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RESEARCH ARTICLE

Impact of Personal Innovativeness in IT on the Behavioural Intentions of Teachers in Kerala: Investigating the Mediating Role of Perceived Usefulness

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ABSTRACT:

This research explores how Personal Innovativeness in Information Technology (PIIT) affects the Behavioral Intentions (BI) of teachers in Kerala to embrace educational technologies, emphasizing the mediating effect of Perceived Usefulness (PU). Utilizing the Technology Acceptance Model (TAM) this study seeks to offer a detailed understanding of how individual innovation attitudes influence technology adoption in education. A structured survey was conducted with 445 teachers from both public and private schools in Kerala and evaluated using Structural Equation Modelling. The findings indicated that PIIT is a strong predictor of both PU and BI, with PU acting as a mediator between PIIT and BI. The study contributes to both theoretical and practical domains. Theoretically, it enhances TAM by incorporating personal and cognitive aspects, providing a better and holistic framework in comprehending the construct of technology adoption in the context of education. Practically, it underscores the need to promote PIIT and ensure user-friendly educational technology designs, especially in the realm of metaverse-based learning platforms. Furthermore, the results imply that Generation Z teachers, as digital natives, might need less assistance with usability but would benefit from systems that focus on engagement, personalization, and innovation. These insights offer valuable direction for educational policymakers, institutions, and instructional designers aiming to expedite digital transformation in Indian education.

Keywords: Personal innovativeness in IT, behavioural intentions, perceived usefulness, mediator, teachers.

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Introduction

The integration of information technology (IT) in education has significantly reshaped pedagogical practices and redefined the dynamics of teaching and learning across the globe. The rapid advancement of digital tools has enabled educators to enhance instructional delivery, foster student engagement, and streamline administrative tasks (Tondeur et al., 2017). In this evolving educational landscape, the adoption and effective utilization of IT by teachers have become critical to maximizing the benefits of technological innovations. As such, understanding the factors that drive or hinder teachers' intention to embrace IT is a topic of growing academic and practical interest (Schmid et al., 2021).

Among the various individual-level factors influencing technology adoption, PIIT—defined as "the willingness to try out new technologies"—has emerged as a significant predictor of behavioral intentions (Agarwal & Prasad, 1998). Teachers having higher levels of personal innovativeness are generally more open to experimenting with and incorporating novel IT tools into their teaching practices. Prior research has established that such individuals are more likely to perceive the potential benefits of technology and to adopt it in their professional routines (Rogers, 2003). However, while this relationship has been explored in different educational contexts, there remains a lack of region-specific evidence, particularly within the Indian state of Kerala.

In the context of the current research, the results suggest that teachers who score high on PIIT are not only more curious and enthusiastic about new technologies but are also better equipped to overcome initial barriers to adoption, such as perceived complexity or uncertainty. These individuals are more inclined to perceive educational technologies, including advanced platforms such as those based on the metaverse, as beneficial, manageable, and aligned with their professional goals. Their positive disposition toward technological experimentation enables them to navigate new tools more effectively and integrate them into their teaching practices with greater confidence.

The state of Kerala, with its diverse educational infrastructure and large teacher population, provides a compelling context for investigating the determinants of IT adoption in schools. Despite various initiatives by governmental and non-governmental bodies to encourage IT use in education (National Council of Educational Research and Training [NCERT], 2020), the level of adoption among teachers remains inconsistent. One possible explanation lies in the complex interplay between individual innovativeness and the perceived utility of technology. Yet, empirical studies examining this relationship within the region are scarce, especially those that consider the mediating influence of perceived usefulness – an important variable in the Technology Acceptance Model (Davis, 1989).

Addressing this knowledge gap, the present study seeks to explore how personal innovativeness in IT influences the behavioral intentions of schoolteachers in Kerala, with particular attention to the mediating role of perceived usefulness. By focusing on this mediational pathway, the study aims to unpack the psychological mechanisms through which innovativeness translates into actual intention to adopt technology. Such an investigation is timely and relevant, given the growing emphasis on digital transformation in education and the critical role of teachers in facilitating this transition (Koehler et al., 2014).

The primary research question guiding this study is: *How does personal innovativeness in IT impact the behavioral intentions of teachers in Kerala, and what is the mediating role of perceived usefulness?* To address this, the study sets out to examine the direct effect of personal innovativeness on behavioral intentions and the indirect effect via perceived usefulness.

