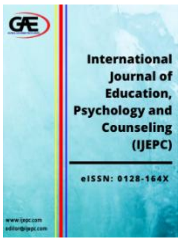
International Journal of Education, Psychology and Counseling
IJEPC
EISSN : 0128-164X
Volume 11 Issue 64 (September 2026) PP. 315-347



INTERNATIONAL JOURNAL OF EDUCATION, PSYCHOLOGY AND COUNSELLING (IJEPC)
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EDUCATOR ACCEPTANCE, PERSONALITY TRAITS, TECHNOLOGICAL COMPETENCE AND 21ST-CENTURY EDUCATIONAL TECHNOLOGY ADOPTION: A PREDICTIVE RELEVANCE ANALYSIS USING PLS*PREDICT*

Mohamad Ridhuan Mat Dangi[1*], Maisarah Mohamed Saat[2], Radziah Mahmud[3], Norliza Omar[4], Shazalina Mohamed Shuhidan[5]

[1]Faculty of Accountancy, UiTM Puncak Alam Campus, Selangor, Malaysia
ridhuan@uitm.edu.my https://orcid.org/0000-0003-3042-873X
[2]Faculty of Management, Universiti Teknologi Malaysia, Johor, Malaysia
maisarahsaat@utm.my https://orcid.org/0000-0003-2777-6207
[3]Faculty of Accountancy, UiTM Puncak Alam Campus, Selangor, Malaysia
radzi132@uitm.edu.my https://orcid.org/0000-0001-9471-9064
[4]Faculty of Accountancy, UiTM Puncak Alam Campus, Selangor, Malaysia
norli795@uitm.edu.my https://orcid.org/0009-0007-5953-0099
[5]Faculty of Accountancy, UiTM Puncak Alam Campus, Selangor, Malaysia
shazalin@uitm.edu.my https://orcid.org/0009-0006-1833-5265
*Corresponding Author

Article Info:

Article history:
Received date: 22.06.2026
Revised date: 02.07.2026
Accepted date: 12.07.2026
Published date: 07.09.2026

Abstract:

The study examines the intention to adopt 21st-century educational technology in higher education, focusing on the factors contributing to educators' intention to adopt. The novel framework conceptualised in this study combines prominent theories and models, including acceptance, five-factor traits, and technological competence. The study uses partial least squares structural equation modelling (PLS-SEM) and predictive relevance analysis with PLS*predict* to test the model's predictive validity. The study found that the conceptualised model was reliable and consistent with sufficient discriminant validity, and the PLS*predict* analysis concluded that the developed conceptual framework has high out-of-sample predictive power. The study's implications for practice and policy include engaging with educators to understand their concerns about technology acceptance,

International Journal of Education, Psychology and Counseling
IJEPC
EISSN : 0128-164X
Volume 11 Issue 64 (September 2026) PP. 315-347

designing personality mapping, aligning with future personality intervention, and ensuring that investment in technology is fully deployed in line with demands and new requirements.

To cite this document:

Mat Dangi, M. R., Mohamed Saat, M., Mahmud, R., Omar, N., & Shuhidan, S. M. (2026). Educator Acceptance, Personality Traits, Technological Competence And 21st-Century Educational Technology Adoption: A Predictive Relevance Analysis Using Pls*predict*. *International Journal of Education, Psychology and Counselling, 11*(64), 315-347.

DOI: 10.35631/IJEPC.11640016

Keyword:

Acceptance, Educational Technology, Intention to Adopt, Personality Traits, Pls*predict,* Technological Competence

Introduction

Technology has grown increasingly prevalent and has been integrated into the educational environment. It has led to the development of educational technology, which has changed the teaching and learning process by enabling learners to engage with multifaceted phenomena, construct flexible knowledge, and cater to individual differences (Hasan, 2022; Salloum et al., 2019; Santoso & Lestari, 2019). In academic settings, Mayes et al. (2015, p. 222) cited The Association for Educational Communications and Technology (AECT)'s definition of educational technology from 1977, which stated that it is a "complex and integrated process of people, procedures, ideas, devices, and organisation for analysing problems and devising, implementing, evaluating, and managing solutions to those problems, involved in all aspects of human learning". The adoption of educational technology enables knowledge to be acquired in an active, constructive, and self-directed manner (Delgado et al., 2015; Salloum et al., 2019), enhances the effectiveness of the teaching-learning process (Mirzajani et al., 2016), transforms the classroom environment into a more accessible and engaging space (Buabeng-Andoh, 2012; Solano et al., 2017), provides cost-effective and flexible learning environments (Dua et al., 2016) and promotes collaboration and engagement among students (Wu et al., 2019) as recognised by policymakers in many countries.

The 21st-century teaching and learning pedagogies are increasingly incorporating educational technology alongside traditional methods to align with the United Nations' Sustainable Development Goal 4, aiming for quality education and the development of 21st-century skills (Asonitou, 2020; Dauda & Olawale, 2020; Grabinski et al., 2015; Iqbal et al., 2019). From myriads of available technologies, the evolution of web applications offers an abundance of possibilities that can be utilised in the teaching-learning process (Namoco, 2022; Thohir et al., 2021). From Web 1.0 to Web 3.0, it offers educators diverse tools to enhance teaching and learning. Educators can utilize these technologies, including various media, hardware, software, and communication tools, to create engaging instructional materials and interact effectively with students (Granic, 2022; Milutinovic, 2022; Santi, 2022).

Despite the availability and potential benefits of educational technology, previous research indicates that educators have not fully utilized 21st-century educational technology in their teaching practices (Al-Htaybat et al., 2018; Foued, 2021; Hasan, 2022; Kearney et al., 2017; Wolugbom et al., 2020). Educators often rely on basic computer tools, such as email, internet resources, presentations, word processing, spreadsheets, videos, and simple data analysis techniques, rather than integrating more advanced technologies into their curriculum (Ahadiat, 2008; Iqbal et al., 2019; Thomas & Chukhlomin, 2020). Despite numerous studies highlighting the importance of technology in education, there remains a gap between what is being taught in universities and what is being implemented in the industry (Blankley et al., 2018; Burritt & Christ, 2016; Kwarteng, 2018; Thomas & Chukhlomin, 2020). While considering the innovative trend in educational technology, it is essential to recognize that educators' acceptance of necessary technological skills for their professional development may be hindered by certain behaviours and traits, potentially leading to the underutilisation of available technology (Instefjord, 2018; Mourão, 2018). Individual intentions to adopt technology revolve around personal interest, social influence (Gurjar & Sivo, 2022; Salloum et al., 2021), and attitudes toward the perceived favourability or unfavourability of these technologies (Guillén-Gámez & Mayorga-Fernández, 2020; Yulisman et al., 2019), which are in turn shaped by personal behaviours and traits. Such factors pose challenges to the effective integration of technology into educational practices, highlighting the need for targeted interventions and support mechanisms to address potential barriers and promote meaningful utilisation. Hence, the present study employed prominent frameworks that are widely used and accepted in predicting and explaining individual behaviours regarding their intention to adopt educational technology in teaching and learning.

Addressing this gap, this study examines the role of acceptance levels, personality traits, and technological competence in predicting the adoption of educational technology in higher education. By investigating the relationships between these factors, the study aims to develop an intervention strategy that considers them, fostering a greater willingness among educators to incorporate technology into their teaching practices. To date, limited research has explored causal-predictive perspectives within the information system field, analysing a model with explanatory power and predictive capabilities (Chin et al., 2020). Therefore, the findings of this study will contribute to the existing literature by identifying the factors influencing technology adoption and establishing a relevant and valid framework for studying these relationships. This will advance the understanding and promotion of educational technology adoption in higher education.

