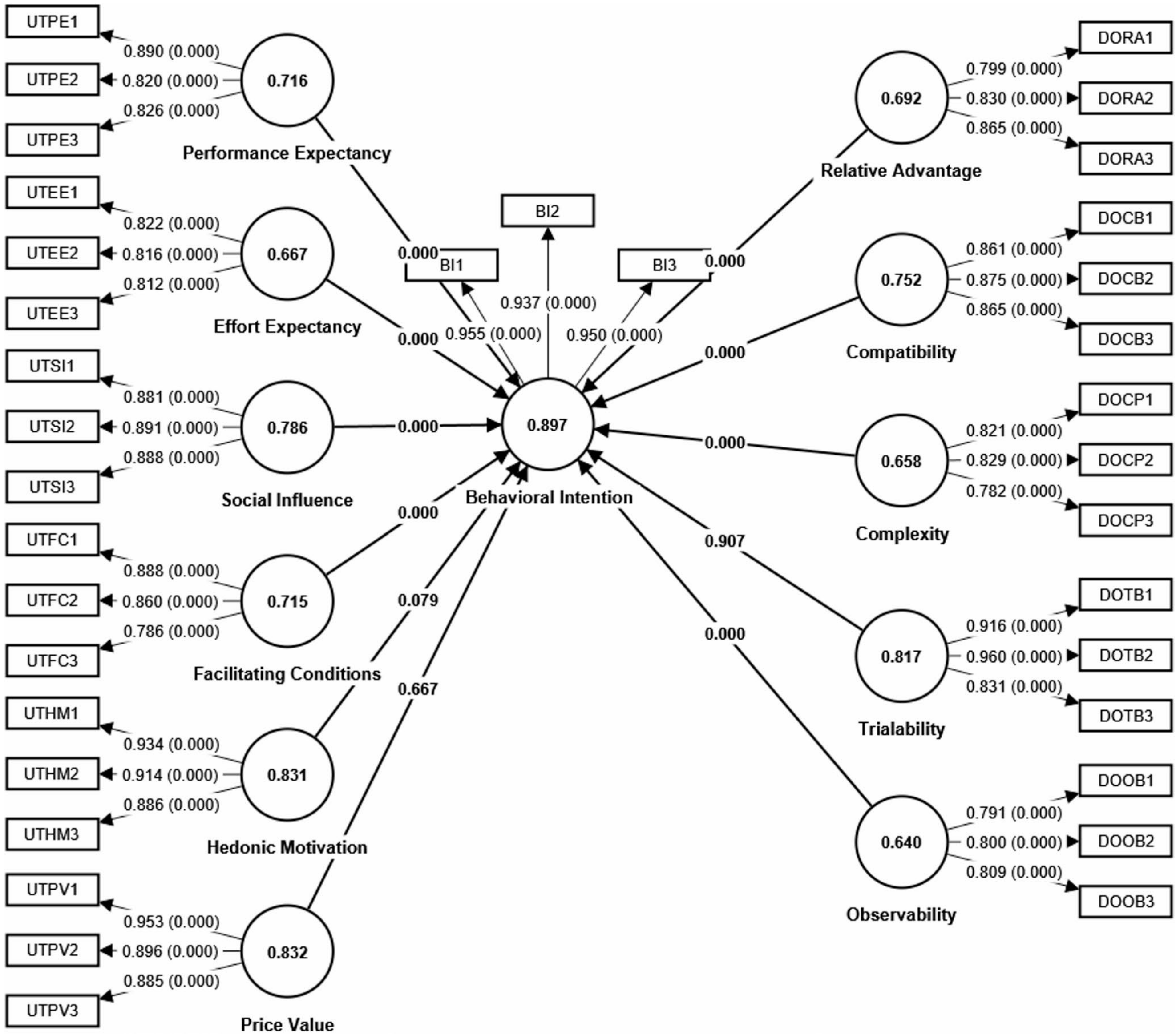


Fig. 4 Bootstrapping for Study Model

students' Behavioral Intention (BI) toward Metaverse Systems [16, 65, 76, 77]. Complementing this, supervised ML classifiers independently predict BI for new student data with high precision, thus strengthening the practical applicability of the model and providing resilience in classification tasks [78]. Together, these methods advance the study's robustness, offering deeper insights into the various factors influencing Metaverse adoption.

The empirical study was conducted using Python, leveraging its rich ecosystem of data science libraries. Scikit-learn was utilized to implement a variety of machine learning classifiers, with Pandas used extensively for data preprocessing and analysis. The primary goal of the ML classifiers was to predict students' "Intention to Use Metaverse Systems" in Engineering and Computer Science fields, where BI was annotations automatically by python code to (Intention$\geq$3 / Not Intention$<$3) based on it values. Classifier performance was rigorously assessed using standard metrics, including Accuracy, Precision, Recall, F-Measure, and ROC AUC, providing a comprehensive evaluation of each model's predictive capabilities as shown in Table 8; Fig. 5.

Each of these metrics was calculated as follows:

- Accuracy: Measures the proportion of correctly classified instances among all instances.

$$\text{Accuracy} = \frac{\text{True Positives} + \text{True Negatives}}{\text{Total Samples}} \tag{1}$$

Table 8 Classifier performance assessment for two class (Intention, not intention) of behavioral intention

Classifier	Accuracy	Precision	Recall	F-Measure	ROC AUC
Linear Discriminant	0.882	0.880	0.882	0.881	0.956
Logistic Regression	0.882	0.880	0.882	0.879	0.964
SVM	0.868	0.877	0.868	0.859	0.941
AdaBoost	0.842	0.838	0.842	0.837	0.842
Random Forest	0.816	0.821	0.816	0.798	0.904
Gradient Boosting	0.789	0.782	0.789	0.783	0.902
Decision Tree	0.776	0.767	0.776	0.768	0.704
Extra Trees	0.763	0.766	0.763	0.725	0.863
Naive Bayes	0.711	0.698	0.711	0.702	0.782
K-Nearest Neighbors	0.737	0.722	0.737	0.695	0.760
Dummy	0.697	0.486	0.697	0.573	0.500
Quadratic Discriminant	0.632	0.546	0.632	0.572	0.508

- Precision: Indicates the proportion of positive predictions that were actually correct, focusing on the model's ability to minimize false positives.

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}} \tag{2}$$

- Recall: Also known as sensitivity or True Positive Rate, recall measures the ability of the model to capture all relevant positive instances.

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}} \tag{3}$$

- F-Measure (F1 Score): Represents the harmonic mean of Precision and Recall, providing a single score that balances these two metrics, particularly useful in cases of class imbalance.

$$\text{F} - \text{Measure} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4}$$

- ROC AUC (Area Under the Receiver Operating Characteristic Curve): Measures the model's ability to distinguish between classes. It is computed by plotting the True Positive Rate (Recall) against the False Positive Rate at various classification thresholds and calculating the area under this curve. The AUC value indicates how well the model distinguishes between classes, with 1.0 representing perfect classification and 0.5 representing random guessing.

$$\text{True Positive Rate (TPR)} = \text{Recall} \tag{5}$$

$$\text{False Positive Rate (FPR)} = \frac{\text{False Positives}}{\text{False Positives} + \text{True Negatives}} \tag{6}$$

The robustness and the high capacity of the parallel multi-analytical framework were empirically pleasing through a thorough empirical evaluation regarding many classifiers relative to different metrics. The results in Table 8; Fig. 6 show that Linear Discriminant Analysis was able to outperform others with an approximate of 0.882 accuracy, precision and recall the entirety of which with the highest

