International Journal of Sociotechnology and Knowledge Development
Volume 18 • Issue 1 • January-December 2026

Digital Technology Adoption in TVET Institutions With an Extended UTAUT

Cyrus Pil Cadavedo
Zamboanga Peninsula Polytechnic State University, Philippines

Celbert Himang
http://orcid.org/0000-0002-5663-3304
Cebu Technological University, Philippines

Joerabell Lourdes Aro
Cebu Technological University, Philippines

Lanndon Ocampo
http://orcid.org/0000-0002-5050-7606
Cebu Technological University, Philippines
Received: July 1st, 2026 | **Accepted:** July 30th, 2026

ABSTRACT

This study explores a structural model of how digital technology is utilized within TVET (Technical Vocational Education and Training) institutions. Guided by the Unified Theory of Acceptance and Use of Technology, the study introduces perceived compatibility in the proposed structural model, including some moderating variables such as qualification sector, gender, age, and experience. Data were gathered from 241 TVET trainers in the Philippines to empirically test the proposed model along with hypothesized relationships using Partial Least Squares–Structural Equation Modeling. Results reveal that performance expectancy, effort expectancy, and facilitating conditions are positively associated with trainers' behavioral intention to adopt digital technology, while social influence and perceived compatibility possess no significant effects. These findings indicate that trainers prioritize efficiency and practicality over peer pressure or perceived alignment. Thus, TVET institutions must strengthen performance-enhancing features, simplify digital platforms, and improve available support systems.

KEYWORDS

Digital Technology, TVET, UTAUT, Perceived Compatibility, Behavioral Intention, Partial Least Squares–Structural Equation Modelling

INTRODUCTION

Information and communication technologies have become integral to navigating complex digital landscapes in modern society (Horova et al., 2024) and may be pivotal for increased organizational productivity (Aruppala et al., 2026). These technological developments have compelled educational institutions to adapt their teaching modalities. Digital innovations reshape education by enhancing services and learning experiences (Hu et al., 2020; Ronchi & Ronchi, 2019). They improve access to information, streamline communication, and support personalized and flexible learning modalities suited to diverse learners. These technologies promote interactivity, collaboration, and knowledge sharing, significantly contributing to the overall effectiveness of educational systems (Liaw et al.,

DOI: 10.4018/IJSKD.423454

This article published as an Open Access article distributed under the terms of the Creative Commons Attribution License (http://creativecommons.org/licenses/by/4.0/) which permits unrestricted use, distribution, and production in any medium, provided the author of the original work and original publication source are properly credited.

2010). Consequently, both educators and learners benefit from enhanced engagement and improved educational quality, driven by greater efficiency and excellence (Hu et al., 2020).

The global influence of digital technology is also evident in the removal of geographical barriers and the expansion of learning opportunities. The global population of massive open online course learners increased to 220 million from 2012 to 2021, while Internet usage grew by 50% between 2005 and 2022, with approximately half of secondary schools now using it for instruction (United Nations Educational, Scientific and Cultural Organization, 2023). Worldwide spending on information technology reached $5.56 trillion in 2025 and is projected to exceed a staggering $6.16 trillion in 2026 worldwide (Gartner, 2026). Similar growth trends have been observed in sectors including healthcare, education, teleworking, and daily use (Vargo et al., 2021).

Within technical vocational education and training (TVET), digital technology has expanded instructional possibilities by strengthening digital literacy and improving learning results. It has supported the development of competencies, enabled adaptation to shifting educational demands, and facilitated innovative training approaches, especially during the COVID-19 pandemic (Mbatha, 2024). Despite limited studies on the integration of digital technology in TVET institutions, with training of some skills such as blueprint reading offered in traditional format (Centillas et al., 2024), it has been supported that the adoption of these technologies has had a positive outcome toward student competencies and industry compatibility for a technology-intensive labor market. In particular, Keelson et al. (2025) demonstrated the significant role of innovative teaching methods toward students' creativity and propensity for taking risks. They also highlighted that using innovative teaching strategies boosts self-confidence and risk taking by engaging learners in practical experiences, problem-solving activities, and skill-building opportunities. Meanwhile, Ismail et al. (2025) illustrated the influence of trainers' self-efficacy on satisfaction and continuance intention to utilize digital technology. On the other hand, Palapa et al. (2026) showed the direct influence of digital learning on digital engagement and digital capability on digital engagement and digital performance in TVET institutions. They also reinforced the significance of strengthening students' digital competencies and fostering stronger engagement to boost academic performance. Furthermore, Wagino et al. (2025) explored the influence of e-learning and problem-based learning in fostering the development of communication, teamwork, and problem-solving among TVET students. Moreover, Fu et al. (2026) demonstrated the positive direct effect of work-integrated learning on TVET students' employability and an indirect effect through digital learning.