Literature Review

1. Personal Innovativeness in IT

Personal innovativeness in IT (PIIT) is indeed a crucial factor in understanding how individuals interact with and adopt new technologies. Research consistently demonstrates its significant impact on technology acceptance and usage across various contexts. Further, it "directly influences perceived ease of use and perceived usefulness", which are key determinants of technology adoption intentions (Lewis et al., 2003). For instance, in the context of

virtual reality simulations for nursing education, PIIT was found to significantly impact students' intentions to use the technology (Fagan et al., 2012). Interestingly, PIIT's influence extends beyond initial adoption to continuance intention. A study on m-commerce users found that PIIT remains a strong determinant of user continuance intention, highlighting its long-term psychological influence (Lu, 2014).

This suggests that personal innovativeness has a persistent effect on technology acceptance decisions across multiple technologies and stages of use. In conclusion, PIIT plays a multifaceted role in technology adoption and use. It not only affects initial perceptions and adoption intentions but also influences long-term usage behavior. Understanding PIIT can help researchers and practitioners better predict and facilitate technology acceptance, making it a valuable construct in information systems research and implementation strategies. Research has consistently demonstrated that individuals with high PIIT are more tolerant of uncertainty, exhibit a greater propensity for risk-taking, and are more likely to adopt innovative digital tools (Fan et al., 2020; Yi et al., 2006). Research indicates that teachers who are open to experimenting with novel instructional technologies can foster a culture of continuous learning and pedagogical innovation (Jääskelä et al., 2017; Liu et al., 2023).

A study conducted across three universities in Russia and China revealed that incorporating AI technologies like ChatGPT in education positively influences educators' outcomes compared to conventional teaching methods (Liu et al., 2023). However, the adoption of technology in teaching is not without challenges. A study in Finland highlighted the necessity to explore the beliefs of teachers in a systematic manner and also the necessity to acknowledge multiple ways of thinking in the development-oriented programs for teachers (Jääskelä et al., 2017).

Further, the recently evolved online mode of education and the development of associated techniques in curriculum, pedagogy, and assessment, creating a gap between technology innovation and pedagogical governance (Dhakal, 2023). In conclusion, while there is evidence supporting the benefits of integrating novel instructional technologies in education, it is crucial to consider teachers' beliefs, pedagogical practices, and the need for ongoing professional development. By addressing such aspects, institutions in the educational sector could help developing an organizational culture that further promotes experimentation with new technologies, fostering a culture of continuous learning and pedagogical innovation (Busuttil & Calleja, 2025; Cronin, 2017; Prestridge, 2017).

TAM is a widely used framework for understanding how individuals adopt technology, focusing on two primary constructs: PU and PEU. Numerous studies have explored how these constructs relate to and influence users' intentions to engage with various technologies. Empirical research consistently demonstrates that both PU and PEU significantly impact users' intentions to adopt technology and their attitudes toward its use. For instance, research involving Malaysian student teachers showed that PU and PEU were crucial factors in their intention to use computers.

In the realm of e-commerce, the findings are somewhat consistent but with some variations. Leong et al. (2011), focusing on mobile entertainment adoption in Malaysia, found that both PU and PEU influenced consumer intention to use (CIU). However, it did not specify which factor had a more substantial effect. Akhlaq and Ahmed (2015), examining online shopping intentions in Pakistan, also found that both PU and PEU were independently predictive of intention to shop online, but again did not indicate which had a stronger effect. In summary, while the studies consistently show that both PU and PEU are significant factors in technology adoption across different contexts in Malaysia and other emerging economies, the claim that PEU exerts the most substantial positive effect on e-purchase intentions is not explicitly supported by the provided papers. The relative strength of PU versus PEU may vary depending on the specific technology and context being studied.

Interestingly, some studies have expanded on the original TAM by adding other variables also in the context of different conceptual models. For example, research on mobile entertainment adoption in Malaysia successfully integrated individual characteristics with TAM, finding that PU, PEU, academic qualification, and past adoption behavior influenced adoption (Leong et al., 2011). Another study examining food delivery applications in Korea found that personal

innovativeness positively affected PEU, while trust positively influenced both PU and PEU (An et al., 2023). In conclusion, while the provided context does not directly address the relationship between PIIT and TAM constructs, it does support the overall importance of PU and PEU in technology acceptance across various domains.