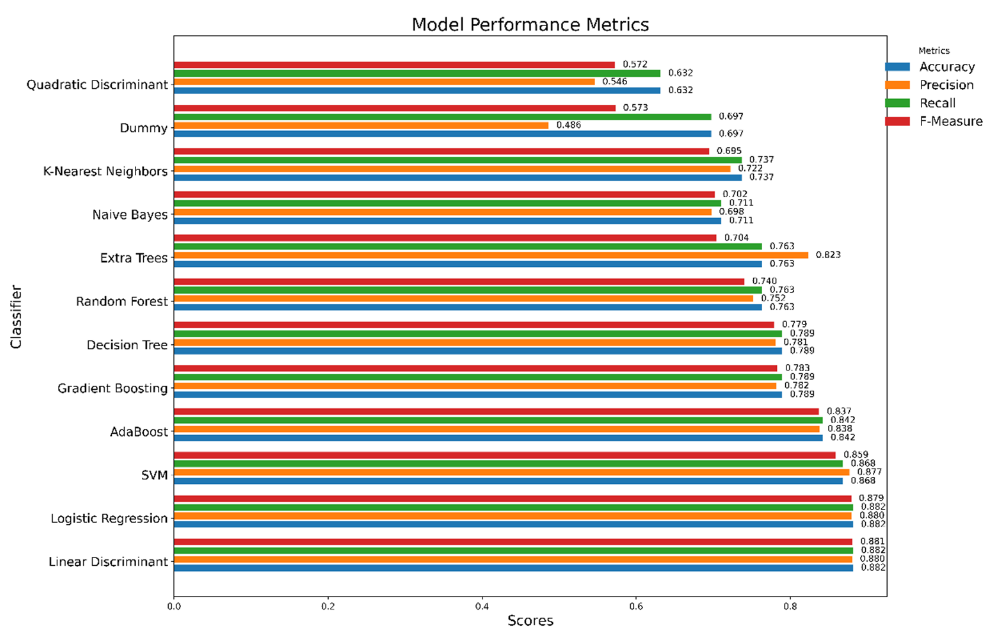


Fig. 5 Classifier Performance Assessment

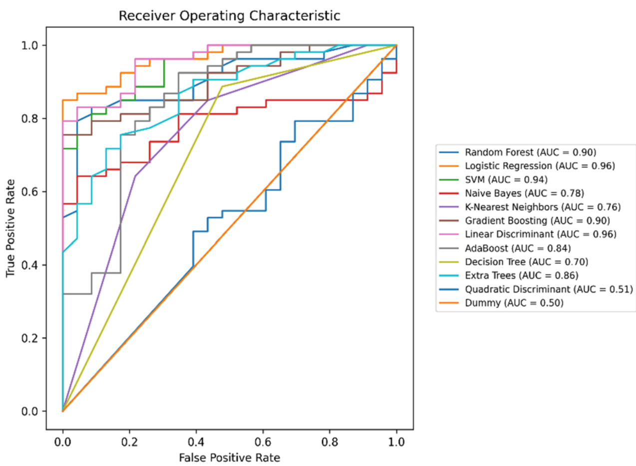


Fig. 6 Receiver Operating Characteristic Area Under Curve to Study Classifier

F-measure of 0.881 and a very sound ROC AUC (Receiver Operating Characteristic Area Under Curve) of 0.956. Following closely, Logistic Regression also exhibited high performance, with an accuracy of 0.882 and a ROC AUC of 0.964.

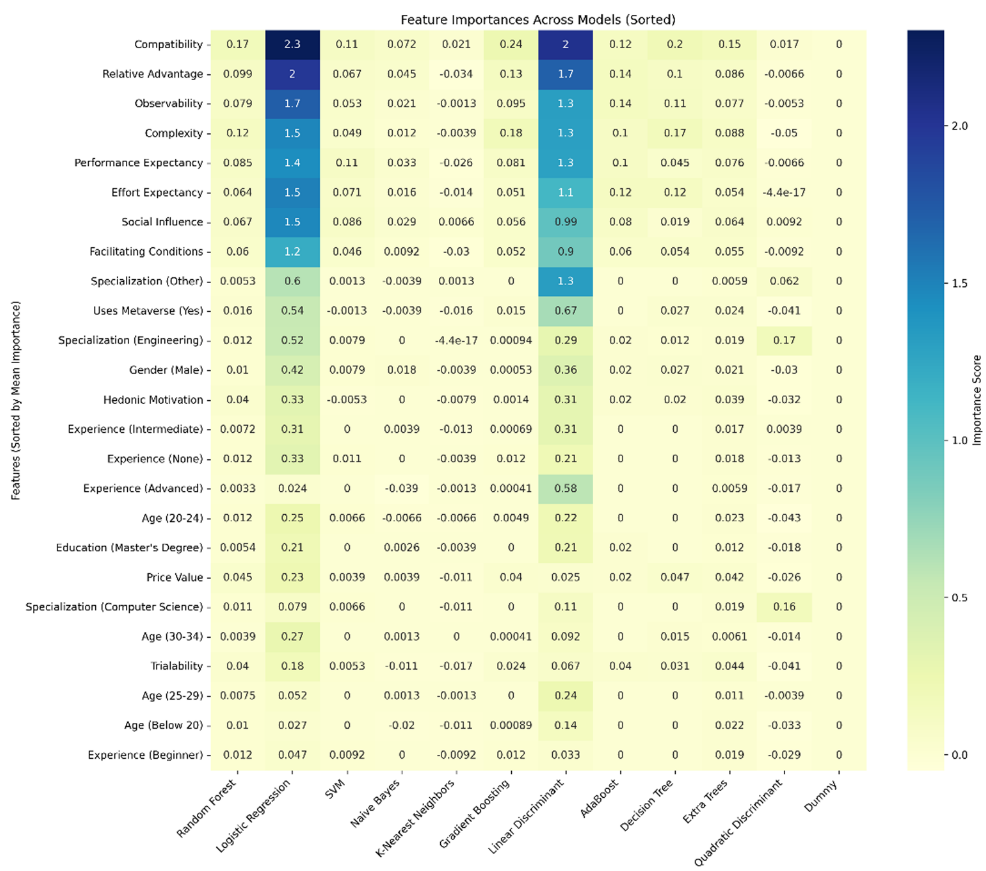
Other advanced classifiers, such as Support Vector Machines (SVM), achieved lower accuracy, 0.868, as well as ROC AUC of 0.942 for SVM. On the other hand, ensemble methods like AdaBoost and Gradient Boosting managed to achieve lower accuracy levels of 0.842 and 0.803 respectively which does imply nonensemble approaches may provide performance benefits in certain situations.

The Decision Trees model yielded an accuracy of 0.763, while Extra Trees slightly exceeded it with 0.789. Both models fared better than Naive Bayes and K-Nearest Neighbors, which respectively returned accuracy values of 0.711 and 0.737, respectively, illustrating their limited efficacy relative to the top-performing classifiers in this dataset. In terms of accuracy, Quadratic Discriminant Analysis has been reported to score a lower level of 0.632, and the benchmark Dummy classifier has yet again shown the poorest performance metrics with an accuracy of 0.697 and ROC AUC of 0.5, effectively establishing a foundational benchmark.

Feature Importances Across Models

Various machine learning models were applied to predict user engagement with the Metaverse Systems and their feature importances are presented in Fig. 7. Heuristically darker colors imply a greater significance in respect of that feature in the performance of the model. The features are ordered according to the mean feature importance hereby showcasing the features that are apparently the most predictive for

Fig. 7 Feature Importances Across Models



all classifiers' cases. It is conspicuous that "Compatibility" and "Relative Advantage" were the most significant variables particularly for Random Forest and Gradient Boosting models. This means that the greater users' perceived compatibility with and benefits from the Metaverse, the more likely they are to engage. On the other hand, "Age" and "Gender" which are demographic variables tended to have low importance across the majority of the models suggesting that these have a lower relative influence on prediction accuracy. Itis vertical perspective of feature importances is quite interesting as it gives an indication of what factors each of the models considers as most important and it helps in making better selections of models and features for future work.

Comparative Analysis of PLS-SEM and Feature Importance in Predicting Behavioral Intention

In this part authors selected two best model perform between classified. Table 9 presents a comparison between the PLS-SEM coefficients and the feature importance scores from Linear Discriminant (LD) and Logistic Regression (LR) for various independent variables predicting Behavioral Intention. The observations reveal several insights into the consistency and differences in variable significance across these analytical methods:

1. Consistency of Key Predictors

Variables such as Compatibility, Observability, Relative Advantage, Performance Expectancy, and Effort Expectancy show high PLS-SEM coefficients and correspondingly high feature importance scores in both LD and LR. This alignment across PLS-SEM, LD, and LR suggests that these variables are robust predictors of Behavioral Intention, consistently influencing the outcome regardless of the analysis method used. Their high feature importance scores indicate they play significant roles in prediction accuracy for machine learning models as well.

2. Moderate Predictors in Machine Learning but Significant in PLS-SEM

Complexity, Social Influence, and Facilitating Conditions have moderate feature importance scores in both LD and LR but exhibit substantial PLS-SEM coefficients. This suggests that while these factors are important in the SEM framework, their predictive contribution in machine learning models might be more context dependent. For instance, Social Influence and Facilitating Conditions could be more significant when specifically examining user intention within structured SEM but might contribute less to unstructured predictive models.