However, significant challenges hinder the seamless integration of digital technology within TVET curricula (Othman et al., 2025). Many institutions remain hesitant to adopt new technologies due to inadequate physical and digital infrastructure, lack of technical support personnel for adequate upkeep, untrained staff, weak collaboration among industry stakeholders, and bureaucratic inefficiencies (Regassa & Desissa, 2025). Some studies also have reported heightened anxiety and stress among teachers when using educational technologies in classroom environments (Fernández-Batanero et al., 2021). These barriers collectively impede effective digital integration. Analysis of trainers' perceptions and acceptance is therefore critical for addressing these issues. Their attitudes and intentions influence how effectively technology can be integrated into TVET delivery.

Several frameworks have been developed to explain users' acceptance of digital technologies and the determinants influencing integration in TVET contexts. The technology acceptance model of Davis (1989) and innovation diffusion theory of Rogers (1995) are widely used; they emphasize the critical roles of perceived usefulness, ease of use, and innovation attributes. The former model highlights that teachers' perceptions of usefulness greatly influence their intention to adopt technology, while combining the two models allows broader consideration of individual and contextual factors, despite limitations concerning compatibility and related constructs (Al-Rahmi et al., 2021; Antonietti et al., 2022). Other significant frameworks include the technology–organization–environment model, which identifies environmental and organizational drivers of information and communications technology adoption in TVET (Rambe et al., 2022). Social cognitive theory (SCT) and theory of planned behavior

(TPB) provide insights into motivational and behavioral components of technology use (Ayanwale et al., 2023). The task-technology fit (TTF) model remains widely applied in education for examining alignment between user tasks and system characteristics (e.g., Alamri et al., 2020). The technological pedagogical content knowledge framework also demonstrates effectiveness in assessing digital competence among teachers in TVET and other sectors (Mishra & Koehler, 2006).

Despite their contributions, each framework has limitations. For instance, SCT may not comprehend outcome expectations as sources of self-efficacy, implying that when people fail to believe in their own capabilities to perform a certain behavior, they will not subsequently derive a positive outcome from that behavior (Bandura, 1977, 1997). Meanwhile, TPB may fail to capture other relevant behavioral influences (Ajzen, 2020). On the other hand, technology–organization–environment has mostly been perceived as complementary to other theories of adoption, rather than presenting an alternative and contradictory standpoint (Baker, 2012). Moreover, technological pedagogical content knowledge also faces issues with measurement and identification of interactions among its knowledge domains (Mishra & Koehler, 2006).

Unified theory of acceptance and use of technology (UTAUT) remains one of the most influential frameworks for explaining technology acceptance. Its strong predictive capability, adaptability, and simplicity allow it to account for approximately 70% of the variance in behavioral intention (Venkatesh et al., 2003). This framework has been applied extensively in multiple disciplines, thus demonstrating its versatility and predictive strength. In education, the model has guided research on e-learning systems, learning management systems, digital classrooms, mobile learning, virtual laboratories, and technology-enhanced pedagogy (e.g., Bayaga & du Plessis, 2024; Himang et al., 2020; Li et al., 2022). In healthcare, researchers have used UTAUT to examine electronic health records, telemedicine adoption, and digital health platforms (e.g., Candra et al., 2025; Demsash et al., 2024). In finance and banking, UTAUT has been applied to predict user acceptance of online banking, financial management systems, and fintech platforms (e.g., Mensah & Khan, 2024; Yohanes et al., 2020). Other applications include marketing (e.g., Twum & Yalley, 2025), supply chain systems (e.g., Sharma et al., 2023), government information systems (e.g., Zeebaree et al., 2022), and manufacturing automation (e.g., Sousa et al., 2026). The breadth of fields using UTAUT demonstrates its robustness as a theoretical lens for examining technology acceptance. Its constructs—performance expectancy, effort expectancy, social influence, and facilitating conditions—have proven consistent predictors across cultures, demographic groups, and institutional settings.