The integration of additional factors, such as trust and individual characteristics, suggests that the TAM can be extended to offer a broader framework in terms of technology adoption behaviors among people. Teachers who exhibit higher innovativeness tend to view IT tools as both beneficial and manageable, which strengthens their intention to integrate such technologies into classroom instruction. Notably, While the provided context does not directly address the statement about Personal Innovativeness in Information Technology (PIIT) and its link to self-efficacy, it does offer relevant information on the relationship between digital competence, self-efficacy, and innovative behavior in educators. Several studies in the context support the notion that self-efficacy could be an important predictor of innovative behavior and digital competence in educators.

Interestingly, the relationship between digital competence and self-efficacy appears to be bidirectional. This suggests that as teachers become more confident in their ability to use digital tools, they may also perceive their environment as more supportive of technology integration. In conclusion, while the specific link between PIIT and self-efficacy is not directly addressed in the provided context, the studies collectively support the idea that self-efficacy is positively associated with innovative behavior and digital competence in educators. This aligns with the general notion that confident educators are more likely to embrace and effectively use digital tools in their teaching practices.

Empirical evidence supports the notion that PIIT is a key enabler of technology adoption in various educational settings. For instance, individuals with high PIIT are more likely to perceive metaverse platforms, virtual reality environments, or e-learning systems as valuable and easy to use (Akour et al., 2022; Wang et al., 2021). Given the rapid evolution of digital teaching aids, fostering PIIT among teachers can substantially impact how educational technologies are embraced and utilized for improved learning outcomes.

2. Behavioural Intentions

Behavioural intention (BI) refers to "an individual's readiness to engage in a particular behavior" - in this context, the adoption of IT in educational settings. Within the TAM framework, BI serves as a critical determinant of actual technology use (Davis, 1989). It is influenced by multiple factors, including perceived usefulness, perceived enjoyment, and PIIT (Al-Adwan et al., 2023). In the teaching profession, behavioral intention captures a teacher's willingness to adopt and consistently use digital tools in the classroom. Studies on educational technology adoption have highlighted the role of cognitive and affective antecedents in shaping BI. For example, perceived enjoyment has emerged as a significant factor influencing users' intentions to engage with hedonic technologies such as the metaverse (Van der Heijden, 2004). Similarly, teachers who find IT enjoyable and engaging are more likely to integrate it into their practice, thereby reinforcing positive behavioral intentions (Wang et al., 2022).

Moreover, BI is also shaped by contextual inhibitors and enablers, such as perceived cyber risks or institutional support (Al-Adwan et al., 2023). These external factors can either strengthen or undermine a teacher's intention to adopt technology. Understanding the interplay between personal, cognitive, and environmental determinants of BI is essential for developing effective interventions that support technology integration in schools.

3. Perceived Usefulness

Perceived usefulness (PU) is defined as "the degree to which a person believes that using a particular system will enhance their job performance" (Davis, 1989). Within educational settings, PU is a robust predictor of technology acceptance and plays a mediating role between antecedent factors such as PIIT and the formation of behavioral intentions (Al-Adwan et al., 2023). Teachers who perceive IT as useful are more inclined to incorporate it into their pedagogy to improve instructional efficiency and student outcomes.

Empirical studies underscore PU's

centrality in determining the effectiveness of IT adoption. In Al-Adwan et al.'s (2023) extended TAM study, PU emerged as the strongest predictor of students' intention to use metaverse-based learning platforms, a finding that may parallel teachers' adoption behavior in Kerala. Similar conclusions have been drawn in prior studies exploring PU's influence on BI across different technological and educational contexts (Chahal & Rani, 2022; Akour et al., 2022).

Additionally, PU is influenced by both personal traits and system characteristics. PIIT and self-efficacy, for example, directly impact PU by shaping users' perceptions of how well they can leverage technology to achieve educational goals (Fagan et al., 2012; Abdullah & Ward, 2016). Therefore, enhancing PU through professional development and user-cantered design of IT systems can be pivotal in increasing technology adoption rates among teachers.