3. Minor Predictors across all Models

Variables such as Price Value, Trialability, and Hedonic Motivation exhibit low or negative PLS-SEM coefficients and low feature importance scores in both machine learning models. This indicates that these variables are not strong predictors of Behavioral Intention in this context, neither in the structural model nor in the machine learning models. The results suggest that these factors are less relevant in predicting Behavioral Intention, possibly because the perceived value, enjoyment, and trialability may not be as influential for the studied population.

The findings highlight the effectiveness of integrating PLS-SEM with high-performing ML classifiers—particularly Linear Discriminant, Logistic Regression—for accurately predicting user intentions. These models demonstrated significant capabilities in distinguishing students inclined toward engagement with Metaverse Systems, making them valuable tools for educational institutions focusing on fields such as Engineering and Computer Science.

The classifiers and performance measures employed in this research not only enhance methodological rigor but also set a platform for future studies. Later studies might aim to improve these models for their performance and applicability to a diverse range of situations or develop specific versions of the models for certain tasks, thus extending the area of applicability.

Table 9 Relationship between PLS-SEM results and feature importance scores across models

Independent Variable	PLS-SEM Coefficient	Support (PLS-SEM)	LD Feature Importance	LR Feature Importance
Compatibility	0.433	Supported	2.040	2.304
Observability	0.383	Supported	1.312	1.708
Relative Advantage	0.347	Supported	1.702	1.982
Performance Expectancy	0.335	Supported	1.299	1.435
Effort Expectancy	0.32	Supported	1.118	1.517
Complexity	0.298	Supported	1.311	1.482
Social Influence	0.297	Supported	0.985	1.472
Facilitating Conditions	0.273	Supported	0.895	1.205
Price Value	0.009	Not Supported	0.025	0.232
Trialability	-0.002	Not Supported	0.067	0.181
Hedonic Motivation	-0.032	Not Supported	0.313	0.331

Network Analysis

Network analysis is a research approach that examines social structures by employing networks and graph theory. Within the scope of our research, which centers on the utilization of Metaverse Systems by Engineering and Computer Science students, Network Analysis presents itself as a beneficial framework for examining the connections and dynamics among different aspects that impact behavioral intention (BI). Network analysis is a method that facilitates the visualization and examination of the relationships between various variables, both independent and dependent. This approach aids in the understanding of the intricate interactions among these components inside a complex system. The utilization of this mapping technique can offer valuable insights into the underlying structure and dynamics of the network comprising these variables, which may not be readily discernible by conventional statistical methodologies such as PLS-SEM or standalone machine learning approaches.

Centrality Metrics

Within the domain of network analysis, a range of centrality metrics were employed to evaluate the relative importance of individual variables within the overall network structure. The centrality measurements included in the study encompassed Degree Centrality, Betweenness Centrality, Closeness Centrality, Eigenvector Centrality, PageRank, Katz Centrality, and Subgraph Centrality [79].

Degree Centrality: it measures the importance of a node based on the number of direct connections it has. A higher degree centrality indicates that a node has more direct connections and may play a central role in facilitating interactions within the network. This metric is useful for identifying hubs or highly connected nodes within a network.

$$C_D(\nu) = \frac{deg(\nu)}{N-1} \tag{7}$$

where deg (v) is the degree of node v (i.e., the number of edges connected to v), and is the total number of nodes in the network.

Betweenness Centrality: it quantifies the importance of a node in terms of its ability to act as a bridge along the shortest paths between other nodes. Nodes with high betweenness centrality control information flow within the network, making them essential for maintaining connectivity and influencing the flow between distant parts of the network.

$$C_B(\nu) = \sum_{s\neq v\neq t} \frac{\sigma_{st}(v)}{\sigma_{st}} \tag{8}$$

where σ_{st} is the total number of shortest paths between nodes s and t, and σ_{st} (v) is the number of those paths that pass-through node v.

Closeness Centrality: it evaluates how close a node is to all other nodes in the network, based on the average shortest path distance. Nodes with high closeness centrality can reach other nodes more quickly, making them influential for efficiently spreading information or resources throughout the network.

$$C_C(\nu) = \frac{N-1}{\sum_{t\neq v} d(v,t)} \tag{9}$$

where d(v, t) is the shortest path distance between nodes v and t, and N is the total number of nodes.

Eigenvector Centrality: it measures a node's influence based on the influence of its neighbors. Unlike degree centrality, which only considers direct connections, eigenvector centrality considers both the quantity and quality of connections. Nodes connected to other highly central nodes are assigned a higher eigenvector centrality, making it useful for identifying influential nodes within clusters.

$$C_E(\nu) = \frac{1}{\lambda} \sum_{u\in neighbors(v)} C_E(u) \tag{10}$$

where λ is a constant (the largest eigenvalue of the adjacency matrix), and the centrality of node v depends on the centrality of its neighbors.

PageRank: its centrality extends eigenvector centrality by incorporating a probability distribution over the nodes, commonly used in web link analysis. PageRank is calculated based on both the quantity and quality of incoming connections, with a damping factor to simulate random jumps within the network. It is particularly effective for ranking nodes in directed networks.

$$PR(\nu) = \frac{1-d}{N} + d\sum_{u\in neighbors(v)} \frac{PR(u)}{deg(u)} \tag{11}$$

where is the damping factor (typically set to 0.85), deg (u) is the degree of node u, and is the total number of nodes.

Katz Centrality: its measures influence by considering both the number and distance of connections. Nodes receive a base score for each connection, which is amplified by a constant factor for each step away from the node. This metric is useful for identifying nodes with a broader reach across multiple levels in a network.

$$C_K(\nu) = \alpha \sum_{u\in neighbors(v)} C_K(u) + \beta \tag{12}$$

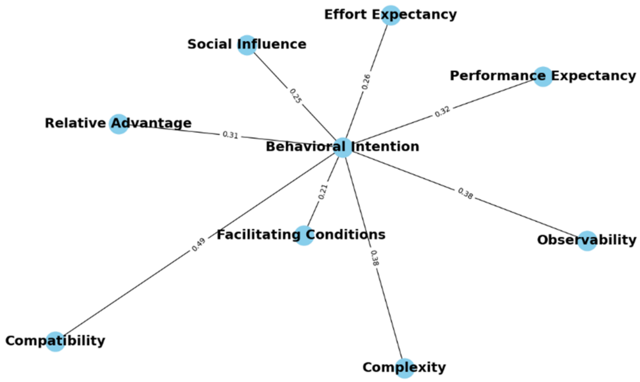


Fig. 8 Networkx_edge

where is a constant attenuation factor (typically chosen such that 0 < < 1 / $_{max}$), $_{max}$ is the largest eigenvalue of the adjacency matrix, and is a constant added to each node.

Subgraph Centrality: it quantifies the extent to which a node participates in all subgraphs of a network, weighing closed walks of different lengths. Higher subgraph centrality indicates a node's significance in local structures, such as triangles and cliques, providing insights into the node's role in tightly-knit network regions.

$$C_S(v) = \sum_{k=0}^{\infty} \frac{(\lambda_k(v))^2}{k!} \quad (13)$$

where $\lambda_k(v)$ is the k-th eigenvalue of the adjacency matrix for walks of length k.

As Fig. 8, one notable finding is the significant prevalence of the Behavioral Intention (BI) variable across all centrality measurements. Table 10 shows BI demonstrated the utmost level of connectivity, as evidenced by its Degree Centrality value of 1.000. This indicates that BI serves as a central bridge inside the network, as indicated by its Betweenness Centrality value of 1.000. Furthermore, it had a Closeness Centrality value of 1.000, suggesting its efficient connectivity to all other nodes within the network. The Eigenvector Centrality and PageRank scores, which are 0.707 and 0.468 respectively, provide additional evidence of its significant influence [80]. This influence extends beyond the quantity of connections to encompass the quality of those connections as well.

On the other hand, many factors such as Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, and the variables inside the DOI model (Relative Advantage, Compatibility, Complexity, Observability) exhibited comparable but notably diminished centrality measures. As an example, the observed Degree Centrality was consistently recorded as 0.125, while the Betweenness Centrality was consistently recorded as zero. These values suggest a lower number of direct connections and a less prominent function in facilitating connections between various nodes.