Although UTAUT is highly predictive, numerous scholars have extended or modified the model to suit specific research contexts. UTAUT's modular theoretical structure lends itself to such expansion by accommodating the integration of additional constructs that reflect context-specific determinants of behavioral intention. For instance, Batucan et al. (2022) incorporated constructs such as enjoyment, interactivity, flexibility, and quality into the UTAUT framework, demonstrating that these variables significantly have shaped digital learning platform adoption within developing economies. In academic settings specifically, UTAUT has been employed to assess teacher readiness for digital tools, acceptance of e-learning content, and adoption of simulation technologies, mobile applications, and digital instructional modules. Notably, Oluyinka et al. (2021) integrated the innovation-diffusion constructs of trialability and compatibility with UTAUT to assess the adoption of Canvas, a widely used learning management system, in selected Philippine universities. Their findings confirmed that compatibility and trialability significantly influenced facilitating conditions and performance expectancy, thereby underlining the conceptual relevance of innovation attributes in technology acceptance within higher education.

The original UTAUT included compatibility only as part of the broader construct of facilitating conditions (Venkatesh et al., 2003). In many studies, compatibility has appeared merely as a single survey item under facilitating conditions (e.g., Bayaga & du Plessis, 2024; Demsash et al., 2024), reducing its conceptual weight. However, compatibility is a critical determinant because it reflects the degree to which a technology aligns with users' needs, values, and prior

experiences. It is therefore essential when evaluating or selecting technologies for integration into educational or organizational systems.

Several studies have highlighted the importance of compatibility for influencing user acceptance across various fields using UTAUT and extended frameworks (e.g., Chen, 2011; Oluyinka, 2021). It has been found to enhance ease of use and promote task efficiency (Khan & Abideen, 2023), influence user intention (Alghazi et al., 2021), and promote behavioral intention in technology adoption (Chen, 2011). Nevertheless, there has been little research that focuses specifically on vocational educators' perceptions on the adoption of digital technology and the integration of perceived compatibility into the theoretical framework. This is a critical oversight, as compatibility remains inadequately defined and underexplored in existing models.

To address this gap, this study aims to assess the influence of perceived compatibility on TVET trainers' use of digital technology in curriculum delivery. It introduces a factor overlooked in the UTAUT model and proposes new constructs and moderators relevant to the practical nature of TVET. This research contributes to ongoing efforts to refine technology adoption theories and deepen understanding of digital integration in vocational education. Furthermore, as established by the literature (e.g., Keelson et al., 2025; Mbatha, 2024), digital adoption offers beneficial changes to curriculum delivery, assessment practices, and capacity building that provide students with a competitive advantage in today's labor market.

To empirically test the hypothesized relationships and moderating effects, this study employs partial least squares (PLS) structural equation modeling (SEM), which is a popular methodological approach for examining relationships among latent variables in UTAT-related studies (e.g., Bayaga & du Plessis, 2024; Himang et al., 2020; Li et al., 2022) and other models of technology acceptance (e.g., Casquejo et al., 2020; Momani, 2020; Qatanani et al., 2026). This method is a robust analytical technique suitable for complex models involving latent variables.

The remainder of this paper is structured as follows. The next section briefly discusses the unified theory of acceptance and use of technology and presents the hypothesized relationships. Later sections outline the research methods and discuss results and insights. The article ends with a conclusion and directions for future work.