Literature Review

Scholars and researchers have employed numerous models, theories, and perspectives to understand and predict human behaviour regarding technology adoption. Among the well-known theories in this context are the theory of reasoned action (TRA) (Fishbein & Ajzen, 1975; Moore & Benbasat, 1996); diffusion of innovation theory (Rogers, 1995); theory of planned behaviour (TPB) (Ajzen, 1991); decomposed theory of planned behaviour (DTPB) (Taylor & Todd, 1995); technology acceptance model (TAM) (Davis, 1989; Davis et al., 1989); revised technology acceptance model (TAM 2) (Venkatesh & Davis, 2000); integrated model of technology acceptance model or TAM version 3 (TAM 3) (Venkatesh & Bala, 2008); unified theory of acceptance and use of technology (UTAUT) (Venkatesh et al., 2003) and motivational model (Vallerand, 1997), have been utilised to predict or explain technology adoption behaviour. Among these models, TAM stands out as the most prominent and influential, particularly in research related to information and technology. TAM is widely recognised for its robustness, parsimony, and suitability in measuring educators' technology (Purnamasari et al., 2021; Santi, 2022; Scherer et al., 2019; Weerasinghe & Hindagolla, 2017).

Research on adopting information technology in the educational context has made it a prominent and widely studied area (Lawrence & Tar, 2018). However, despite this attention, researchers often struggle to select appropriate models or constructs, given the plethora of options available (Abdul Wahab et al., 2017; Khan et al., 2018; Krieger et al., 2021; Schmidt et al., 2020). There are a variety of theoretical models have been used, modified, and integrated across various disciplines, including social sciences, psychology, sociology, education, marketing, and information systems, with the aim of understanding and predicting factors influencing IT adoption (Alshurafat et al., 2021; Ayele & Birhanie, 2018; Venkatesh et al., 2003; Yoon, 2020). While each model has limitations regarding significance level, parsimony, and explanatory power, a reasonable solution is to select and assimilate relevant constructs from multiple models (Abbasi, 2011; Lai, 2017; Santi, 2022; Setiyawan & Santoso, 2022). By doing so, researchers can produce noteworthy results and contribute to the body of knowledge by formulating comprehensive frameworks. Granic (2022), in a systematic review, underscores this need by observing a lack of a holistic understanding of the factors influencing and reliably predicting the successful acceptance and adoption of technology in educational processes. Thus, gaining insights into these aspects can be beneficial and aid in enhancing research and academic practices by identifying the most influential predictive factors or antecedents impacting educational technology adoption.

Technology Acceptance Model and Intention to Adopt

Understanding educators' technology acceptance and behavioural intentions is challenging for academic institutions (Khlaif, 2018; Milutinovic, 2022). Factors such as behaviour, personal beliefs, and attitudes are key areas of investigation to ensure successful technology integration in education (Alshurafat et al., 2021; Ayele & Birhanie, 2018; Chao, 2019; Huang & Liaw, 2018; Khlaif, 2018; Mohd Muzi et al., 2021; Purnamasari et al., 2021). Behaviour and personal beliefs are observable actions linked to individuals' attitudes, which can be influenced by their observations and performance (Kanwal & Rehman, 2017; Mohd Muzi et al., 2021). Educators' perception of technology, whether or not it fulfills their needs in teaching-learning activities, can impact their intention to adopt technology (Hamidi & Chavoshi, 2018).

In behavioural studies, the Technology Adoption Model (TAM) has been widely used to predict technology acceptance, with perceived usefulness (PU) and perceived ease of use (PEU) being core constructs influencing adoption intention (Scherer et al., 2019). Studies have shown the applicability of TAM in various contexts, such as social media, e-learning platforms, and Google Classroom adoption (Elkaseh et al., 2016; Tanduklangi, 2017; Al-Maroof & Al-Emran, 2018). However, discrepancies in technology acceptance across different contexts highlight the need to consider various factors influencing adoption (Granic, 2022; Lai, 2017). Furthermore,

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EISSN : 0128-164X
Volume 11 Issue 64 (September 2026) PP. 315-347
TAM's flexibility allows for integration with other theories, like the theory of planned behavior (TPB) or the unified theory of acceptance and use of technology (UTAUT), to explore broader influences on technology adoption conditions (Buabeng-Andoh, 2018; Teo, 2019; Yang & Su, 2017). External factors like system characteristics, individual differences, and innovation diffusion constructs have also been added to TAM to account for broader contextual influences (Chao, 2019; Salloum et al., 2021).

Although in the original TAM, attitude acts as a mediator between PU and PEU on the one hand and behavioural intention (BI) on the other. However, several researchers have explored models where attitude plays a more direct role in technology adoption, including in educational contexts. For example, Venkatesh and Davis (2000) proposed the TAM3 model, which extends TAM by including additional constructs like "enjoyment" and "computer anxiety". In this model, attitude directly influences intention, perceived usefulness, and perceived ease of use. Several studies have expanded TAM to accommodate additional variables influencing technology acceptance and usage. Hussain et al. (2016), who expanded the TAM to include perceived enjoyment (PE), found that users' adoption of interactive mobile maps for learning was positively influenced by all three factors (PEU, PU, and PE).

Meanwhile, Herrador-Alcaide et al. (2020) emphasized that perception is the main predictor influencing individual attitudes toward accepting educational technology. Subsequently, Kumar and Mantri (2021) highlighted that educators' confidence as a key determinant of a positive attitude toward technology integration in teaching-learning activities. This suggests that educators' attitudes (AU) regarding technology adoption are crucial in addition to PEU and PU, emphasising the need to concentrate on attitude beyond its mediating function in TAM. Nonetheless, researchers conclude that positive attitudes among educators have been consistently associated with increased technology integration in teaching practices (Atabek, 2020; Guillén-Gámez & Mayorga-Fernández, 2020; Palta, 2019; Weng et al., 2018) reflecting the vital role of attitude in driving technology adoption in education. Accordingly, the following hypotheses are formulated:

H1: There is a positive influence of educators' perceived usefulness (ACPU) on their intention to adopt 21st-century educational technology.
H2: There is a positive influence of educators' perceived ease of use (ACPEU) on their intention to adopt 21st-century educational technology.
H3: There is a positive influence of educators' attitude towards use (ACAU) on their intention to adopt 21st-century educational technology.

Big Five Personality Traits Model and Intention to Adopt

Educators' intention to adopt technology in the classroom can also be influenced by their personality, background, and other external factors (Barnett et al., 2015; Camadan et al., 2018; Dalpé et al., 2019). Personality encompasses individual characteristics, behaviour tendencies, and long-term emotional styles that reflect a person's emotional responses and long-term emotional states. Research has confirmed that an individual's passion and commitment to their environment are closely tied to their personality (Thohir et al., 2021; Vlachogianni & Tselios, 2022), which may have a strong influence on educators, whether there is a tendency for them to adopt educational technology. Building on this perspective, some researchers emphasise the importance of considering personality traits in educators when studying the adoption of educational technologies (Camadan et al., 2018; Göncz, 2017; Raza & Shah, 2017; Thohir et al., 2021). In this context, personality is often viewed as a crucial yet complex and multifaceted variable, meriting further exploration. Personality significantly influences individuals' beliefs, with the Big Five personality model extensively employed in empirical studies as a widely used psychometric construct (Oshio et al., 2018; Soto, 2018). This model has facilitated researchers in efficiently categorising thousands of personality traits and utilising them to gauge individual intentions toward technology adoption (Kim et al., 2019; Tas et al., 2021; Vlachogianni & Tselios, 2022).