The findings of this study highlight the significant impact of Behavioral Intention on the adoption of Metaverse Systems within the population of Engineering and Computer Science students. The significance of this characteristic within the network implies that any treatments or methods designed to encourage the adoption of Metaverse System should prioritize Behavioral Intention as a core focus.

Correlation Matrix of Network Analysis

The correlation matrix provides insight into the associations among the several independent and dependent variables being examined. It is worth mentioning that the dependent variable of Behavioral Intention demonstrates statistically significant positive relationships with several of the independent variables. Table 11 shows that variable of compatibility has the highest correlation with behavioral intention, with a coefficient of 0.489. This is followed by complexity, which has a correlation coefficient of 0.377, and observability, which has a correlation coefficient of 0.376. The robust correlations observed in this study indicate that several factors, namely Compatibility, Observability, and the perceived complexity of utilizing Metaverse Systems, exert a

Table 10 Centrality metrics

	Degree Centrality	Betweenness Centrality	Closeness Centrality	Eigenvector Centrality	PageRank	Katz Centrality	Sub-graph Centrality
Performance Expectancy	0.125	0.000	0.533	0.250	0.066	0.306	1.936
Behavioral Intention	1.000	1.000	1.000	0.707	0.468	0.501	8.489
Effort Expectancy	0.125	0.000	0.533	0.250	0.057	0.306	1.936
Social Influence	0.125	0.000	0.533	0.250	0.055	0.306	1.936
Facilitating Conditions	0.125	0.000	0.533	0.250	0.049	0.306	1.936
Relative Advantage	0.125	0.000	0.533	0.250	0.065	0.306	1.936
Compatibility	0.125	0.000	0.533	0.250	0.091	0.306	1.936
Complexity	0.125	0.000	0.533	0.250	0.074	0.306	1.936
Observability	0.125	0.000	0.533	0.250	0.074	0.306	1.936

Table 11 Correlation matrix of network analysis

	1	2	3	4	5	6	7	8	9	10	11	12
1 Performance Expectancy	1.000	-0.043	0.046	-0.020	-0.003	-0.044	-0.026	-0.013	0.060	-0.100	-0.022	0.320
2 Effort Expectacy	-0.043	1.000	-0.083	-0.112	-0.010	0.041	-0.039	0.073	-0.007	-0.041	-0.018	0.262
3 Social Influence	0.046	-0.083	1.000	0.026	0.032	-0.038	-0.023	-0.067	-0.038	0.023	0.011	0.248
4 FacilitatingConditions	-0.020	-0.112	0.026	1.000	0.029	-0.083	-0.033	-0.047	0.020	0.050	0.021	0.213
5 Hedonic Motivation	-0.003	-0.010	0.032	0.029	1.000	-0.051	0.020	0.073	0.073	-0.112	0.039	0.051
6 Price Value	-0.044	0.041	-0.038	-0.083	-0.051	1.000	-0.047	-0.056	0.026	0.045	0.062	-0.033
7 Relative Advantage	-0.026	-0.039	-0.023	-0.033	0.020	-0.047	1.000	0.048	0.019	0.026	-0.056	0.315
8 Compatibility	-0.013	0.073	-0.067	-0.047	0.073	-0.056	0.048	1.000	0.135	0.019	0.029	0.489
9 Complexity	0.060	-0.007	-0.038	0.020	0.073	0.026	0.019	0.135	1.000	0.044	0.010	0.377
10 Trialability	-0.100	-0.041	0.023	0.050	-0.112	0.045	0.026	0.019	0.044	1.000	0.050	0.027
11 Observability	-0.022	-0.018	0.011	0.021	0.039	0.062	-0.056	0.029	0.010	0.050	1.000	0.376
12 Behavioral Intention	0.320	0.262	0.248	0.213	0.051	-0.033	0.315	0.489	0.377	0.027	0.376	1.000

substantial influence on students' Behavioral Intentions to adopt such systems.

In contrast, it was seen that variables such as Price Value had a negative correlation coefficient of -0.033 with Behavioral Intention. This suggests that the perceived cost of Metaverse Systems may act as a hindrance for students in their adoption of such systems. The variables of Performance Expectancy and Relative Advantage exhibited significant positive associations with Behavioral Intention, with correlation coefficients of 0.320 and 0.315, respectively. Nevertheless, it is worth noting that variables such as Hedonic Motivation and Trialability had modest positive correlations with Behavioral Intention, with coefficients of 0.051 and 0.027 respectively. These findings suggest that these variables have a limited impact within the given context.

The findings presented in this study underscore the diverse factors that influence Behavioral Intention, in addition to the network centrality metrics. The correlation matrix demonstrates that Compatibility, Complexity, and Observability hold significant importance in the network, thereby reinforcing their pivotal roles in comprehending and potentially facilitating the acceptance of Metaverse Systems within the Engineering and Computer Science student community.

Discussion

This study utilizes two influential theories, namely UTAUT2 and DOI, to investigate the concept of Behavioral Intention for Engineering and Computer Science students while study focused on these students to keep academic background as uniform as possible to tests study model. Based on the UTAUT2 paradigm, the construct of Facilitating Conditions emerges as the most robust predictor, underscoring the significance of environmental and organizational factors in shaping user behavior. Effort Expectancy and Social Influence are among the prominent indicators identified in the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2). Conversely, within the DOI framework, Complexity and Relative Advantage are identified as key factors, underscoring the significance of individuals' perceptions of the ease of use and benefits associated with adopting modern technologies.

The empirical findings demonstrate the effectiveness of using Partial Least Squares Structural Equation Modeling (PLS-SEM) with machine learning techniques, specifically Linear Discriminant Analysis, and Logistic Regression, in accurately predicting students' intents. These classifiers with high performance have demonstrated notable ability in distinguishing between pupils who are more inclined to engage with Metaverse Systems and those who are not. This characteristic renders them particularly advantageous for educational institutions with a specific emphasis on fields such as Engineering and Computer Science.

PLS-SEM Analyses

In this part, authors discussed each hypothesis and comparison with literature. Table 12 shows a summary of this comparison.

H1: Performance Expectancy -> Behavioral Intention (BI)

The findings of our investigation reveal a positive route coefficient of 0.335, which is accompanied by a significant p-value of less than 0.001. This observation serves to strengthen the existing body of academic research in fields such as educational metaverses [25, 30], despite conflicting with the conclusions drawn from the use of metaverse technology to basketball instruction [28]. The T statistic value of 15.119 indicates strong statistical validity, hence enhancing the credibility of the UTAUT framework in various technology adoption contexts.

H2: Effort Expectancy -> Behavioral Intention (BI)

The study conducted reveals a notable route coefficient of 0.32, which is accompanied by a significant p-value of less than 0.001. The statement supports the notion of a fragmented literary landscape, specifically in relation to the findings in educational metaverses as reported by Khalil et al. [30] and Teng et al. [25]. The substantial T statistic (15.512) presents a counterargument to the incongruous findings observed in prior studies, such as Yang et al. [28] and Lee et al. [26], thereby suggesting the potential influence of contextual variables on Effort Expectancy.

H3: Social Influence (UTSI) -> Behavioral Intention (BI)

The route coefficient of 0.297 and the corresponding p-value of less than 0.001 are significant. The findings shown in this study align with the substantial body of research conducted in previous educational metaverse studies [25, 30], hence questioning the validity of the unfavorable outcomes reported in basketball learning [28]. The T statistic of 13.375 provides more evidence of the empirical consistency of the association between Social Influence and Behavioral Intention.

H4: Facilitating Conditions (UTFC) -> Behavioral Intention (BI)

The obtained results in our study demonstrate a coefficient of 0.273 and a p-value of less than 0.001. These findings align well with previous research conducted in specific educational settings [25, 27]. The empirical grounding of the link is supported by the T statistic of 13.907, which contributes to a deeper understanding of the current literature that has previously reported negative findings [26, 28].

H5: Hedonic Motivation (UTHM) -> Behavioral Intention (BI)

This study deviates from previous scholarly works by presenting a path coefficient of -0.032, which exhibits a p-value of 0.079, indicating a lack of statistical significance. The distinction carries greater significance in relation to research that has questioned the ability of Hedonic Motivation to accurately predict outcomes [26, 28], in contrast to the limited supporting evidence derived solely from mobile learning environments [27].

H6: Price Value (UTPV) -> Behavioral Intention (BI)

The results of our study reveal a negligible path coefficient of 0.009 and a p-value of 0.667, which lacks statistical significance. These findings contribute additional empirical support to the existing skepticism regarding the influence of Price Value on technology adoption, as previously discussed by Lee et al. [26] and Aburbeian et al. [46].