LITERATURE REVIEW AND HYPOTHESES

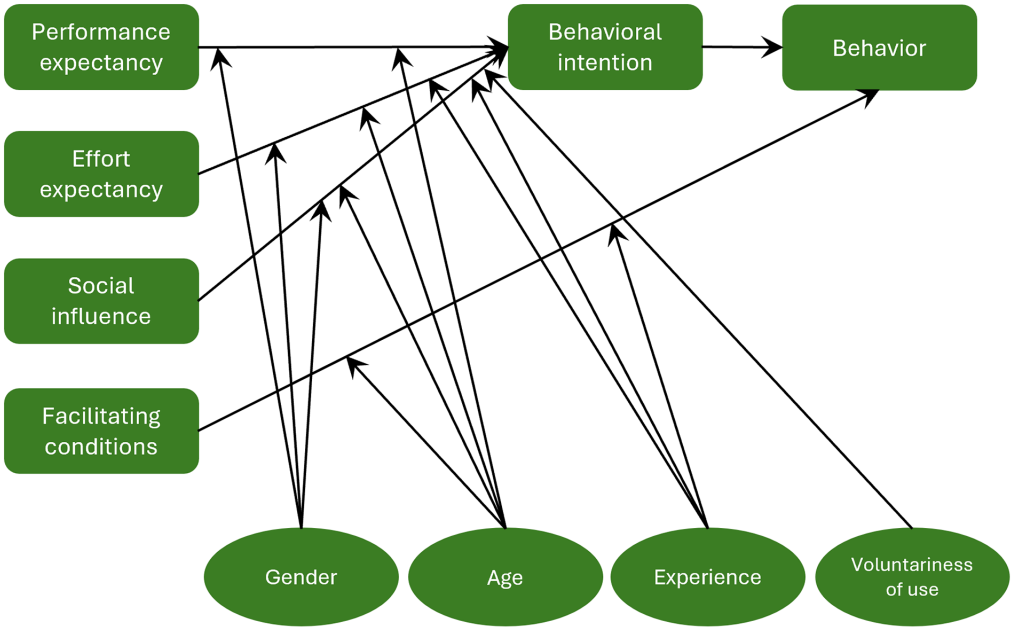
The Framework of UTAUT

UTAUT, developed by Venkatesh et al. (2003), offers a robust theoretical framework for explaining and predicting user acceptance and utilization of technology across organizational, educational, and institutional contexts. UTAUT emerged from the recognized need to consolidate the fragmented landscape of technology acceptance research, which had previously been distributed across multiple competing theoretical frameworks. Prior to its development, the field was characterized by a multiplicity of models, each offering partial yet incomplete explanations of technology adoption behavior. These included the theory of reasoned action (Fishbein & Ajzen, 1975), TPB (Ajzen, 1991), technology acceptance model (Davis, 1989), motivational model of PC utilization (Thompson et al., 1991), innovation diffusion theory (Rogers, 1995), and SCT (Bandura, 1986). While each model contributed meaningful theoretical insights, each also exhibited limitations when applied independently in diverse empirical contexts.

To resolve the inconsistencies in explanatory power across these frameworks, Venkatesh et al. (2003) synthesized constructs from all eight theories into a unified model capable of explaining variance in behavioral intention and actual technology use behavior with greater reliability and generalizability. The resulting model introduces four core determinants of technology acceptance: performance expectancy, effort expectancy, social influence, and facilitating conditions. These constructs collectively serve as predictors of users' behavioral intention to adopt technology and their subsequent actual use behavior. Additionally, UTAUT incorporates four moderating constructs—

gender, age, experience, and voluntariness of use—to account for demographic and contextual differences. The model is illustrated in Figure 1.

Figure 1. Unified Theory of Acceptance and Use of Technology



Note. Adapted from "User acceptance of information technology: Toward a unified view," by V. Venkatesh, M. G. Morris, G. B. Davis, and F. D. Davis, 2003, MIS Quarterly, 27(3), pp. 425–478.

Empirical validation of the original model has demonstrated that UTAUT explains up to 70% of the variance in behavioral intention and approximately 50% of the variance in actual use behavior, establishing it as one of the most predictively powerful and empirically validated models in the technology acceptance literature (Venkatesh et al., 2003). The development of UTAUT represented a significant theoretical advance toward understanding technology-related behavioral patterns. Preceding frameworks such as the technology acceptance model emphasized perceived usefulness and perceived ease of use but did not adequately account for broader organizational dynamics and social influences (Venkatesh et al., 2003). Theory of reasoned action and TPB highlighted the importance of attitudes and subjective norms but directed comparatively less attention toward technology-specific attributes. SCT emphasized self-efficacy and observational learning, while TTF theory centered on the alignment between technological characteristics and task requirements. UTAUT achieved a theoretical integration that preserved the strengths of these prior models while resolving their individual limitations through a more holistic, multidimensional approach. Since its publication, UTAUT has been widely adopted and refined across two decades of global research. Its successor model, UTAUT2, introduced by Venkatesh et al. (2012), adapted the framework for consumer settings by incorporating new constructs: hedonic motivation, price value, and habit. However, the original UTAUT remains the dominant model in organizational and educational environments because of its strong applicability to structured systems such as schools, universities, corporations, hospitals, and governmental institutions.