The Big Five personality model, including openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism, has been extensively studied in relation to technology and education. For instance, individuals with high openness to experience, curiosity, and a willingness to learn are likely adopters due to their positive technology attitudes (Azucar et al., 2018; Barnett et al., 2015; Oshio et al., 2018). Conscientiousness, known for dependability and organisation, may indirectly influence adoption by aligning with technology integration goals (Aftab et al., 2018; Dalpé et al., 2019). Extraversion, associated with social interaction, often leads to the technology used for communication, social media, or gaming apps (Azucar et al., 2018; Sriyabhand & John, 2014; Xu et al., 2016). Agreeableness, marked by trust and cooperation, positively impacts the perceived usefulness of technology and encourages its use for collaboration (Barnett et al., 2015; Lane & Manner, 2011), with self-control and desire to help others further advocate for technology integration (Ramírez-Correa et al., 2019). Conversely, neuroticism, linked to anxiety and insecurity (Oshio et al., 2018), presents conflicting views. While some may view technology as threatening (Sriyabhand & John, 2014), others use it for support, suggesting the potential for positive influence under specific conditions (Bendersky & Shah, 2013; Tang et al., 2016).

Understanding the diverse ways personality traits influence technology adoption in education can inform strategies to promote its successful integration. Therefore, it is reasonable to investigate this phenomenon from a personality perspective. Technology usage is often discretionary, reflecting individual needs, motives, preferences, and values associated with personality traits (Farhad Khan et al., 2014; Landers & Lounsbury, 2006; Vlachogianni & Tselios, 2022). Educators play a pivotal role in improving teaching and learning by employing creative and innovative ideas through technology (Salloum et al., 2021). As each individual possesses all the Big Five personality traits to varying degrees, it is essential to identify which traits are most prominent in educators, as these are likely to influence their innovation and intention to use technology. Göncz (2017) suggests paying more attention to understanding how educators' actions and personalities affect students' learning experiences. Past literature has widely recognized that academic achievement is influenced not only by learners' intellectual abilities but also by educators' teaching and learning styles, which are in turn influenced by educators' personalities (Camadan et al., 2018; Gurjar & Sivo, 2022; Milutinovic, 2022; Pornsakulvanich et al., 2012; Siddiquei & Khalid, 2018). Based on these viewpoints and existing literature, this study examines the personality traits of educators that are believed to influence their intention to adopt educational technology. Hence, it is hypothesised that:

H4: There is a positive influence of educators' openness to experience (PTOE) trait on their intention to adopt 21st-century educational technology.
H5: There is a positive influence of educators' conscientiousness (PTCO) trait on their intention to adopt 21st-century educational technology.

H6: There is a positive influence of educators' extraversion (PTEX) trait on their intention to adopt 21st-century educational technology.
H7: There is a positive influence of educators' agreeableness (PTAG) trait on their intention to adopt 21st-century educational technology.
H8: There is a positive influence of educators' neuroticism (PTNE) trait on their intention to adopt 21st-century educational technology.

Technological Competence and Intention to Adopt

Technological competency is crucial for educators to effectively incorporate technology into teaching and learning, encompassing knowledge, skills, creativity, attitude, and qualifications (Al-Furaih & Al-Awidi, 2020; Yulisman et al., 2019). Proficiency in utilizing technological devices, technical skills, and innovation is crucial for enhancing teaching efficacy and learning experiences (Candolfi Arballo et al., 2019). Educators must possess various emotional, sociological, motoric, and cognitive skills to navigate the technological landscape effectively (Hizam et al., 2021). It is not only about mastering technological operations but also integrating them with pedagogical content (Glaesser, 2018; Graziano et al., 2017). They must manage classrooms while incorporating technology into teaching practices, curriculum planning, and facilitating learning (Al-Furaih & Al-Awidi, 2020; Santoso & Lestari, 2019; Thomas & Chukhlomin, 2020).

Educators' competencies are crucial for successfully adopting technologies in teaching and learning (Uerz et al., 2018). Having sufficient competency not only increases the likelihood of successful adoption but also enhances the learning process for students, aligning with education objectives, such as mentoring and fostering students' cognitive and productive activities (Al-Furaih & Al-Awidi, 2020). This fusion of talent with digital competency is crucial for developing future accountants with the necessary skills and creating a modernized educational environment conducive to 21st-century teaching and learning (Apostolou et al., 2020).

Transforming educators' competencies involves not just transferring knowledge but mastering specific competencies that enable students to acquire knowledge independently (Aguiar & Gouveia, 2020; Hizam et al., 2021). Competency in education must be reconceptualised and operationalized to include current concepts and life skills, with technological competency being particularly crucial for educators to utilise technologies for innovative teaching, critical thinking, reasoning, and deepening student understanding (Foulger et al., 2017; Graziano et al., 2017). Several studies (e.g., Al Khateeb, 2017; Biggins et al., 2017; Fussell & Truong, 2022; Instefjord, 2018; Lai et al., 2021) proposed that these core areas imply the knowledge, skills, and abilities in using technology as part of educators' competency to design, create, manipulate, and self-actualise the use of technology for teaching and learning practice. Due to compelling evidence pointing towards a positive relationship between technological competence and the intention to adopt educational technologies, this study hypothesised that:

H9: There is a positive influence of educators' technological competence (COMP) on their intention to adopt 21st-century educational technology.

By incorporating key models and concepts from the aforementioned literature, this study attempts to create a unified framework to predict educators' intentions to implement educational technology in higher education. It identifies a mutually beneficial association between educator acceptance, the Big Five personality characteristics, technological

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EISSN : 0128-164X
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competence, and the intention to adopt technology in the 21st-century. Understanding factors influencing educators' decisions and the adoption and integration of technology is crucial. The following two fundamental research objectives thus direct the study:

1. Do the educators' acceptance, five-factor traits and technological competence influence their intention to adopt 21st-century educational technology?
2. Do the factors of acceptance, five-factor traits, and technological competence framework have a high predictive power to predict values for new observations?

Methodology

A survey involving 275 educators from business and management disciplines in Malaysian public universities was conducted. The selection of Malaysian public universities was based on their high ranking in the QS World University Ranking and their significant contribution in producing graduates compared to private universities (Abd Jalil, 2018). Participants were sourced from the universities' website database, and the sample size was determined using Krejcie and Morgan's method, which offers a standardized approach for estimating sample sizes (Sekaran, 2003; Sekaran & Bougie, 2016). The adequacy of the sample size was confirmed through Cohen's d statistical analysis, a widely recognized technique in the behavioural sciences (Cappelleri et al., 1994). Over a period of five months, 195 completed responses were received.

The study referenced 10 educational technology categories identified by Watty et al. (2014) and Adam (2020), which are relevant to the evolving landscape of higher education. Respondents were asked to reflect on these categories concerning their current teaching and learning practices in the classroom. The survey questionnaire included brief explanations and definitions of intention to adopt technology and 21st-century educational technology adoption. The questionnaire consisted of five sections: Section A collected demographic information, Section B assessed intention to adopt technology (ITA1–ITA15), Section C measured acceptance behaviour through perceived usefulness (ACPU1–ACPU7), perceived ease of use (ACPEU1–ACPEU7), and attitude towards use (ACAU1–ACAU7), Section D evaluated personality traits using 31 items categorised into five factors: openness to experience (PTOE1–PTOE6), conscientiousness (PTCO1–PTCO6), extraversion (PTEX1–PTEX6), agreeableness (PTAG1–PTAG6), and neuroticism (PTNE1–PTNE7), while Section E assessed technological competence with 18 items (COMP1–COMP18). Responses were recorded using a 5-point Likert Scale ranging from "Strongly Disagree" to "Strongly Agree". The questionnaire instruments were adapted from studies by Gholami et al. (2018), Abu Karsh (2018), Sultan et al. (2011), Agarwal and Prasad (1997), Barnett et al. (2015), and Al Khateeb (2017).

Data analysis was performed using the partial least squares (PLS) method, chosen for its suitability for causal-predictive analysis and exploration of potential relationships in the data (Ramayah et al., 2018; Shmueli et al., 2019). Unlike covariance-based structural equation modelling (CB-SEM), which requires larger sample sizes, PLS is more suitable for exploratory studies (Henseler et al., 2009). The SmartPLS 4.1.0.2 software was used for data analysis following established inner and outer model guidelines.