Theoretical Background

TAM, initially introduced by Davis (1989), has become one of the most influential and extensively used theoretical frameworks for understanding user behavior in technology adoption. Its primary strength lies in its simplicity and predictive capability, establishing it as a foundational model across a wide range of disciplines and technological contexts. The major constructs involved in this model, like PEU and PU are key predictors of user attitudes, intentions, and ultimately, behavior toward adopting new technologies (Chismar & Wiley-Patton, 2003; Ratna & Mehra, 2015). Over the years, TAM has undergone extensive empirical testing and validation in various organizational and educational settings, demonstrating both robustness and flexibility. Its application spans numerous domains, including academic settings, where it has been used to assess the adoption of e-learning systems (Ratna & Mehra, 2015), corporate environments, where it has supported the evaluation of knowledge management information systems (Money & Turner, 2004), and healthcare, where it has informed the use of Internet-based health applications (Chismar & Wiley-Patton, 2003).

In the construction industry, TAM has been employed to explore the adoption of Building Information Modelling (BIM) tools (Lai & Lee, 2020), showcasing its ability to accommodate highly specialized technological systems. TAM's broad applicability has prompted researchers to extend and enrich the original model by integrating it with other theoretical perspectives to enhance its explanatory power. For example, the Technology Readiness Index (TRI) has been incorporated to capture users' predisposition toward new technologies (Lai & Lee, 2020), while the Uses and Gratifications Theory has been used to explore motivational dimensions in media consumption and social media engagement (Park et al., 2007). These extensions emphasize the model's adaptability and highlight its relevance in an increasingly complex digital landscape, where users' experiences, motivations, and contextual factors significantly influence their technology-related behaviors. In summary, the enduring relevance of the Technology Acceptance Model lies in its ability to explain user acceptance across a diverse array of technological platforms and user populations. Its conceptual clarity, empirical rigor, and adaptability make it an indispensable tool for researchers and practitioners aiming to understand and facilitate technology adoption in both traditional and emerging contexts.

Interestingly, while TAM has shown consistent results in many studies, some research has revealed contradictions. Additionally, the importance of perceived ease of use may vary depending on the nature of the task (Gefen & Straub, 2000). These findings suggest that while TAM provides a strong theoretical foundation, its applicability may be influenced by specific contexts and user groups. TAM has indeed been extensively validated and extended across various domains, including education, as evidenced by the provided research papers. In the educational context, TAM has been applied to examine the acceptance of various technologies. For instance, Abuhassna et al. (2023) discusses TAM's role in accepting online learning platforms, analysing research from 2002 to 2020 (Abuhassna et al., 2023). The study identified several online learning environments where TAM has been applied, including MOOCs, Moodle, e-learning, flipped learning, and blended learning.

Interestingly, while TAM has been widely validated, some studies have found contradictions or variations in its application. For example, Chismar and Wiley-Patton (2003), in their study found that perceived ease of use cannot anticipate

the intention to use, which is in contrast with the original model (Chismar & Wiley-Patton, 2003). Additionally, Teo et al. (2019), which studied TAM in the Nepali context, found no influence of perceived usefulness or attitude on behavioral intention, contradicting theorized relationships (Teo et al., 2019). However, traditional TAM has faced criticism for its limited scope in addressing contextual and psychological variables. Researchers have expanded TAM to include personal traits (e.g., PIIT), emotional factors (e.g., perceived enjoyment), and inhibitors (e.g., perceived cyber risk) to enhance its explanatory power (Zhang et al., 2022; Taherdoost, 2018). Such extensions are particularly relevant in education, where user behavior is influenced by a complex array of intrinsic and extrinsic motivations.

In the context of educational IT adoption, PIIT has been recognized as a critical external variable influencing PU and PEU. A study on fitness app adoption revealed that "personal innovativeness predicts perceived usefulness and ease of use, with perceived usefulness being the strongest predictor of intention to use" (Acikgoz et al., 2022). Similarly, in mobile money services context, "personal innovativeness was found to affect adoption decisions, although its impact was lower compared to perceived ease of use and perceived usefulness" (Gbongli et al., 2019).

Interestingly, some studies reveal that PIIT can have varying effects depending on the context and user characteristics. For example, in the adoption of mobile devices by older adults, "personal innovativeness was found to be partially mediated by perceived ease of use and perceived usefulness in its relationship with behavioral intention" (Lee, 2019). Additionally, in the context of complex IT systems, personal innovativeness with IT (PIIT) moderated the effects of perceived usefulness and satisfaction on innovative use of IT, although the moderating role varied depending on the specific type of IT investigated (Wang et al., 2013). Furthermore, incorporating PIIT into TAM allows a better understanding in terms of the personal drivers behind technology acceptance among teachers.