Perceived Compatibility

Perceived compatibility refers to how well trainers view digital technology as aligning with existing practices in TVET curriculum training delivery. Specifically, it measures whether trainers find digital tools suitable for their teaching methods and strategies. It reflects their commitment to integrating digital tools into their professional activities. The factor of compatibility is crucial for successful technology adoption since it enhances ease of use and promotes task efficiency (Khan & Abideen, 2023; Wang et al., 2017). Alghazi et al. (2021) found that compatibility significantly influences user intention to use mobile devices in education. Chen (2011) also emphasized the importance of incorporating technology compatibility into models like UTAUT, particularly in educational contexts, as it enhances the ability of the models to predict behavioral intentions. Furthermore, Rahi and Ghani (2018) found that compatibility has a direct effect on intention to adopt Internet banking, while the findings of Darwish et al. (2024) revealed that compatibility has a significant positive association with the attitudes of students toward computer-based teaching in Egyptian universities.

However, some studies have argued that compatibility's predictive significance varies depending on context and the interplay of other constructs. Kishore and McLean (2007) found that compatibility did not have a significant relationship with technology infusion behavior, contributing to what the authors described as mixed findings about this construct in the literature. Similarly, a systematic review by Xue et al. (2024) noted that the impact of UTAUT predictors shows nuanced variance across different institutional and technological contexts, suggesting that no single construct consistently dominates across all settings. This result suggests that the importance of compatibility varies by technology type and user environment. It is not always the strongest factor influencing intention. These findings highlight the need to assess the role of compatibility alongside other variables in TVET contexts.

Based on these factors, we propose hypothesis H1: Perceived compatibility significantly and positively influences trainers' behavioral intention to use digital technology in TVET curriculum delivery.

Performance Expectancy

Performance expectancy refers to the perceived benefit of using technology to improve job performance (Venkatesh et al., 2003). In this study, performance expectancy measures trainers' behavioral intentions to use digital technology for TVET curriculum delivery. It consistently proves to be a critical predictor of behavioral intention to adopt technology. Nikolopoulou et al. (2021) emphasized its significant influence on the adoption of educational technology. Mbazu et al. (2024) and Ajigini (2023) highlighted its role in driving educators' intentions with technology acceptance. Similarly, Onaolapo and Oyewole (2018) confirmed its predictive strength for mobile learning adoption. In addition, empirical results from Abbad (2021) have shown that performance expectancy is the most powerful predictor of behavioral intentions to use e-learning systems in developing countries. Overall, performance expectancy has emerged as a dominant factor in behavioral intention across both mandatory and voluntary adoption contexts. However, Utomo et al. (2021), in a study examining the effects of performance expectancy on behavioral intention to use digital mobile applications, found that there is no significant relationship between the two.

Therefore, we propose hypothesis H2: Performance expectancy significantly and positively influences trainers' behavioral intention to use digital technology in TVET curriculum delivery.

Effort Expectancy

Effort expectancy refers to the perceived ease of using technology; this construct emphasizes simplicity and user-friendliness (Venkatesh et al., 2003). This study adopts a similar definition, focusing on how TVET trainers perceive effort expectancy in relation to the trainer's intention to integrate digital technology into their teaching practices. Nikolopoulou et al. (2021) found that effort expectancy does not have a significant relationship with educators' intentions to adopt technology,

particularly in environments requiring quick adaptation. These findings underscore the need to design tools that lower cognitive and physical barriers to encourage user engagement. The influence of effort expectancy, however, may decline over time as users gain experience. Venkatesh et al. (2003) noted that with familiarity, the effect of effort expectancy on behavioral intention diminishes, giving way to factors like performance expectancy and facilitating conditions. Thus, while ease of use drives initial adoption, other factors often take precedence as familiarity increases.

Therefore, we formulate hypothesis H3: Effort expectancy significantly and positively influences trainers' behavioral intention to use digital technology in TVET curriculum delivery.

Social Influence

Social influence refers to the extent to which trainers perceive that important people believe they should use digital technology in their teaching practices. It includes external encouragement and support for technology adoption that may affect their behavioral intention to adopt digital technology. Recent studies have affirmed the significant relationship between social influence and behavioral intention. Menon and Shilpa (2023) highlighted social influence as a significant predictor of users' intention to adopt AI-based large language model technologies such as translation tools and ChatGPT, particularly emphasizing its importance among less-experienced users. Williams et al. (2015) further validated this relationship through a systematic review that provided consistent evidence on the impact of social influence on behavioral intention across various technologies. Meanwhile, Singh et al. (2020) found a significant moderating effect of social influence on the relationship between satisfaction and recommendation to use. Collectively, these studies highlight social influence as a pivotal factor in driving technology adoption.