H7: Relative Advantage (DORA) -> Behavioral Intention (BI)

The path coefficient of 0.347, which exhibits statistical significance with a p-value of less than 0.001, is supported by empirical evidence from many areas. These domains include Islamic banking as studied by Jamshidi and Kazemi [50] and Ouaddi Rachid et al. [51], as well as social media marketing as investigated by Farajnezhad et al. [54]. The T statistic of 15.775 provides more evidence supporting the notion that Relative Advantage plays a significant role in the technology adoption framework.

H8: Compatibility (DOCB) -> Behavioral Intention (BI)

The findings of our study, which indicate a significant path coefficient of 0.433 with a p-value of less than 0.001, provide support for comparable findings in several domains, including Islamic banking, social media marketing, and IoT [50, 51, 54, 61]. The T statistic of 19.598, which is remarkably high, positions Compatibility as a crucial issue that merits additional scholarly investigation.

H9: Complexity (DOCP) -> Behavioral Intention (BI)

The obtained path coefficient of 0.298, along with a statistically significant p-value of less than 0.001, indicates a

Table 12 Summary of hypotheses testing and comparison with literature

No.	Independent Variable	Result	Literature Result	Advantages
H1	Performance Expectancy	Supported	Supported in educational Metaverse studies [25, 30], mobile learning tools [27], and food delivery apps [26]. Not supported in Metaverse for basketball learning [28] and e-government services [29].	Evidence reinforces the positive influence of Performance Expectancy on Behavioral Intention in Metaverse systems, particularly in educational contexts among engineering and computer science students. This finding contributes to consistency within literature that has shown mixed results.
H2	Effort Expectancy	Supported	Supported in educational Metaverse studies [25, 30], mobile learning tools [27], e-government services [29], and IoT [61]. Not supported in Metaverse for basketball learning [28] and food delivery apps [26].	Confirms Effort Expectancy as significant in Metaverse adoption, emphasizing its importance in user-friendly technological environments and contributing context-specific insights to the literature where inconsistencies exist.
H3	Social Influence	Supported	Supported in educational Metaverse [25, 30], mobile learning tools [27], and food delivery apps [26]. Not supported in Metaverse for basketball learning [28] and e-government services [29].	Reinforces the role of Social Influence in Metaverse adoption, suggesting that peer and societal factors are significant among students, offering clarity where previous studies showed inconsistencies.
H4	Facilitating Conditions	Supported	Supported in educational Metaverse [25] and mobile learning tools [27]. Not supported in Metaverse for basketball learning [28], e-government services [29], teachers using mobile internet [41], and food delivery apps [26].	Highlights the importance of Facilitating Conditions in Metaverse adoption, suggesting that adequate infrastructure and support are crucial, providing insights into contexts where prior studies found limited significance.
H5	Hedonic Motivation	Not Supported	**Supported** in mobile learning tools [27] and teachers using mobile internet [41]. **Not supported** in Metaverse for basketball learning [28] and food delivery apps [26].	Suggests that Hedonic Motivation may not be a significant factor in Metaverse adoption in this context, indicating that functional aspects might be more important than enjoyment, thereby refining the understanding of user motivations.
H6	Price Value	Not Supported	Supported in mobile learning tools [27] and e-government services [29]. Not supported in Metaverse prospects [46], teachers using mobile internet [41], and food delivery apps [26].	Aligns with studies finding Price Value insignificant, suggesting cost may not be a primary concern for students in Metaverse adoption, enhancing understanding of where Price Value is less impactful.
H7	Relative Advantage	Supported	Supported across various domains: Islamic credit cards [50], Islamic banking [51], halal meat supply chain [5253], e-paper products [], social media marketing [54].	Confirms the role of Relative Advantage in Metaverse adoption, consistent with prior studies, highlighting those perceived benefits over existing options drive Behavioral Intention.
H8	Compatibility	Supported	Supported in Islamic credit cards [50], IoT [61], halal meat supply chain [52], Islamic banking [51], and social media marketing [54]. Not supported in e-paper products [53].	Emphasizes the importance of Compatibility in Metaverse adoption, suggesting that alignment with users' values and needs is crucial. This supports existing literature and underlines its significance in technology adoption among students.
H9	Complexity	Supported (Positive Influence)	Not supported (no significant effect) in Islamic credit cards [50], Islamic banking [52], e-paper products [53]. Negative influence (complexity reduces BI) in halal meat supply chain [52] and social media marketing [54].	Findings suggest a positive relationship between Complexity and Behavioral Intention, indicating that complexity may not deter and might even attract students to Metaverse systems. This offers new insights and avenues for further research.
H10	Trialability	Not Supported	Supported in social media marketing [54].Not supported in Islamic credit cards [50], e-paper products [53], IoT [61], and Islamic banking [51].	Aligns with prior studies indicating Trialability is not significant in Metaverse adoption among students, suggesting the ability to try the system before adoption is less critical in this context.
H11	Observability	Supported	Supported in e-paper products [53], Islamic banking [51], and social media marketing [54]. Not supported in Islamic credit cards [50].	Supports the significance of Observability, indicating that visible benefits of Metaverse systems encourage adoption among students, highlighting the importance of observable results in technology adoption decisions.

departure from the prevailing literature, particularly within the domain of Islamic banking [50, 51]. This implies that Complexity, which was previously believed to be negatively associated, can really possess its own set of advantages that justify the need for additional investigation.

H10: Trialability (DOTB) -> Behavioral Intention (BI)

The study's results align with the prevailing absence of evidence in the current body of literature [50, 51, 53, 61], as indicated by the very minuscule path coefficient of -0.002 and the high p-value of 0.907.

H11: Observability (DOOB) -> Behavioral Intention (BI)

The obtained data in our study demonstrates a path coefficient of 0.383, which is statistically significant with a p-value of less than 0.001. These results are consistent with previous research conducted in the fields of Islamic banking and social media marketing [50, 51, 54]. The significant T statistic value of 16.029 highlights the relevance of Observability within the technology adoption ecosystem.

Machine Learning

The comparison of classifier performance highlights the strength of a multi-analytical framework, with Linear Discriminant and Logistic Regression emerging as the top performers across various metrics, including accuracy, F-measure, and ROC AUC. These models demonstrated high predictive consistency and outperformed both ensemble methods and other individual classifiers. The findings suggest that while advanced and ensemble methods provide flexibility, simpler, non-ensemble classifiers may offer enhanced performance under certain conditions. This reinforces the value of selecting a model based on both the dataset characteristics and specific predictive goals, illustrating the robustness of LD and Logistic Regression for Behavioral Intention modeling in this context.

Agreement between PLS-SEM and Machine Learning

Study highlights that Compatibility, Performance Expectancy, Effort Expectancy, and Relative Advantage are primary drivers of Behavioral Intention, consistently showing high importance across PLS-SEM, LD, and LR models as shown in Table 9. In contrast, variables such as Price Value, Trialability, and Hedonic Motivation are less impactful. The results suggest that while PLS-SEM and machine learning models differ in approach, their alignment on core predictors provides a robust validation of these variables' roles in influencing Behavioral Intention. This comparative analysis offers valuable insights into variable importance and the consistency of findings across statistical and predictive models. Through this ML models may can expanding applicability beyond other students in a different majors of than CS and engineering students.

Network Analysis

The significant drivers identified in both the path analysis and network analysis are "Compatibility" and "Performance Expectancy," suggesting that these factors play a crucial role in affecting "Behavioral Intention."

The analysis of interactions reveals that the centrality metrics of most factors are comparable, indicating a balanced structural influence among them. However, it is important to note that these variables exhibit varying degrees of impact on "Behavioral Intention." This observation implies the existence of additional types of linkages or conditional effects that are not accounted for in the Partial Least Squares Structural Equation Modeling (PLS-SEM) framework.