Given its strong empirical grounding and flexibility, TAM serves as a suitable framework for the current study. By incorporating PIIT and examining the mediating role of PU, this research aims to bridge theoretical and practical gaps in understanding how teachers in Kerala form intentions to adopt educational technologies. The insights gained can inform strategies to foster a more innovation-driven and tech-ready teaching workforce.

Hypotheses

On the basis of the theoretical framework and the literature given above, we reached the following hypothesis: -

H1 : Personal innovativeness in IT is positively related with behavioural intentions among teachers in using technology.

H2 : PIIT is positively related with PU of technology among the users.

H3 : Perceived usefulness of technology is positively related with behavioural intentions among teachers in using technology.

H4 : Perceived usefulness of technology mediates the relationship between personal innovativeness in IT and behavioural intentions among teachers in using technology.

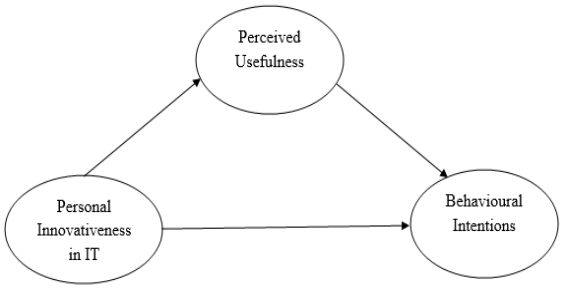

Fig 1. *Conceptual Model*

Methodology

The present study utilized a quantitative research design, employing the survey method to gather data from participants. A structured questionnaire served as the primary instrument for data collection. The target population consisted of schoolteachers from various educational

institutions across the state of Kerala, India, encompassing both public and private sector schools. This diverse sample facilitated a comprehensive understanding of teachers' attitudes and intentions regarding the adoption of educational technologies in different institutional contexts. The questionnaire was divided into two main sections. The first section aimed to capture demographic information of the respondents, including age, gender, academic qualifications, teaching experience, subject specialization, and familiarity with information technology. Collecting this background information was essential for profiling the participants and enabling subgroup analyses. The second section focused on measuring the key constructs outlined in the research model—namely, Personal Innovativeness in Information Technology (PIIT), Perceived Usefulness (PU), and Behavioral Intention (BI). The scales used in the study for measuring various variables are attached as Appendix.

A total of 11 items were included in this section, each carefully selected and adapted from previously validated instruments published in the academic literature to ensure conceptual relevance and content validity in the context of the current study. To ensure clarity and contextual appropriateness, minor adjustments were made to the wording of the questionnaire items, aligning them with the educational environment of Kerala. A total of 445 completed responses were obtained, making this one of the more extensive and representative samples in studies focusing on technology adoption among Indian schoolteachers. The robust sample size enhances the reliability of the findings and supports the generalizability of the results within the regional educational landscape.

Data Analysis

The questionnaire collected information regarding the respondents, including factors such as age, gender, field of study, teaching experience, and proficiency with information technology. This data was essential for comprehending the background characteristics of the sample group and enabling further subgroup analyses. The second section of the questionnaire consisted of 11 items designed to evaluate the constructs outlined in the research model. These items were carefully adapted from established and previously validated tools in the existing literature. Also, to enhance the scientific nature of the study, reliability and validity of the scales were tested. Participants indicated their level of agreement with each statement by selecting any one option from strongly agree to strongly disagree. To verify the reliability of the measurement scales, a pilot test was conducted with a group of 30 university students.

The pilot study results indicated that all constructs achieved satisfactory levels of consistency internally. This was assured once Cronbach's Alpha values crossed the minimum recommended value of 0.70 (Hair et al., 2019), thereby demonstrating acceptable reliability. In addition to internal consistency, content validity was rigorously assessed. A panel of five academic experts with extensive expertise in educational technology and information systems was convened to review the questionnaire. The experts evaluated each item for clarity, relevance, and alignment with the intended constructs. Based on their recommendations, minor revisions were made to enhance the wording and comprehensibility of a few items, thereby improving the overall content validity of the instrument (Artino et al., 2014).