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The study framework (Figure 1) depicted the relationships among acceptance, personality traits, technological competence, and intention to adopt technology, with hypotheses suggesting positive influences toward the endogenous construct. This framework was developed to assess predictive relevance using PLS*predict*.

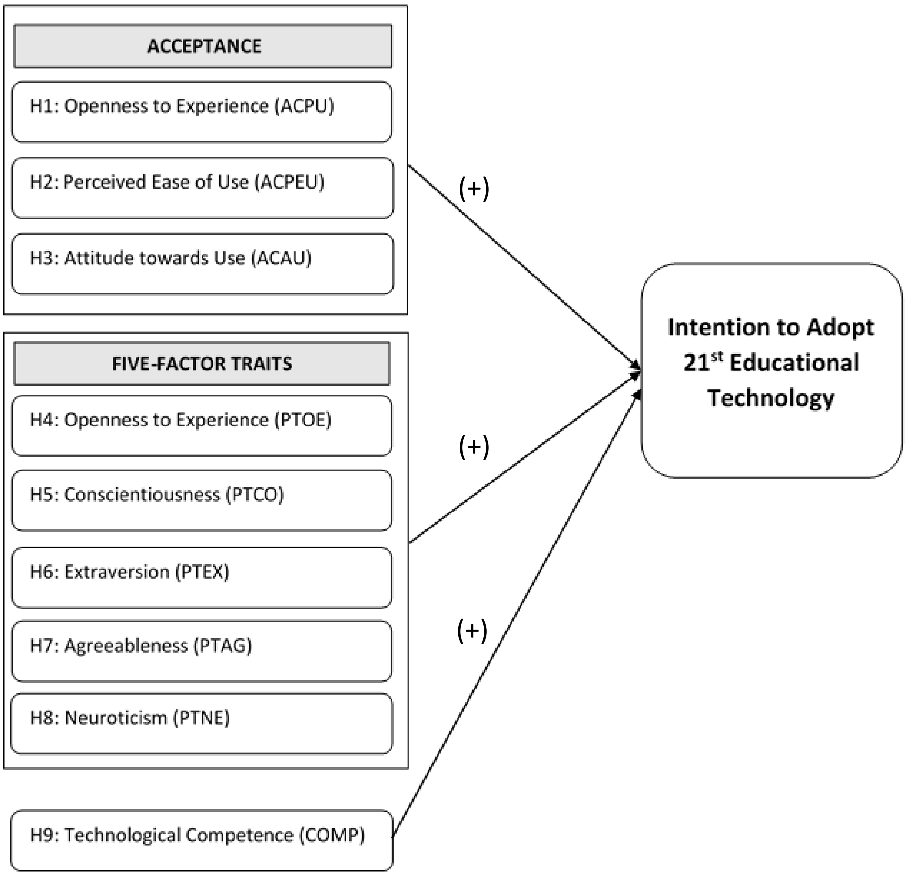

Figure 1: Conceptual Framework of the Study

Results

Profile of Respondents

The demographic analysis of the respondents indicated a majority of females, accounting for 74.9%, while males constituted 25.1%. This gender distribution aligns with the prevailing trend in the higher education sector in Malaysia, where females are predominant. The age distribution showed that the largest group fell within the 40-49 years old category at 53.3%, followed by the 30-39 years old group at 30.2%, with individuals under 30 and above 50 making up 16.5%. The educational qualification breakdown showed that 66.2% held a doctoral degree, 32.8% had a master's degree, and 1% had professional qualifications. Senior lecturers formed the largest academic rank group (59.5%), followed by associate professors (22.6%) and lecturers (13.8%). Professors and assistant professors were equally represented at 2.1% each. Technology usage revealed a moderate adoption rate, with 52.3% reporting frequent use and the remaining respondents admitting some infrequent experience in their teaching practice.

Assessment of Reflective Measurement (Outer Model)

Internal Consistency and Convergent Validity

The study followed a two-stage modelling approach recommended by Joseph F. Hair et al. (2018) and Benitez et al. (2020) to design and evaluate the reflective measurement model. The first stage focused on assessing the reliability and validity of individual items and constructs, followed by analysing structural relationships (Joseph F. Hair et al., 2017). Internal consistency, reliability, convergent validity, and discriminant validity were evaluated based on established guidelines as suggested in previous studies (e.g., Chin, 2010; Joseph F. Hair et al., 2017; Henseler et al., 2009; Roldán & Sánchez-Franc, 2012).

Reliability analysis (Appendix A) revealed factor loading estimates ranging from 0.573 to 0.906, all significant at the 1% level, surpassing the recommended threshold of 0.708 for uni-dimensionality (Joseph F. Hair et al., 2017). To ensure each indicator explained at least 50% of the variance, four items with loadings below 0.5 were removed following the recommendations by Avkiran and Ringle (2018) and Hulland (1999). Similarly, items from exogenous constructs with loadings below 0.4 (e.g., Neuroticism-PTNE2: 0.328) were removed to achieve convergent validity (Benitez et al., 2020; Fornell & Larcker, 1981). Overall, item removal remained within acceptable limits of 15.29%, below the 20% guideline suggested by Hair et al. (2010) and Joseph F. Hair et al. (2017).

Both Dijkstra-Henseler's ρA and Dillon-Goldstein's ρ scores surpassed 0.70, confirming the constructs' high reliability (Benitez et al., 2020; Dijkstra & Henseler, 2015; J.F. Hair et al., 2018; Nunnally & Bernstein, 1994). Additionally, redundancy scores remained below the problematic threshold of 0.95. Detailed evaluations of validity and reliability are presented in Appendix A.

Discriminant Validity

In order to enhance the evaluation of discriminant validity, the heterotrait-monotrait (HTMT) ratio was utilised in this research in accordance with well-established guidelines in the field of information systems (Benitez et al., 2020; Henseler et al., 2015; Voorhees et al., 2016). As detailed in Appendix B, the HTMT results demonstrate satisfactory levels of discriminant validity across all constructs. All values fall below the lenient threshold of 0.90 and the stricter recommendation of 0.85 (Franke & Sarstedt, 2019; Voorhees et al., 2016). Additionally, the 95% confidence intervals for each HTMT ratio exclude the value of 1, signifying statistically significant differences between all latent variables (Henseler et al., 2015). This comprehensive analysis confirms the model's discriminant validity.

Assessment of the Structural Model (Inner Model)

Structural Model Collinearity Assessment

Assessing potential collinearity among exogenous constructs is crucial before examining structural relationships to ensure an accurate representation of causal effects. The study utilised the Variance Inflation Factor (VIF) to detect multicollinearity, with values above 5 indicating problematic multicollinearity (Joseph F. Hair et al., 2017; Hair et al., 2011), and values between 3 and 5 warranting further investigations (Becker et al., 2015; Mason & Perreault, 1991).

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EISSN : 0128-164X
Volume 11 Issue 64 (September 2026) PP. 315-347

Additionally, tolerance values below 0.2 suggest multicollinearity (Hair et al., 2010). The study adopted a stringent criterion of VIF 3.3 or higher to ensure robust results.

Addressing collinearity is essential to prevent misleading conclusions, insignificant estimates, and unexpected signs in path coefficients, which could obscure the interpretation of causal relationships within the model. Analysing collinearity before structural relationships helps minimize bias in path coefficients and strengthens the validity of causal inferences (Hair et al., 2014). The results in Table 1 exhibit that the VIF values of all exogenous constructs in the model were below the threshold of 5 and 3.3. The VIF also satisfied the threshold for tolerance level demonstrated by the values greater than 0.20, thus signifying no multicollinearity problem in this model. Therefore, all constructs are maintained to be measured in the model.