In the field of network analysis, it is a widely adopted technique to employ a threshold to focus on robust interactions while simultaneously excluding weaker ones. If a threshold of 0.2 is applied and it is observed that the variables "Hedonic Motivation," "Price Value," and "Trialability" are absent from the Fig. 4, it implies that their relationships, which are probably assessed by path coefficients or similar metrics, are below this threshold. This finding is consistent with the outcomes obtained using Structural Equation Modeling (SEM), which similarly suggested that these variables do not possess a significant direct impact on "Behavioral Intention." The utilization of a threshold in the visual depiction of the network serves to enhance its interpretability by simplifying the representation. However, it is important to acknowledge that this approach may inadvertently conceal intricate connections that fall below the predetermined threshold. While it is acknowledged that these variables may have some significance in influencing behavior or intention, their effect is not significant enough to meet the specific analysis requirements established. Hence, the exclusion of their presence in network visualization should be duly acknowledged within the framework of these diverse elements.

Agreement Between PLS-SEM and Network Analysis

High Agreement: The observed route coefficients in Partial Least Squares Structural Equation Modeling (PLS-SEM) analysis demonstrate strong positive associations with the construct of Business Intelligence (BI), as indicated by their values exceeding 0.29. Additionally, the statistical significance of these relationships is confirmed by the p-values, which are all below the threshold of 0.05. This observation is consistent with the results of network analysis, which indicate a strong positive relationship between these variables and business intelligence (BI).

Partial Agreement: The variables in question exhibit notable path coefficients (more than 0.30) and p-values ($p<0.05$) within the context of Partial Least Squares Structural Equation Modeling (PLS-SEM) analysis. This indicates that they hold significance as predictors for Business Intelligence (BI). Although their centrality scores in the network analysis are low, their strong association with BI does render them statistically significant. This observation implies that their significance is somewhat indirect or embedded within a more intricate network of connections, which corresponds with the notion of them functioning as indirect channels.

Low Agreement: The observed path coefficients, particularly those pertaining to Price Value and Trialability, exhibit low values, indicating little influence on Business Intelligence (BI). Additionally, the p-values associated with these coefficients are found to be non-significant ($p>0.05$), further supporting their limited significance in the context of BI. These findings align with the low degree centrality and weak connection with BI as revealed by the network analysis.

The considerable robustness of the findings is evident from the great agreement observed between the outcomes of the Partial Least Squares Structural Equation Modeling (PLS-SEM) and network analysis. This alignment serves to enhance the credibility of the identified elements that influence Behavioral Intention (BI). The establishment of this methodological consensus functions as a means of validating the research using many methods, so bolstering the dependability and robustness of the study's findings. Moreover, the data additionally indicates promising directions for future investigation, specifically pertaining to the variables of Performance Expectancy and Effort Expectancy. Although the centrality scores of these factors were found to be lower in the network analysis, their strong positive correlations with BI in the PLS-SEM suggest the potential for indirect effects or interactions with other variables. In summary, the alignment between the two analytical methodologies employed yields a comprehensive and resilient understanding of the variables that impact the acceptance of Metaverse Systems within the Engineering and Computer Science student population.

Conclusion

This research presents a thorough analysis of factors influencing Behavioral Intention to use Metaverse Systems, integrating theories like UTAUT2 and DOI with a unique multi-method approach that combines PLS-SEM, machine learning classifiers, and network analysis. The study identifies Compatibility, Performance Expectancy, Effort Expectancy, and Social Influence as significant predictors of Behavioral Intention, with high consistency across analytical methods. Machine learning classifiers, such as Linear Discriminant Analysis and Logistic Regression, achieved notable predictive performance, confirming these factors' roles in distinguishing users' behavioral intentions.

The alignment between PLS-SEM, network analysis, and machine learning models strengthens the validity of these findings, establishing methodological consensus that underscores the robustness of Compatibility and Performance Expectancy as central drivers of Behavioral Intention. Additionally, network analysis results support the exclusion of variables like Hedonic Motivation, Price Value, and Trialability from the core model due to their limited direct influence, while suggesting that indirect pathways or contextual factors may yet affect their impact.

In conclusion, this study provides a solid analytical foundation for understanding Metaverse technology adoption among Engineering and Computer Science students, bridging methodological approaches for a more comprehensive understanding. Future research could further explore the indirect effects of factors like Performance Expectancy and Effort Expectancy, leveraging insights from both statistical and network-based frameworks to refine predictive models and application strategies in educational and technological adoption contexts.

Limitations and Future Work

The study has certain limitations that should be acknowledged. Additionally, there are potential avenues for future research that could build upon the findings of this study.

- The study employed a sample that predominantly comprised students in the fields of Engineering and Computer Science. However, broadening the scope of the study would yield findings that are more applicable to a wider range of individuals.
- The analysis suggests the existence of intricate interactions and conditional effects among variables that are not well accounted for in the present model.
- Thresholding in Network Analysis: The utilization of a threshold value of 0.2 may have resulted in the exclusion

of certain variables that could have been potentially significant, thus indicating the necessity for a more sophisticated approach in forthcoming research endeavors.

- Future Development – Interactive Website: Building upon the findings of this study, a promising avenue for future work involves the development of an interactive website. This platform would allow users to fill out a survey and receive real-time predictions of their Behavioral Intention (BI) to adopt Metaverse systems, powered by machine learning models validated in this research. This practical application could bridge the gap between theoretical findings and real-world use, enabling individuals, educators, and institutions to better understand factors influencing Metaverse adoption.

Acknowledgements It is important to express sincere appreciation to Dr. Mostafa Al-Emran, a faculty member at the British University in Dubai, United Arab Emirates, for his exceptional knowledge and significant technical contributions that significantly enhanced the quality of the research.

Author Contributions K.M.A. analyzed the data for the meta-analysis; All authors contributed to the search, coding, and writing up of the review; All authors contributed to the article and approved the submitted version.

Funding This research was funded by an internal grant from Abu Dhabi University for the AY 2024/2025 funding round. This project is supported under Cost Center 19300882.

Data Availability The authors of this essay will provide raw data that supports their conclusions, without any unwarranted hesitation.

Declarations

Conflict of interest Tthe authors of this article have no financial or non-financial interests in relation to the publishing of this article.

Informed Consent The study was conducted paying close respect to ethical guidelines to protect participant confidentiality and preserve the integrity of the research. There were explicit assurances given to each participant that the answers they submitted would remain anonymous and confidential. Respondents' responses would not be linked to their personal identity in any reports or analysis that were released. Furthermore, the participants were adequately informed that their involvement in the survey was entirely voluntary and that they might leave the study at any time without facing any unfavorable consequences.

References

1. Gonzalez-Romo NI, Mignucci-Jiménez G, Hanalioglu S, et al. Virtual neurosurgery anatomy laboratory: A collaborative and remote education experience in the metaverse. Surg Neurol Int. 2023;14:90. https://doi.org/10.25259/SNI_162_2023.
2. Singh G, Mantri A, Sharma O, Kaur R. Virtual reality learning environment for enhancing electronics engineering laboratory experience. Comput Appl Eng Educ. 2021;29:229–43. https://doi.org/10.1002/cae.22333.
3. Talan T, Kalinkara Y. Students' opinions about the educational use of the metaverse. Int J Technol Educ Sci. 2022;6:333–46. https://doi.org/10.46328/ijtes.385.
4. Hussain S. Metaverse for education – Virtual or real? Front Educ (Lausanne). 2023;8. https://doi.org/10.3389/feduc.2023.1177429.
5. Kaddoura S, Al Husseiny F. The rising trend of metaverse in education: challenges, opportunities, and ethical considerations. PeerJ Comput Sci. 2023;9:e1252. https://doi.org/10.7717/peerj-cs.1252.
6. Azoury N, Hajj C. (2023) Perspective Chapter: The Metaverse for Education. In: Waller L, Waller S, editors Higher Education - Reflections From the Field - Volume 1 [Working Title]. IntechOpen.
7. Kutbay E, Bozbuğa N. Health education: Gamification, health Literacy, and the new Era; metaverse. Health Education: Gamification Health Lit New Era; Metaverse. 2022. https://doi.org/10.26650/B/ET07.2022.012.13.
8. Hayawi K, Shahriar S, Serhani MA, Alothali E. Inevitable-Metaverse: A novel Twitter dataset for public sentiments on metaverse. Res Sq. 2022. https://doi.org/10.21203/rs.3.rs-1906763/v1.
9. Cho K-H, Park J-B, Kang A. Metaverse for exercise rehabilitation: possibilities and limitations. Int J Environ Res Public Health. 2023;20. https://doi.org/10.3390/ijerph20085483.
10. Ball M. (2022) The Metaverse, 22nd ed. Liveright, [S.I.].
11. Maghaydah S, Al-Emran M, Maheshwari P, Al-Sharafi MA. Factors affecting metaverse adoption in education: A systematic review, adoption framework, and future research agenda. Heliyon. 2024;10:e28602. https://doi.org/10.1016/J.HELIYON.2024.E28602.
12. Venkatesh T, Xu. Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology. MIS Q. 2012;36:157. https://doi.org/10.2307/41410412.
13. Rogers EM. Diffusion of innovations. 4th ed. New York: Free; 1995.
14. Riva G, Wiederhold BK. What the metaverse is (Really) and why we need to know about it. Cyberpsychol Behav Soc Netw. 2022;25:355–9. https://doi.org/10.1089/cyber.2022.0124.
15. Ren L, Yang F, Gu C, et al. A study of factors influencing Chinese college students' intention of using metaverse technology for basketball learning: extending the technology acceptance model. Front Psychol. 2022;13:1049972. https://doi.org/10.3389/fpsyg.2022.1049972.
16. Alhamad AQ, Alomari KM, Alshurideh M, et al. The adoption of metaverse systems: A hybrid SEM - ML method. 2022 Int Conf Electr Comput Commun Mechatronics Eng (ICECCME). 2022. https://doi.org/10.1109/ICECCME55909.2022.9988215.