In contrast, Venkatesh et al. (2003) noted that social influence has less influence in voluntary contexts. Furthermore, Abbad (2021) found that social influence did not significantly predict behavioral intention to use e-learning systems, potentially attributable to the current generation of learners who, having been immersed in digital environments from an early age, tend to make technological adoption decisions independently of instructor or peer influence. These contrasting insights indicate that the effectiveness of social influence may depend on institutional culture and the voluntary nature of adoption.

Considering these factors, we propose hypothesis H4: Social influence significantly and positively influences trainers' behavioral intention to use digital technology in TVET curriculum delivery.

Facilitating Conditions

Facilitating conditions encompass the availability of resources, infrastructure, technical support, and tools that enable trainers to effectively use digital technology in their teaching and training activities. Meanwhile, behavioral intention is the manifestation of the trainer's commitment and proactive attitude toward integrating digital tools to enhance educational processes and outcomes in their professional activities. Abbad et al. (2021) highlighted that facilitating conditions significantly influence technology integration and also highlighted the importance of the availability of necessary resources and technical support during integration.

However, Venkatesh et al. (2012) theorized that hedonic motivation (intrinsic motivation) can independently drive behavioral intention, implicitly reducing the relative importance of external facilitating conditions in consumer contexts. Similarly, Compeau and Higgins (1995) established that self-efficacy is a critical and independent determinant of technology adoption behavior, suggesting that even in environments where facilitating conditions are adequately provisioned, adoption may stagnate when users lack confidence in their ability to effectively use the technology. Additionally, Utomo et al. (2021) reported that facilitating conditions did not significantly affect behavioral intention toward using mobile healthcare applications, emphasizing the complexity of the role of facilitating conditions in technology adoption. These findings underscore the importance of pairing robust facilitating conditions with initiatives to enhance digital technology utilization.

Therefore, we propose hypothesis H5: Facilitating conditions significantly and positively influence trainers' behavioral intention in TVET curriculum delivery.

Behavioral Intention

Behavioral intention is a critical determinant of technology usage, reflecting trainers' plans or willingness to adopt digital technology in their teaching practices and TVET curriculum delivery. It signifies their commitment to integrating digital tools into professional activities. Digital technology utilization, on the other hand, refers to the actual use of digital technology by TVET trainers for planning, conducting, supervising, and assessing teaching and training activities; this construct captures the frequency and scope of their engagement with these tools. Venkatesh et al. (2003) established a direct link between behavioral and actual technology use across various contexts. This relationship has been further corroborated in educational contexts, where behavioral intention has a significant influence on educators' and learners' actual adoption of digital technologies (Raman et al., 2022).

However, the behavioral intention-to-use relationship is not unconditional. Jeyaraj (2021), through a meta-analysis of 113 prior studies, found that this relationship yields inconsistent results across contexts, with organizational and contextual factors moderating its strength, such that intentions do not always translate into actual use behavior. Similarly, Limayem et al. (2007) demonstrated that practical constraints including habitual patterns and situational barriers can significantly weaken the predictive power of behavioral intention toward actual technological utilization, particularly as user experience accumulates over time. These findings indicate that while behavioral intention is a strong predictor, it must be complemented by addressing external and contextual challenges to ensure effective technology utilization.

Therefore, we formulate hypothesis H6: Behavioral intention significantly and positively influences trainers' digital technology utilization in TVET curriculum delivery.

Moderating Role of Qualification Sector

The area of specialization or qualification sector, as defined by the Technical Education and Skills Development Authority (TESDA, 2021) in the Philippines, refers to the specific subject or field taught by TVET trainers. In this study, qualification sector serves as a moderator between perceived compatibility and behavioral intention; we examine whether trainers' perceptions of digital technology differ based on their specialization or curriculum assignment. Specialization significantly shapes behavioral intention, as Malahay (2021) highlighted its impact on teaching performance, particularly in content knowledge and curriculum application. Alea et al. (2020) also demonstrated a strong correlation between specialization and readiness for distance learning. Conversely, Babalola (2023) found that there is no significant difference between virtual learning and student performance based on the area of specialization. These findings underscore the need to study specialization as a moderating variable, leading to hypothesis H7: The qualification sector moderates the relationship between perceived compatibility and behavioral intention to use digital technology in TVET curriculum delivery.