Table 1 Participants' profile (N = 445)

Demographic		Frequency	Percentage
Gender	Male	218	49
	Female	227	51
Age	<20	159	36
	20-30	189	42
	>30	97	22
Education	UG	289	65
	PG	156	35
University	Public	312	70
	Private	133	30

For the purpose of data analysis, this study utilized the Partial Least Squares Structural Equation Modeling (PLS-SEM) technique. PLS-SEM was chosen due to its robustness, flexibility, and appropriateness for exploratory and predictive research. Unlike covariance-based SEM, PLS-SEM does not impose stringent assumptions regarding data distribution, multivariate normality, or large sample sizes, rendering it suitable for social science research where such assumptions are often challenging to satisfy (Hair et al., 2019). This

approach is particularly beneficial when the research model is complex, involves multiple constructs, or when the primary aim is theory development rather than theory testing. The data collected via the questionnaire were analysed using SmartPLS 4 software (Ringle et al., 2022), which is widely acknowledged for its user-friendly interface and robust capabilities for implementing the PLS-SEM technique.

Structural model

Once the evaluation of the measurement model was successfully done, we moved on to assess the structural model to investigate the proposed relationships among the constructs. This assessment included analysing path coefficients (β), the coefficient of determination (R^2), and the model's predictive relevance (Q^2). As shown in Table 2, the significance of the path coefficients was evaluated using a bootstrapping method with 5,000 resamples. Among the proposed paths, PIIT had the strongest positive effect on BI, with a standardized path coefficient of β = 0.219 and a p-value of less than 0.001. This indicates that PIIT and BI are positively corelated. This result further implies that when PIIT is higher in individuals, there is a higher chance to develop stronger behavioral intentions toward adopting technology.

Further, to evaluate the explanatory power of this model, the coefficient of determination (R^2) values was examined to determine the variance proportion explained in the endogenous constructs. As illustrated in Table 3, the combined effects of PIIT and Perceived Ease of Use (PEU) accounted for 75.8% of the variance in BI (R^2 = 0.758), which is deemed substantial according to Henseler et al. (2009). This high R^2 value signifies that the model elucidates a considerable proportion of the variance in behavioral intention, thereby providing robust support for the overall model fit. Additionally, PEU was found to account for 42.3% of the variance in its associated endogenous variable (R^2 = 0.423), reflecting a moderate level of explanatory power. These findings imply that the proposed model effectively captures a significant portion of the factors influencing the key dependent variables.

Furthermore, the predictive relevance of the model was evaluated using the Q^2 statistic, computed via the blindfolding procedure. As depicted in Table 3, all endogenous constructs yielded Q^2 values significantly greater than zero, confirming that the model possesses adequate predictive relevance (Hair et al., 2019). These results reinforce the model's capability to predict the behavior of the latent variables and demonstrate the robustness of the hypothesized structural relationships.

Table 2: Hypotheses Testing

Hypothesis	path	Beta	Mean	STDEV	T statistics	Confidence interval	P values	Assumption
H1	PIIT-> BI	0.219	0.22	0.075	2.938	0.076, 0.469	0.005	yes

Table 3: Assessment of predictive power and predictive relevance

Construct	R^2	Assumption	Q^2	Assumption
BI	0.758	Substantial	0.587	Large
PEU	0.423	Moderate	0.285	Medium

Indirect effect assessment

The importance of the indirect effects among the constructs in the research model was evaluated to clarify the mediating mechanisms at play. These results are presented in Table 4. The findings indicate that all examined indirect effects were statistically significant, thereby reinforcing the hypothesized mediational relationships within the structural model. Particularly, the indirect effect of PIIT on BI via PEU was significant, with a standardized coefficient of β = 0.006 and a p-value of less than 0.01. Although this indirect effect is relatively small in magnitude, its significance highlights the mediating role of PEU in the connection between PIIT and BI. This suggests that students with higher personal innovativeness in IT are more inclined to find metaverse technologies easier to use, which subsequently boosts their intention to adopt these technologies.

The results highlight the importance of fostering both innovativeness and perceptions of ease of use in educational contexts where emerging

technologies like the metaverse are being introduced. Essentially, by enhancing students' confidence and comfort in using new technologies (as captured by PEU), educators and institutions can effectively amplify the positive influence of PIIT on students' willingness to engage with advanced digital learning environments such as the metaverse. These findings provide valuable insights for designing interventions and instructional strategies aimed at enhancing technology adoption in academic settings. They also reinforce the theoretical proposition that perceived ease of use serves as a critical mediator in technology acceptance frameworks.