17. Sebastian G. A study on metaverse Awareness, cyber Risks, and steps for increased adoption. Int J Secur Priv Pervasive Comput. 2022;14:1–11. https://doi.org/10.4018/IJSPPC.308785.
18. Toraman Y. User acceptance of metaverse: insights from technology acceptance model (TAM) and planned behavior theory (PBT). EMAJ: Emerg Markets J. 2022;12:67–75. https://doi.org/10.5195/emaj.2022.258.
19. Hwang I, Shim H, Lee WJ. Do an organization's digital transformation and employees' digital competence catalyze the use of telepresence? Sustainability. 2022;14:8604. https://doi.org/10.3390/su14148604.
20. Alfaisal R, Hashim H, Azizan UH. Metaverse system adoption in education: a systematic literature review. J Computers Educ. 2022. https://doi.org/10.1007/s40692-022-00256-6.
21. Choi D, Lee HK, Kim DY. Mood management through metaverse enhancing life satisfaction. Int J Consum Stud. 2023;47:1533–43. https://doi.org/10.1111/ijcs.12934.
22. Jang J, Kim J. Exploring the impact of avatar customization in metaverse: the role of the class mode on task engagement and Expectancy-Value beliefs for fashion education. Mob Inform Syst. 2023;2023:1–13. https://doi.org/10.1155/2023/2967579.
23. Park S, Kim S. Identifying world types to deliver gameful experiences for sustainable learning in the metaverse. Sustainability. 2022;14:1361. https://doi.org/10.3390/su14031361.
24. Rosli MS, Saleh NS. Predicting the acceptance of metaverse for educational purposes in universities: A structural equation model and mediation analysis of the extended technology acceptance model. SN Comput Sci. 2024;5:1–20. https://doi.org/10.1007/S42979-024-03015-9/METRICS.
25. Teng Z, Cai Y, Gao Y, et al. Factors affecting learners' adoption of an educational metaverse platform: an empirical study based on an extended UTAUT model. Mob Inform Syst. 2022;2022:1–15. https://doi.org/10.1155/2022/5479215.
26. Lee SW, Sung HJ, Jeon HM. Determinants of continuous intention on food delivery apps: extending UTAUT2 with information quality. Sustainability. 2019;11:3141. https://doi.org/10.3390/su11113141.
27. Syed Ahmed M, Kabir SMA. The acceptance of smartphone as a mobile learning tool: students of business studies in Bangladesh. Malaysian Online J Educational Technol. 2018;6:38–47. https://doi.org/10.17220/mojet.2018.02.003.
28. Yang F, Ren L, Gu C. A study of college students' intention to use metaverse technology for basketball learning based on UTAUT2. Heliyon. 2022;8:e10562. https://doi.org/10.1016/j.heliyon.2022.e10562.
29. Syamsudin, Meiyanti R, Satria D et al. (2018) Exploring factors influence behavioral intention to use E-government services using unified theory of acceptance and use of technology 2 (UTAUT2). 2018 International Seminar on Research of Information Technology and Intelligent Systems, ISRITI 2018 237–242. https://doi.org/10.1109/ISRITI.2018.8864474
30. Khalil A, Haqdad A, Sultana N. Educational metaverse for teaching and learning in higher education of Pakistan. J Posit Sch Psychol. 2023;7(2):1183–97.
31. Buyan CA, De Jesus NM, Castro ET. Technology adoption and usage behaviors in field incident management system utilization. Int J Adv Comput Sci Appl. 2023;14:1010–8. https://doi.org/10.14569/IJACSA.2023.01406108.
32. Ismail I, 'Aini A, Mahmud N, Hasan HA. (2021) Relationship between Information Technology (IT) Acceptance and employee performance using technology acceptance model (TAM). Proceedings of the 3rd international conference on economics, business and economic education science, ICE-BEES 2020, 22–23 Jul. https://doi.org/10.4108/EAI.22-7-2020.2307899
33. Rogers EM, Singhal A, Quinlan MM. (2019) Diffusion of Innovations. In: Stacks DW, Salwen MB, Eichhorn KC, editors An integrated approach to communication theory and research, Third edition. Routledge, Taylor et Francis Group, New York; London, pp 415–434.
34. McLean G, Osei-Frimpong K, Al-Nabhani K, Marriott H. Examining consumer attitudes towards retailers' m-commerce mobile applications – An initial adoption vs. continuous use perspective. J Bus Res. 2020;106:139–57. https://doi.org/10.1016/J.JBUSRES.2019.08.032.
35. Almazroa M, Gulliver S. Understanding the usage of mobile payment systems- the impact of personality on the continuance usage. 2018 4th Int Conf Inform Manage ICIM 2018. 2018;188–194. https://doi.org/10.1109/INFOMAN.2018.8392833.
36. Lu Y, Yang S, Chau PYK, Cao Y. Dynamics between the trust transfer process and intention to use mobile payment services: A cross-environment perspective. Inf Manag. 2011;48:393–403. https://doi.org/10.1016/j.im.2011.09.006.
37. Chang CW, Chang SH. The impact of digital disruption: influences of digital media and social networks on forming digital natives' attitude. Sage Open. 2023;13. https://doi.org/10.1177/21582440231191741.
38. Asandimitra N, Narsa IM, Irwanto A, Ishartanto H. The effect of money attitude, subjective norm, perceived behavioural control, and perceived risk on millennial's saving intention. BISMA (Bisnis Dan Manajemen). 2021;14:1–14. https://doi.org/10.26740/BISMA.V14N1.P1-14.
39. Mersh K, Auburn T. The role of social identity strategies in the cultural transitions of international students: social creativity, social mobility and place identity. SN Social Sci. 2021;1. https://doi.org/10.1007/S43545-021-00149-Y.
40. Bixter MT, Blocker KA, Mitzner TL, et al. Understanding the use and non-use of social communication technologies by older adults: A qualitative test and extension of the ATAUT model. Gerontechnology. 2019;18:70–88. https://doi.org/10.4017/GT.2019.18.2.002.00.
41. Nikolopoulou K, Gialamas V, Lavidas K. Habit, hedonic motivation, performance expectancy and technological pedagogical knowledge affect teachers' intention to use mobile internet. Computers Educ Open. 2021;2:100041. https://doi.org/10.1016/j.caeo.2021.100041.
42. Tanner K. Survey designs. Res Methods: Inform Syst Contexts: Second Ed. 2018;159–92. https://doi.org/10.1016/B978-0-08-102220-7.00006-6.
43. Kanwal F, Rehman M, Bashir K, Qureshi U. Critical factors of E-Learning adoption and acceptance in pakistan: A literature review. Eng Technol Appl Sci Res. 2017;7:1888–93. https://doi.org/10.48084/etasr.1257.
44. Chaveesuk S, Khalid B, Bsoul-Kopowska M, et al. Comparative analysis of variables that influence behavioral intention to use MOOCs. PLoS ONE. 2022;17:e0262037. https://doi.org/10.1371/JOURNAL.PONE.0262037.
45. Tvaronavičienė M, Mazur N, Mishchuk H, Bilan Y. Quality of life of the youth: assessment methodology development and empirical study in human capital management. Economic Research-Ekonomska Istraživanja. 2022;35:1088–105. https://doi.org/10.1080/1331677X.2021.1956361.
46. Aburbeian AM, Owda AY, Owda M. A technology acceptance model survey of the metaverse prospects. AI. 2022;3:285–302. https://doi.org/10.3390/ai3020018.
47. Johnson VL, Kiser A, Washington R, Torres R. Limitations to the rapid adoption of M-payment services: Understanding the impact of privacy risk on M-Payment services. Comput Hum Behav. 2018;79:111–22. https://doi.org/10.1016/j.chb.2017.10.035.
48. Chen WC, Chen CW, Chen WK. (2019) Drivers of Mobile Payment Acceptance in China: An Empirical Investigation. Information 2019, Vol 10, Page 384 10:384. https://doi.org/10.3390/INFO10120384