Table 1: Collinearity Values among Exogenous Constructs

Exogenous Constructs	Endogenous Constructs	Variance Inflation Factor (VIF)
Perceived Usefulness (ACPU)		2.377
Perceived Ease of Use (ACPEU0		2.633
Attitude towards Use (ACAU)	Intention to Adopt	2.849
Openness to Experience (PTOE)		1.825
Conscientiousness (PTCO)		1.571
Extraversion (PTEX)		1.669
Agreeableness (PTAG)		1.881
Neuroticism (PTNE)		1.724
Technological Competence (COMP)		1.327

Evaluation of Path Coefficients, Significance Levels, and Their Effect Sizes

This study evaluated the structural model using various criteria such as R-squared, cross-validated redundancy, Q^2 measurement, and path coefficient assessments (Hair et al., 2019). Path coefficients and their significance levels for the relationships between exogenous and endogenous constructs were presented in Table 2, with the main endogenous construct showing a positive influence on all hypotheses. Using a bootstrapping procedure, two hypotheses were found significant at the 0.01 level: perceived usefulness ($\beta1 = 0.329$, $t = 3.834$) and technological competence ($\beta = 0.198$, $t = 3.157$) while, at the 0.05 level, attitude towards use ($\beta3 = 0.194$, $t = 2.072$), conscientiousness ($\beta5 = 0.108$, $t = 1.716$) and technological competence ($\beta = 0.198$, $t = 3.157$) showed significant positive relationships with intention to adopt.

Furthermore, all significant hypotheses exhibited confidence intervals (C.I.) with consistent signs (5% and 95%) and statistically differed from zero ($p < 0.05$ or no overlap with the C.I. at the 95% level). This confirms the accuracy and precision of the estimated significance. While the 10% significance level marginally includes the extraversion hypothesis ($\beta = 0.084$, $p = 0.083$), it remains statistically unsupported under the chosen 5% threshold. Finally, the remaining hypotheses for perceived ease of use ($p = 0.418$), openness to experience ($p = 0.225$), agreeableness ($p = 0.484$), and neuroticism ($p = 0.448$) were not significant at any level ($p > 0.1$), indicating no support for their relationships with intention to adopt.

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Table 2: Structural Model Evaluation

Relationship	Path Coefficient	f^2
Acceptance:		
Perceived Usefulness → Intention to Adopt (H1)	0.329*** (3.834) [0.184, 0.469]	0.10
Perceived Ease of Use → Intention to Adopt (H2)	0.019 (0.204) [-0.134, 0.164]	None
Attitudes towards Use → Intention to Adopt (H3)	0.194** (2.072) [0.051, 0.352]	0.03
Five-Factor Trait:		
Openness to Experience → Intention to Adopt (H4)	0.049 (0.734) [-0.054, 0.154]	None
Conscientiousness → Intention to Adopt (H5)	0.108** (1.716) [0.001, 0.216]	0.02
Extraversion → Intention to Adopt (H6)	0.084 (1.423) [-0.020, 0.180]	None
Agreeableness → Intention to Adopt (H7)	0.003 (0.042) [-0.112, 0.118]	None
Neuroticism → Intention to Adopt (H8)	0.008 (0.127) [-0.101, 0.095]	None
Technological Competence→ Intention to Adopt (H9)	0.198*** (3.157) [0.090, 0.290]	0.06

Note: *t*-values (one-tailed test) are presented in parentheses. Percentile bootstrap confidence intervals are presented in brackets. f^2 is the effect size.

Indicator loadings need to be 0.708 for the constructs to achieve the uni-dimensionality to ensure every indicator has equal factor scores loaded, indicating that the observed variables' variance was explained by at least 50% or more (Joseph F. Hair et al., 2017). However, indicators with threshold loadings' values exceeding 0.4, 0.5, 0.6, or 0.7 were retained (Wülferth, 2013), while those below 0.4 must be removed from the model (Avkiran & Ringle, 2018; Hulland, 1999).

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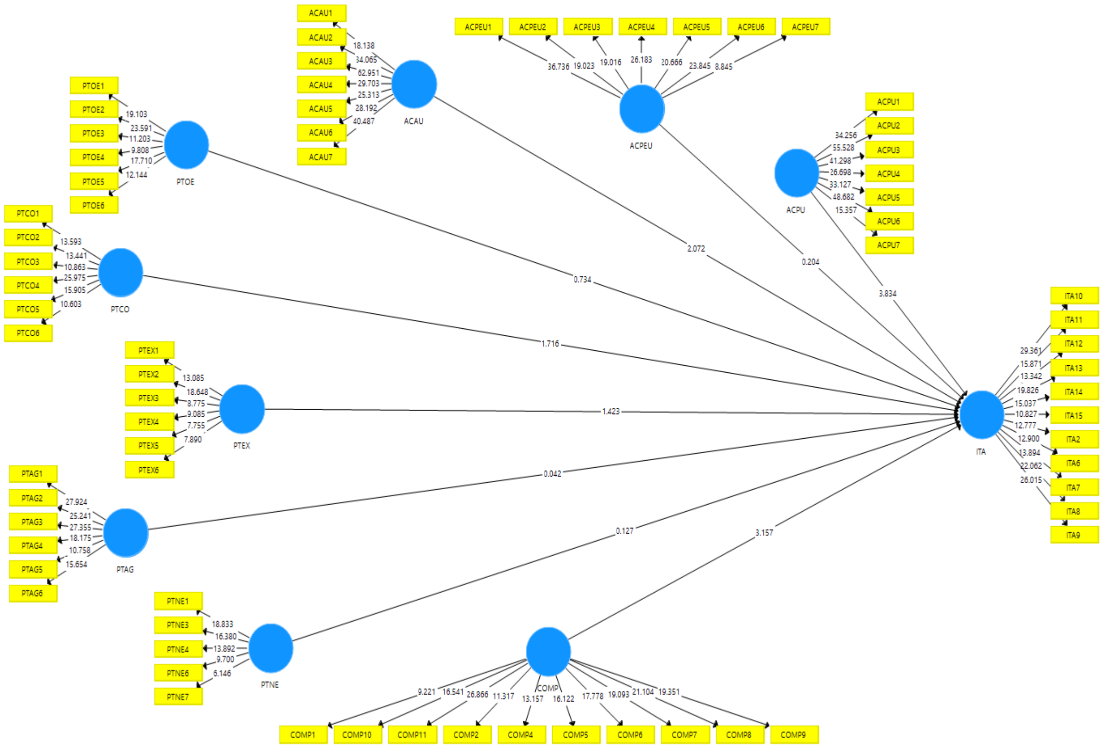

Figure 2: PLS Bootstrapping of the Structural Model

Figure 2 of the measurement model shows that most indicator loadings were over 0.5; hence, the AVE obtained the required minimum threshold of 0.5. Four indicators (ITA1, ITA3, ITA4, and ITA5) were removed one after another from the lowest loadings, which contributed to the endogenous construct's AVE value of below 0.60. To achieve the convergent validity of at least 50% or more than half variance of its scale indicators, several items from the exogenous constructs, such as Neuroticism (PTNE2: 0.328), eight items from Technological Competence (COMP3: 0.547, COMP12: 0.490, COMP13: 0.480, COMP14: 0.422, COMP15: 0.293, COMP16: 0.312, COMP17: 0.341 and COMP18: 0.353) were removed as well (Benitez et al., 2020; Fornell & Larcker, 1981). Overall, only 15.29% of items of the whole measurement were removed, which is less than the general guideline of 20% removal; thus, it is safe to assume the instrument design credibility (Joseph F. Hair et al., 2017; Hair et al., 2010). The details of all accepted and removed items are displayed in Appendix F.

Assessment of Coefficient of Determination (R^2) - In-Sample Predictive Power

Table 3 displays the R-squared (R^2) values for intention to adopt from the initial and modified measurement models. After ensuring reliability and validity, the final R^2 value of 0.524 indicates a strong magnitude and acceptable explanatory power in understanding the intention to adopt educational technology. This means that the framework capable of providing insight to understand the intention to adopt educational technology is predicted by the exogenous constructs: acceptance, personality traits, and technological competence. The slight variance in R^2 values between the initial and modified models was due to eliminating items with factor loadings below 0.5. Hair et al. (2014) suggest that an R^2 exceeding 0.20 is highly acceptable in behavioural studies, supporting the adequacy of the obtained value.