Table 4: Indirect effects assessment

Path	beta	Mean	STDEV	T statistics	P values
PIIT -> PEU-> BI	0.006	0.008	0.018	0.342	0.758

Discussion

The findings of this study reveal that PIIT exerts a statistically significant and positive impact on Behavioral Intention (BI), thereby providing strong empirical support for Hypothesis 1 (H1). This result reinforces the theoretical proposition that individuals with higher levels of innovativeness are more likely to engage with and adopt new technologies. The relationship identified in this study is consistent with a robust body of prior literature, which has consistently recognized PIIT as a key antecedent to both behavioral intention and perceived ease of use (E.g. Chahal & Rani, 2022; Wang et al., 2021). These prior studies have similarly found that innovative individuals tend to demonstrate proactive engagement with emerging digital tools and exhibit a greater willingness to experiment with technology-driven educational solutions.

In the context of the current research, the results suggest that teachers who score high on PIIT are not only more curious and enthusiastic about new technologies but are also better equipped to overcome initial barriers to adoption, such as perceived complexity or uncertainty. These individuals are more inclined to perceive educational technologies, including advanced platforms such as those based on the metaverse, as beneficial, manageable, and aligned with their professional goals. Their positive disposition toward technological experimentation enables them to navigate new tools more effectively and integrate them into their teaching practices with greater confidence. This openness to innovation significantly enhances their behavioral intention to adopt educational technologies, as they are less deterred by potential challenges and more motivated by the opportunities for pedagogical enhancement and student engagement that these tools offer.

Furthermore, the strong association between PIIT and BI underscores the importance of fostering a culture of innovation and technological curiosity within the teaching community. By encouraging personal innovativeness—through professional development programs, institutional support, and exposure to cutting-edge tools—educational institutions can empower teachers to become active participants in the digital transformation of education. This is particularly relevant in the context of the metaverse, where immersive and interactive learning environments require not just technical proficiency but also a forward-thinking mindset and a readiness to explore uncharted pedagogical territories.

In the educational context, students with a high degree of PIIT are likely to engage with novel technological tools with curiosity and enthusiasm, viewing challenges as opportunities for growth and personal development rather than as obstacles. Their willingness to explore and experiment with new technologies enhances their technological confidence and competence. Consequently, their ability to navigate and utilize advanced tools, such as metaverse-based learning platforms, is improved, reinforcing their intention to adopt such platforms. Furthermore, due to their inherent comfort with digital environments, highly innovative students are less likely to perceive new educational technologies as complex or difficult to use. This technical confidence positively influences their perceptions, making them more inclined to find metaverse-based systems intuitive and beneficial, even in the early stages of implementation. They are also better positioned to recognize and leverage the educational advantages offered by these platforms, such as immersive learning experiences, interactive content, and increased engagement.

Furthermore, the analysis reveals that PEU

significantly impacts both personal innovativeness in information technology (PIIT) and behavioral intention (BI), thereby supporting the proposed hypotheses concerning these relationships. When students perceive a learning platform as user-friendly, they can allocate more cognitive and emotional resources toward engaging with the content and enjoying the learning experience. A user-friendly interface minimizes frustration, reduces the learning curve, and enhances motivation, which is particularly crucial when integrating complex technologies such as the metaverse into educational settings. Interestingly, and somewhat unexpectedly, the direct effect of PEU on BI was found to be statistically insignificant.

This finding aligns with previous studies (e.g., Yang et al., 2022; Wang et al., 2022), although it contradicts the results of other researchers (e.g., Akour et al., 2022; Faqih et al., 2021). One plausible explanation for this inconsistency lies in the characteristics of the study's respondent group, which comprised university students from Generation Z (born between 1995 and 2010) (Meet et al., 2022). Generation Z individuals are widely regarded as digital natives; they have grown up surrounded by digital technologies and possess an innate familiarity with a wide range of modern technological tools (Larionova et al., 2018). Consequently, Gen Z students often approach new digital platforms—such as those incorporating virtual and augmented reality—with ease and confidence. Their advanced digital literacy enables them to operate complex systems with minimal guidance, reducing the significance of perceived ease of use as a determining factor in their behavioral intentions. In essence, for this demographic, ease of use may be considered a baseline expectation rather than a motivational driver. Therefore, their intention to adopt the metaverse for learning purposes may be more strongly influenced by other factors, such as perceived usefulness, personal innovativeness, and the novelty or engagement potential of the technology itself.