49. Ebubedike AH, Mohammed TA, Nellikunnel S, Teck TS. Factors influencing consumer's behavioural intention towards the adoption of mobile payment in Kuala Lumpur. Int J Prof Bus Rev. 2022;7:e0584. https://doi.org/10.26668/businessreview/2022.v7i6.e584.
50. Jamshidi D, Kazemi F, Jamshidi D, Kazemi F. Innovation diffusion theory and customers' behavioral intention for Islamic credit card. J Islamic Mark. 2020;11:1245–75. https://doi.org/10.1108/JIMA-02-2018-0039.
51. Rachid O, Kamal L, Amina Echbani. Islamic bank selection criteria in morocco: the innovation diffusion theory perspective. Afr Sci J. 2022;3. https://doi.org/10.5281/zenodo.7065222.
52. Qader G, Shahid ZA, Junaid M, et al. The role of diffusion of innovation theory towards the adoption of Halal meat supply chain. J Islamic Mark. 2023;14:1211–28. https://doi.org/10.1108/JIMA-01-2021-0032.
53. Sholahuddin S, Setyawan A, Trisnawati R. (2019) The role of innovation characteristic toward adoption intention of E-Paper Product. https://doi.org/10.4108/EAI.6-12-2018.2286310
54. Farajnezhad S, Bodaghi Khajeh Noubar H, Fakhimi Azar S. The impact of diffusion of innovation model on user behavioral intention in adopting social media marketing. Int J Nonlinear Anal Appl. 2021;12:1611–32. https://doi.org/10.22075/IJNAA.2021.5291.
55. Nadile EM, Williams KD, Wiesenthal NJ, et al. Gender differences in student comfort voluntarily asking and answering questions in Large-Enrollment college science courses. J Microbiol Biol Educ. 2021;22. https://doi.org/10.1128/jmbe.00100-21.
56. Naik GL, Deshpande M, Shivananda DC et al. (2021) Online teaching and learning of higher education in India during COVID-19 emergency lockdown. Pedagogical Research 6:. https://doi.org/10.29333/pr/9665
57. Tandon U, Mittal A, Bhandari H, et al. E-learning adoption by undergraduate architecture students: facilitators and inhibitors. Eng Constr Architectural Manage. 2022;29:4287–312. https://doi.org/10.1108/ECAM-05-2021-0376.
58. Sheth J. Impact of Covid-19 on consumer behavior: will the old habits return or die? J Bus Res. 2020;117:280–3. https://doi.org/10.1016/j.jbusres.2020.05.059.
59. Silva JHO, Favoretto C, Amancio IR, et al. Consumer behavioral intention to use restaurant, concert and education services online during and after the COVID-19 pandemic: evidence from Brazil. Int J Qual Service Sci. 2022;14:504–23. https://doi.org/10.1108/IJQSS-04-2021-0056.
60. Arain AA, Hussain Z, Rizvi WH, Vighio MS. Extending UTAUT2 toward acceptance of mobile learning in the context of higher education. Univers Access Inf Soc. 2019;18:659–73. https://doi.org/10.1007/s10209-019-00685-8.
61. Lu Y. Examining user acceptance and adoption of the internet of things. Int J Bus Sci Appl Manage. 2021;16. https://doi.org/10.13140/RG.2.2.36737.58728.
62. Ahmed AA, Usman Z, Trialability and observability of accrual basis international public sector accounting standards implementation in Nigeria. Gusau J Acc Finance. 2023;4:35–53. https://doi.org/10.57233/GUJAF.V4I1.199.
63. Ibrahim S, Vasalou A, Benton L. (2022) Understanding the Situated Practices of School Technology Leaders in the Early Stages of Educational Technology Adoption. In: Conference on Human Factors in Computing Systems - Proceedings. Association for Computing Machinery.
64. Denis J-L, Hébert Y, Langley A, et al. Explaining diffusion patterns for complex health care innovations. Health Care Manage Rev. 2002;27:60–73. https://doi.org/10.1097/00004010-200207000-00007.
65. Akour IA, Al-Maroof RS, Alfaisal R, Salloum SA. A conceptual framework for determining metaverse adoption in higher institutions of Gulf area: an empirical study using hybrid SEM-ANN approach. Computers Education: Artif Intell. 2022;3:100052. https://doi.org/10.1016/j.caeai.2022.100052.
66. Hair JF, Ringle CM, Gudergan SP, et al. Partial least squares structural equation modeling-based discrete choice modeling: an illustration in modeling retailer choice. Bus Res. 2019;12:115–42. https://doi.org/10.1007/s40685-018-0072-4.
67. Rivadeneira DXR, Toledo JAJ. Machine learning as a teaching strategy education: A review. EAI Endorsed Trans Scalable Inform Syst. 2024;11. https://doi.org/10.4108/EETSIS.5703.
68. Akin AC, Polat M, Mat B, et al. Determining the variables affecting the prices of animal products by the network analysis in Türkiye. Ankara Üniversitesi Veteriner Fakültesi Dergisi. 2023;70:359–66. https://doi.org/10.33988/AUVFD.1065921.
69. Alawadhi M, Alhumaid K, Almarzooqi S, et al. Factors affecting medical students' acceptance of the metaverse system in medical training in the united Arab Emirates. South East Eur J Public Health. 2023. https://doi.org/10.56801/seejph.vi.310.
70. Alomari KM. Predicting the intention to use social media among medical students in the united Arab emirates: A machine learning approach. South East Eur J Public Health. 2023. https://doi.org/10.56801/seejph.vi.308.
71. Wang G, Shin C. Influencing factors of usage intention of metaverse education application platform: empirical evidence based on PPM and TAM models. Sustainability. 2022;14:17037. https://doi.org/10.3390/su142417037.
72. Adepoju A, Adeniji A. Technology acceptance of E-Banking services in an unnatural environment. SEISENSE J Manage. 2020;3:34–50. https://doi.org/10.33215/sjom.v3i3.336.
73. Sann R, Lai P-C, Liaw S-Y, et al. Multidimensional scale development and validation: university service quality (UNIQUAL). J Hospitality Tourism Insights ahead-of-print. 2023. https://doi.org/10.1108/JHTI-08-2022-0343.
74. Hair JF, Hult GTM, Ringle CM, et al. Evaluation of the structural model. Partial least squares structural equation modeling (PLS-SEM) using R. Cham: Springer; 2021. pp. 115–38.
75. Pan L, Xu X, Lu L, Gursoy D. How cultural confidence affects local residents' wellbeing. Serv Ind J. 2021;41:581–605. https://doi.org/10.1080/02642069.2018.1540595.
76. Almarzouqi A, Aburayya A, Salloum SA. Prediction of user's intention to use metaverse system in medical education: A hybrid SEM-ML learning approach. IEEE Access. 2022;10:43421–34. https://doi.org/10.1109/ACCESS.2022.3169285.
77. Alsariera YA, Baashar Y, Alkawsi G, et al. Assessment and evaluation of different machine learning algorithms for predicting student performance. Comput Intell Neurosci. 2022;2022:4151487. https://doi.org/10.1155/2022/4151487.
78. Alfaisal R, Hashim H, Azizan UH. Convolutional neural network for sentiment analysis on Metaverse-Related tweets: A deep learning approach. SN Comput Sci. 2024;5:1–8. https://doi.org/10.1007/S42979-024-03121-8/METRICS.
79. Zhan J, Gurung S, Parsa SPK. Identification of top-K nodes in large networks using Katz centrality. J Big Data. 2017;4:1–19. https://doi.org/10.1186/s40537-017-0076-5.
80. Shelke S, Attar V. Source detection of rumor in social network – A review. Online Soc Netw Media. 2019;9:30–42. https://doi.org/10.1016/J.OSNEM.2018.12.001.