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While Falk and Miller (1992) propose 0.10 as the minimum threshold for explaining variance in an endogenous construct, and Cohen (1988) considers values above 0.26 substantial, the complexity of human behavior, influenced by individual experiences and motivations, makes analysis challenging as human behaviour inherently contains a higher degree of unexplainable variability. Individual personality differences also lead to diverse responses, even in similar conditions. Therefore, an R^2 above 0.50, as seen in this study, is deemed adequate. Excessively high R^2 values (above 0.90) in models predicting human attitudes, behaviours, perceptions, and intentions may suggest an overestimation of explained variance. While previous literature has emphasized surpassing minimum thresholds, with 50% widely accepted (e.g., Benitez et al., 2020; Bere & Rambe, 2016; Chao, 2019; Faqih, 2016; Herrador-Alcaide et al., 2020; Huang & Liaw, 2018; Kim et al., 2017; Salloum et al., 2019; Teeroovengadum et al., 2017) particularly in innovation adoption and information systems research contexts, this threshold remains relevant in understanding human behavior.

Table 3: Coefficient of Determination (R^2)

Endogenous Construct	Initial Model	Modified Model
Intention to adopt (ITA)	0.560	0.524

Assessing Effect Sizes (f^2)

This section examines the model's effect sizes (f2) to understand how much variation each exogenous construct explains in the endogenous construct (Hair et al., 2014). Generally, values of 0.02, 0.15, and 0.35 represent small, medium, and large effects, respectively (Cohen, 1988). However, educational research often acknowledges the significance of even small effects due to the complex influences of factors influencing learning outcomes (Kraft, 2018). This study's four exogenous constructs (ACPU, ACAU, PTCO, and COMP) exhibit statistically significant f^2 values, implying practical importance for future research. Conscientiousness (PTCO) demonstrated a small effect ($f^2 = 0.02$), while the remaining constructs showed small to medium effects ($f^2 = 0.10$, 0.03, and 0.06 for ACPU, ACAU, and COMP, respectively). This aligns with past research in education and information systems, where small to medium effect sizes are common (Roldán & Sánchez-Franc, 2012; Stout & Ruble, 1995; Wong & Wong, 2017). Meanwhile, Ferguson (2009) emphasizes that interpreting effect size alongside confidence intervals (C.I.) provides a more nuanced understanding. In this study (refer to Table 2), none of the significant results cross zero, confirming their robustness.

Assessment of the Predictive Relevance (Q^2)

Evaluating the model's ability to predict the endogenous construct, known as predictive relevance, is crucial in this analysis. The common blindfolding procedure, implemented within the SmartPLS 4.1.0.2 software, is well-suited for this purpose. While the blindfolding procedure generally applies to various model specifications, it primarily serves this purpose within the context of structural models.

The technique involves temporarily removing single data points from the reflective model, replacing them with the mean, and then re-estimating the model parameters (Rigdon, 2014; Sarstedt et al., 2014). After this process, smaller differences between the predicted and original values indicate higher Q^2 values and, in turn, greater predictive accuracy. To check the predictive relevance of the PLS-path model, the general guideline for the Q^2 values higher than

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0, 0.25, and 0.50 depicts small, medium, and large, respectively (Fornell & Cha, 1994; Geisser, 1975; Joseph F. Hair et al., 2017; Hair et al., 2019; Stone, 1974). These values offer insights into how the exogenous constructs successfully predict the endogenous construct. In this study, the blindfolding technique applied an omission distance of 7 (non-integer) to analyse the model's predictive relevance. Table 4 shows that the Q2 value for the endogenous construct (ITA: Q^2 = 0.26) is more than zero, indicating a sufficient predictive relevance of the model, ranging from medium to large.

Table 4: Redundancy Q^2 Value

Endogenous Construct	SSO	SSE	1-SSE/SSO
Intention to adopt	2145	1591.710	0.26

Note: SSO= Sum of Squares due to Overall; SSE=Sum of Squares due to Error

Assessment of the Predictive Model Using PLSpredict - Out-of-Sample Predictive Power

The final assessment of the structural model analysis is to execute the extension results interpreted from the R^2 and Q^2 using PLS*predict* provided by SmartPLS (Ringle et al., 2015). The assessment is necessary to ensure the analysis and reporting of PLS-SEM results are robust, complete, extendable to future investigations, exclude the dataset, and achieve the study's goal (Hair et al., 2019). Shmueli and Koppius (2011) asserted that a model's predictive ability is crucial to generating accurate predictions of new observations that can be used to interpret temporally. Furthermore, the predictive ability can be extended to out-of-sample prediction using cross-validation with holdout samples (Evermann & Tate, 2016) to provide a wide range of model applications according to the phenomenon and context. A recent requirement emphasizes the importance of robust and complete analysis reporting for PLS-SEM results. This includes ensuring generalizability, addressing excluded datasets, and achieving research goals (Hair et al., 2019). To address this, PLS*predict* is utilised to assess the model's out-of-sample predictive ability.

While R^2 reflects in-sample explanatory power, it does not guarantee out-of-sample prediction accuracy (Dolce et al., 2017; Shmueli & Koppius, 2011; Shmueli et al., 2019). Similarly, Q^2 has limitations too, as it does not capture the full extent of prediction error and does not fully exclude entire observations (Chin et al., 2020; Shmueli et al., 2016). Therefore, Shmueli et al. (2016) propose a procedure for out-of-sample prediction involving estimating the model on the "training sample" and evaluating its predictive performance on the "holdout sample". This approach ensures the model possesses both explanatory and predictive power, which is crucial for causal-predictive research in information systems (Chin et al., 2020).

The PLS*predict* analysis in this Study involves K-fold cross-validation with k = 10 and the sample size beyond the minimum sample size requirement ($n \geq 153$) proposed by Shmueli et al. (2019). Ten repetitions (r = 10) were used for prediction (Hair et al., 2019) since this study aims to predict new observations using multiple estimated models.

Evaluation of $Q^2_{predict}$

As a rule of thumb, $Q^2_{predict}$ values should be greater than 0 for the key construct and its indicators. Negative values indicate a lack of predictive power. Furthermore, either RMSE or MAE is chosen based on the data distribution (symmetrical or non-symmetrical). These values

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should be lower than the Naïve Linear Model (LM) benchmark, which indicates high, medium, low, or no predictive power, respectively (Shmueli et al., 2019). Table 5 presents the Q^2predict value at the construct level, focusing on the key construct of "Intention to Adopt" (ITA), which is considered good at the construct level since the Q^2 value is above zero ($Q^2_{predict} = 0.455$).

Table 5: $Q^2_{predict}$ at the Construct Level

Endogenous Construct	RMSE	MAE	$Q^2_{predict}$
Intention to adopt	0.747	0.551	0.455

Note: RMSE= Root mean squared error; MAE= Mean absolute error

Evaluation of $Q^2_{predict}$ with RMSE and MAE Value

Tables 6 and 7 compare RMSE and MAE values between PLS and LM prediction errors at the indicator level. The choice of RMSE or MAE is based on the non-highly symmetrical distribution of the endogenous data, as indicated by the Kolmogorov-Smirnov and Shapiro-Wilk tests analysed in SPSS. Visualizations of the non-symmetrical distributions for each item can be found in Appendix C. The results confirm that all $Q^2_{predict}$ values for the endogenous constructs' indicators are greater than zero. This suggests the model's indicators outperform the naïve benchmark, indicating meaningful results.

However, visually inspecting the prediction errors from SmartPLS and Kolmogorov-Smirnov and Shapiro-Wilk tests (Appendix C) suggests the data is not normally distributed. Despite this, the distribution is not considered highly non-symmetrical. Therefore, the RMSE is used for the predictive assessment. Interestingly, the MAE analysis also aligns with the RMSE results, with PLS demonstrating lower values than the LM benchmark for all indicators, indicating high out-of-sample predictive power.