Implications

The contributions of this study are recognized as twofold offering both theoretical and practical value.

Theoretical Contribution:

This study offers a noteworthy theoretical advancement by proposing a modified TAM model to examine behavioral intention (BI) toward the adoption of metaverse-based learning platforms in higher education. Although TAM has been extensively utilized in previous research, it has been critiqued for its focus on technological and enabling factors while neglecting personal characteristics and potential barriers. To address these limitations, this study introduces a more comprehensive framework that incorporates technical, human, and both enabling and inhibiting factors, thereby enhancing the model's explanatory and predictive capabilities. The findings validate the applicability of this extended TAM model in the context of metaverse adoption in higher education and contribute to the expanding academic discourse on the metaverse—a technology that has attracted significant interest in recent years.

Despite a substantial body of literature on the metaverse, its educational potential in higher learning institutions remains underexplored. This study addresses this gap by providing empirical insights into how higher education institutions (HEIs) can utilize metaverse-based platforms to improve learning outcomes. The proposed model accounts for 75.8% ($R^2 = 0.758$) of the variance in students' intentions to adopt metaverse-based learning, indicating a substantial level of explanatory power. Furthermore, this research is among the pioneering studies in the Indian higher education context to systematically investigate the key determinants of metaverse adoption. As such, it establishes a foundational benchmark for future research and offers actionable guidance for HEIs seeking to integrate immersive digital technologies into their instructional ecosystems.

Practical Contribution:

From a practical perspective, this study highlights the pivotal role of Perceived Ease of Use (PEU) in promoting the effective adoption of metaverse technologies within educational settings. A platform characterized by complexity or navigational challenges may be perceived as less beneficial, thereby reducing students' motivation to engage with it. Consequently, it is imperative that metaverse-based learning platforms are intuitive,

user-friendly, and designed with a focus on user experience. Key design principles include clear guidance, simple interfaces, and accessible features. To further enhance platform usability, it is crucial to provide comprehensive training and support resources, such as tutorials, instructional videos, and user manuals, to assist users in comprehending the platform's full range of features and functionalities. Additionally, given the prevalent use of mobile devices, optimizing the metaverse platform for smartphones and tablets can significantly improve accessibility and convenience for students, facilitating seamless learning experiences at any time and location. Another significant practical implication arises from the influence of Personal Innovativeness in Information Technology (PIIT), which exerts a substantial and direct impact on Behavioral Intention (BI). Students with high PIIT are more inclined to explore, adopt, and benefit from emerging technologies like the metaverse. These learners often excel in environments that nurture curiosity, experimentation, and personalized learning.

Therefore, instructors and educational designers should incorporate elements that enable individualized learning experiences—such as adaptive learning paths, real-time feedback, and customizable content—to accommodate diverse learner preferences. Furthermore, metaverse learning environments should be structured to encourage risk-taking and resilience. As personal innovators tend to embrace challenges and perceive failure as an integral part of the learning process, educators must cultivate a supportive atmosphere that promotes experimentation. Providing safe spaces for students to fail, reflect, and improve can foster a growth mindset, leading to more meaningful engagement and long-term skill development.

Conclusion

This study elucidates the pivotal role of personal innovativeness in influencing teachers' behavioral intentions to adopt educational technology, particularly within the regional context of Kerala. The empirical findings substantiate the proposed model by identifying PIIT as a significant determinant of BI, mediated by perceived usefulness. Teachers exhibiting high levels of PIIT are more inclined to perceive technology as advantageous, intuitive, and congruent with their pedagogical objectives. This supports the assertion that, beyond infrastructural and institutional preparedness, individual attitudes and predispositions toward innovation are crucial for successful technology integration in classrooms. The model's substantial explanatory power further highlights its robustness and relevance to contemporary educational practices. In conclusion, this research offers significant contributions to the literature on technology acceptance and educational innovation. It underscores the necessity for targeted interventions that not only enhance the technical design of learning platforms but also foster innovative mindsets among educators. Institutions must prioritize professional development initiatives that bolster teachers' confidence in utilizing new technologies, provide opportunities for personalized exploration, and encourage risk-taking in instructional design. Future research could extend these findings by incorporating additional moderating variables such as institutional support or perceived risks, and by replicating the study across diverse cultural or geographic contexts to enhance generalizability.

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