Table 6: Out-of-Sample Predictive Power Using $Q^2_{predict}$ and RMSE Value

Endogenous Construct	Indicators	$Q^2_{predict}$	RMSE (PLS)	RMSE (LM)	PLS < LM RMSE
Intention to adopt	ITA2	0.254	0.572	0.628	-0.056
	ITA6	0.193	0.607	0.722	-0.115
	ITA7	0.250	0.665	0.849	-0.184
	ITA8	0.266	0.701	0.894	-0.193
	ITA9	0.235	0.574	0.680	-0.106
	ITA10	0.214	0.613	0.784	-0.171
	ITA11	0.218	0.664	0.815	-0.151
	ITA12	0.214	0.675	0.790	-0.115
	ITA13	0.217	0.746	0.906	-0.160
	ITA14	0.280	0.830	0.955	-0.125
	ITA15	0.160	0.688	0.779	-0.091

Note: PLS= Partial least squares path model; LM= Linear regression model; RMSE= Root mean squared error

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Table 7: Out-of-sample Predictive Power Using $Q^2_{predict}$ and MAE Value

Endogenous Construct	Indicators	$Q^2_{predict}$	MAE (PLS)	MAE (LM)	PLS < LM MAE
Intention to adopt	ITA2	0.254	0.450	0.495	-0.045
	ITA6	0.193	0.440	0.538	-0.098
	ITA7	0.250	0.525	0.634	-0.109
	ITA8	0.266	0.555	0.680	-0.125
	ITA9	0.235	0.456	0.543	-0.087
	ITA10	0.214	0.478	0.589	-0.111
	ITA11	0.218	0.533	0.621	-0.088
	ITA12	0.214	0.531	0.602	-0.071
	ITA13	0.217	0.570	0.702	-0.132
	ITA14	0.280	0.641	0.752	-0.111
	ITA15	0.160	0.540	0.593	-0.053

Note: PLS= Partial least squares path model; LM= Linear regression model; MAE= Mean absolute error

Table 6 and Table 7 verify that the $Q^2_{predict}$ values for endogenous constructs' indicators are larger than zero, suggesting the power of the PLS-SEM analysis indicators used for this study not only outperforms the most naïve benchmark but is also meaningful. As illustrated in Appendix D and Appendix E, the plots demonstrated that the PLS-SEM errors are not normally distributed. Subsequent analysis of normal distribution utilising the Kolmogorov-Smirnov and Shapiro-Wilk tests, as detailed in Appendix C, confirms the non-normal distribution of the results. However, upon visual inspection of the prediction errors extracted from SmartPLS, it is noted that the distribution does not exhibit significant non-symmetry. Therefore, the predictive assessment for this study relies on the RMSE. Furthermore, examination of the MAE also yields results that do not substantially differ from those obtained with RMSE. Specifically, when comparing the RMSE values of PLS-SEM with the naïve LM benchmark, as presented in Table 6, it is evident that all indicators for intention to adopt exhibit lower PLS values than LM (PLS < LM), signifying high out-of-sample predictive power. This pattern is similarly observed in the MAE values (Table 7) for both PLS and LM across all endogenous indicators. Additionally, the MV prediction summary shows that all indicators' mean bias in this study is too small: ITA2 = 0.001; ITA6 = 0.001; ITA7 = 0.001; ITA8 = 0.001; ITA9 = 0.001; ITA10 = 0.001; ITA11 = 0.001; ITA12 = 0.001; ITA13 = 0.001; ITA14 = 0.001 and ITA15 = 0.002, indicating the present model that predicts the endogenous indicators in this study is sufficiently well.

Discussion on the Key Results

This section will explain the key results from the two research objectives. First is the significant influence of the three theoretical spectrums. The analysis reveals several important relationships between the proposed constructs and the intention to adopt educational technology. Perceived usefulness, technological competence, and conscientiousness exhibit positive and statistically significant relationships, suggesting that individuals who perceive technology as valuable, possess the necessary skills to use it effectively and demonstrate high levels of conscientiousness are more likely to adopt educational technology.

While attitude towards use and openness to experience displayed positive trends, they did not reach statistical significance in this study. In this sense, the attitude of educators is multifaceted, which resembles how they perform their behavioural intention. However, these attitudes are not static and can be shaped by information processing and behaviour. This aligns with the TAM, which posits that attitude towards use influences individual behaviour by filtering information and shaping perceptions about technology adoption (Herrador-Alcaide et al., 2020; Kumar & Mantri, 2021). On the other hand, the insignificant positive relationship of openness to experience may stem from the characteristics of educators, who often exhibit a preference for routine over variety, less abstractness and entertainment, and holding on to established knowledge (Iqbal et al., 2019; Thohir et al., 2021; Vlachogianni & Tselios, 2022). Previous research suggests that openness to experience can vary across professions and individuals. Examples of professions typically associated with high openness include social workers, fashion designers, and musicians (Aguiar & Gouveia, 2020; Guia, 2017). Given this, educators may tend to have lower levels of openness to experience, potentially reflecting a preference for the technical aspects of the education profession rather than novelty and innovation.

The study found that perceived ease of use, agreeableness, and neuroticism did not correlate significantly with the intention to adopt. First, this is not surprising since the relationship in TAM may not always predict educators' technology adoption due to their diverse behaviours (Scherer & Teo, 2019). Educators' values and beliefs regarding new technologies, such as resistance to adapting to evolving student needs, can influence adoption (Gurjar & Sivo, 2022). This can manifest as initial attempts at using technology followed by abandonment due to difficulty, fear of failure, or fear of mistakes as a major barrier (Granic, 2022). Secondly, the agreeableness trait is often characterised by helpfulness, compliance, altruism, empathy, trust, kindness, cooperation, and politeness (Dalpé et al., 2019; Kavirayani, 2018; Thohir et al., 2021). However, research within the Big Five personality framework suggests that despite these desirable qualities, agreeableness does not directly translate to a stronger motivation to learn (Barnett et al., 2015; Kim et al., 2019). This lack of intrinsic learning motivation could partly explain the findings regarding educators' adoption of educational technology. Thirdly, the neuroticism trait, characterised by emotional instability stemming from anxiety, depression, and insecurity (Azucar et al., 2018), aligns characterized by emotional instability and negative emotions, may be less likely to embrace new experiences due to concerns about self-efficacy and self-esteem (Berninzoni, 2020; Oshio et al., 2018; Vlachogianni & Tselios, 2022). This tendency towards avoiding new experiences might explain why educators with higher levels of neuroticism perceive learning and adopting new technologies as challenging, leading them to avoid the effort to adopt technology.

Second, the study identifies the strategic factors influencing educators' intention to adopt 21st-century educational technology (ITA) and evaluates the model's predictive power using PLS*predict*. The proposed constructs and corresponding items indicate the model's reliability and consistency. While the study partially supported the conceptual framework, significant relationships were identified between certain constructs and educators' technology adoption intention. All constructs achieved an Average Variance Extracted (AVE) above 0.5, indicating good convergent validity. Additionally, reliability was assessed through Cronbach's α, Dillon-Goldstein's ρ, and Dijkstra-Henseler's ρA, demonstrating satisfactory to strong reliability across all constructs (Benitez et al., 2020; Fornell & Cha, 1994; Fornell & Larcker, 1981)

The model discussed in the study demonstrates strong in-sample predictive power, indicating its ability to explain the intention to adopt educational technology, with a Q^2 value of 0.26, signifying sufficient predictive relevance. Notably, the research highlights the model's high out-of-sample predictive power, particularly in predicting ITA values for future observations in 21st-century education, showing promise for future applications with different datasets for a more robust framework (Dolce et al., 2017) in a search for a concrete justification and application of a solid framework. While previous studies focused on model selection efficacy, there is a gap in the information systems field regarding studies using a causal-predictive perspective to examine models with explanatory and predictive capabilities (Chin et al., 2020).

Conclusively, this study contributes to the literature by offering a novel perspective on the intention to adopt 21st-century educational technology in the context of higher education. By examining acceptance, personality traits, and technological competence within a single, rigorous framework, the study provides valuable insights for future research. Notably, the causal-predictive results bridge the gap between theoretical and practical considerations, offering an exceptional assessment of the real-world applicability of the proposed model. This has significant implications for successful policymaking in technology adoption, specifically when targeting educators' behavioural intentions in higher education institutions.

Study Implications

This research provides theoretical implications by integrating the Technology Acceptance Model (TAM), Big Five personality traits, and competency to understand the intention to adopt 21st-century educational technology. The study highlights the relevance of the original TAM in predicting technology adoption in developing country university contexts and challenges the traditional view of attitude as a weak mediator. The research aligns with current findings by treating attitude as an independent construct with a positive influence on intention. Furthermore, examining all Big Five personality traits offers a more comprehensive understanding of their impact on educators' adoption intentions compared to previous studies that focused on selected traits. Next, the study also emphasizes the significance of technological competence and skills in influencing educators' adoption intentions, stressing the importance of considering individual differences. The combination of acceptance, personality traits, and technological competence emerges as crucial indicators of educators' willingness to adopt educational technologies in the context of Industry 4.0 and the increasing demand for digitally driven skills.

The study also emphasises the importance of addressing barriers to technology integration in academic institutions, such as lack of training, inadequate resources, unclear policies, and concerns about career progression. Failure to overcome these obstacles can lead to unemployment risks for graduates and disrupt the future workforce by impeding technology adoption and skills development. Support and incentives from both government and institutions are crucial to encouraging academics to embrace educational technologies.

Instead of a one-size-fits-all approach, the curriculum should consider pedagogical considerations like seamlessly integrating technology into existing lessons and exploring how technology can enhance specific learning objectives. Furthermore, addressing educators' potential anxieties, such as fear of failure or lack of confidence, can be crucial for fostering a supportive learning environment. This could involve building a community where educators can share experiences, collaborate, and learn from each other. Finally, ensuring continuous learning opportunities can keep educators updated on the latest educational technologies and their potential applications, fostering a culture of continuous improvement and technology adoption within the tertiary education community. These efforts are crucial to achieving Sustainable Development Goal 4.4 and 4.4.1, promoting quality education, reducing digital

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Education, Psychology and Counseling
EISSN : 0128-164X
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inequalities, and ensuring future generations have equitable access to Information and Communication Technology (ICT) skills.

Limitations and Future Research

Although the framework adequately explained the intention to use 21st-century technology, the findings have limitations. First, the empirical data were collected at a public university. Future research could investigate private universities to assess the framework's generalizability. This would expand the study context, contribute to the existing literature, and provide a broader perspective on technology adoption in Asia. Second, the respondents were educators from business and management disciplines. Hence generalisation about the intention to adopt technologies among other educators in different teaching fields is beyond the scope of this study. Therefore, additional data may be required to include a sample population of various academia for further exploration. That said, since this study utilises PLS*predict*, it relies on a specific dataset for model development. Therefore, the generalizability of the predictive model may be limited to the context of the dataset used. Thus, future research must explore the applicability of the predictive model across different datasets and settings to assess its robustness and generalizability.

Third, while PLS*predict* helps assess predictive power, it does not directly explain the underlying mechanisms driving those predictions. Further investigation might be needed to understand the "why" behind the predictions. Predictive models generated by PLS*predict* may require updating and maintenance over time to ensure their relevance and accuracy. Changes in the underlying data distribution or relationships between variables may necessitate retraining the predictive model periodically. Future research could investigate methods for efficiently updating and maintaining predictive models to keep pace with evolving data and environmental conditions. Since PLS*predict* is still in the infancy of its use by researchers, further testing, and validation of PLS*predict* across diverse research domains beyond its current applications in social sciences and management research could be beneficial.

This study successfully develops and tests the proposed framework using PLS-SEM to assess its path coefficients and predictive power. However, the framework could be further enhanced by incorporating additional factors from other theories, models, and perspectives to improve its reliability, validity, and predictive power. Future research could explore constructs like technology complexity, resistance levels, educator satisfaction, sociological aspects (awareness, education level, privacy concerns), economic factors (income source, technology expenses), and environmental characteristics (policies, competitive pressure, uncertainty). Additionally, exploring control variables such as gender, internet or technology experience, age, media exposure, and past privacy or security breaches could add further value.

Conclusion

Previous studies examining factors influencing educators' adoption of educational technology often lack strong predictive validity. They frequently rely on specific existing models without robust analysis of the model's ability to predict future outcomes. This study uses a second-generation analysis technique, PLS-SEM, to evaluate a novel conceptual framework for the social sciences education field.

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This research contributes to the field by identifying the significant influence of acceptance, personality traits, and technological competence on educators' technology adoption intention in higher education. Furthermore, this study highlights the specific technology categories relevant to 21st-century education, addressing the scarcity of research in this area. This is crucial in the context of Industry 4.0, which necessitates curriculum and teaching practices to adapt to the demands of the new economic landscape. This study also demonstrates the applicability of PLS-SEM and PLS-Predict for examining predictive relationships in educational technology research, offering valuable insights for future researchers.

This study could assist the government, higher education institutions, faculty, schools, departments, and relevant councils by providing a holistic view of the issue and the need to improve technology adoption in education. The findings highlight the importance of faculty, higher education institutions, and policymakers in technology adoption, personality-based treatments, and technical competence. The findings may also reveal factors influencing instructors' technology adoption decisions, providing a platform for future study and encouraging technology integration in higher education. If the institutions consider personality traits, they could design individualised personality mappings to align with future interventions to understand their educators' unique characteristics that are not homogeneous for everyone. Besides, this study's findings added new knowledge on educational technology adoption, particularly in higher education, and to understand the reasons behind the underutilisation of 21st-century educational technology among educators. This research contributes to the ongoing discussion about technology integration in education by identifying key drivers and highlighting technology adoption in this context.

Acknowledgements: The authors would like to express their sincere gratitude to Universiti Teknologi MARA (UiTM) Cawangan Selangor and Universiti Teknologi Malaysia (UTM), for providing the necessary resources, facilities, and continuous support throughout the course of this research. The access to academic resources, research facilities, and a conducive learning environment has been invaluable in facilitating the successful completion of this study. The authors also appreciates the encouragement and assistance provided by the faculty members and staff of both universities, whose support has contributed significantly to the progress of this research.

Funding Statement: No Funding

Conflict of Interest Statement: The authors declare that there is no conflict of interest regarding the publication of this paper. All authors have contributed to this work and approved the final version of the manuscript for submission to the International Journal of Education, Psychology and Counselling (IJEPC).

Ethics Statement: This study was conducted in accordance with the ethical guidelines of Universiti Teknologi MARA (UiTM). Informed consent was obtained from participants, and all information collected was treated confidentially and used solely for academic purposes. The researcher also confirms that all sources have been properly acknowledged and that no plagiarism, data fabrication, or falsification has occurred in this study.

Author Contribution Statement: All authors contributed significantly to the development of this manuscript. Mohamad Ridhuan Mat Dangi was responsible for the conceptualization, methodology, data collection, formal analysis, and drafting of the manuscript. Maisarah Mohamed Saat contributed to the methodology, supervision, and critical revision of the manuscript. Radziah Mahmud was responsible for the validation of the research findings and critical revision of the manuscript. Norliza Omar contributed to the provision of resources, validation of the study, and critical revision of the manuscript. Shazalina Mohamed Shuhidan was responsible for the overall supervision, project administration, and critical revision of the manuscript. All authors have read and approved the final version of the manuscript prior to submission.

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