Moderating Role of Age

In the UTAUT framework, age, as a demographic characteristic of TVET trainers, serves as a moderator that influences how trainers perceive technology's usefulness. Younger trainers are more likely to perceive greater performance benefits from adopting digital tools; Venkatesh et al. (2003) empirically demonstrated that the influence of performance expectancy on behavioral intention is stronger among younger workers, with age serving as a significant moderator of this relationship. In support of this result, Ghalandari (2012) confirmed that age moderates the relationship between performance expectancy and behavioral intention, indicating that age-related differences systematically shape how individuals evaluate the utility of technology. However, Venkatesh et al. (2003) further

theorized that as users accumulate experience, often facilitated through training and technical support, the moderating influence of age on the relationship between effort expectancy and behavioral intention weakens, suggesting that adequate organizational support can mitigate age-related barriers to adoption. Chang et al. (2019) further challenged the universal significance of age as a moderator, finding no influence of age on technology adoption behavior in the context of hotel online bookings. Additionally, Khater et al. (2020) demonstrated that the moderating effect of age on the relationship between performance expectancy and behavioral intention is not supported. These mixed findings highlight the importance of tailoring strategies to different age groups to ensure that digital tools are perceived as beneficial across generations of trainers. Therefore, we propose hypothesis H8: Age moderates the relationship between performance expectancy and behavioral intention to use digital technology in TVET curriculum delivery.

Age also plays a role in examining how the relationship between effort expectancy and behavioral intention varies across different age groups. Venkatesh et al. (2003) noted that younger users adapt more quickly to new technologies, thus demonstrating stronger relationships between effort expectancy and behavioral intention. Alharbi et al. (2022) observed that effort expectancy had a substantial moderating effect on learning management system usage among younger teachers aged 31–40 years, while the effect was not significant for those aged 41 years and above. Additionally, Chang et al. (2019) observed that age acts as a moderating factor, in which the link between effort expectancy and behavioral intention diminishes as users grow older. They suggested that while younger cohorts prioritize the utility of a system, older individuals are more sensitive to its perceived complexity. These findings suggest that while age may sometimes diminish the importance of effort expectancy, providing sufficient support can mitigate its moderating effect. Hence, we propose hypothesis H9: Age moderates the relationship between effort expectancy and behavioral intention to use digital technology in TVET curriculum delivery.

Age, as a demographic characteristic, categorizes users into specific age groups and plays a crucial role in moderating the relationship between social influence and behavioral intention. Studies have highlighted that age moderates the effect of social influence on behavioral intention in various ways. Venkatesh et al. (2003) observed that younger trainers are more likely to be influenced by peer and organizational expectations, compared to older trainers. A study by Ghalandari (2012) demonstrated the significant moderating effects of age between social influence and behavioral intention in the context of e-banking services acceptance. Furthermore, in the context of hotel online bookings, gender significantly moderates the impact of social influence on booking intentions, with the effect being more pronounced in men (Chang et al., 2019). This result implies that hotel managers can drive higher engagement from men by emphasizing that online booking is a widespread and contemporary movement. These findings underscore that age significantly affects how social influence impacts trainers' behavioral intentions and highlights the need for tailored approaches to technology adoption. Therefore, we propose hypothesis H10: Age moderates the relationship between social influence and behavioral intention to use digital technology in TVET curriculum delivery.

Several studies have indicated that age influences how facilitating conditions affect users' behavioral intention to use technology. In particular, Alharbi et al. (2022) highlighted that age plays a major role in teachers' lives, because younger teachers are more concerned with their performance, while older ones are more concerned about facilitating conditions in the adoption of a learning management system. Additionally, Ghalandari (2012) established that age functions as a moderator between facilitating conditions and the intention to adopt e-banking. Moreover, Zhou et al. (2021) indicated that while the availability of support and resources significantly drives the behavioral intentions of older users, these same facilitating conditions appear to have a negligible impact on the intentions of younger consumers in the e-commerce sector. Therefore, we propose hypothesis H11: Age moderates the relationship between facilitating conditions and behavioral intention to use digital technology in TVET curriculum delivery.

Moderating Role of Gender

In this study, gender acts as a moderator in the relationship between performance expectancy and behavioral intention to use digital technology in TVET curriculum delivery. According to Ghalandari (2012), gender influences how performance expectancy impacts behavioral intention to adopt e-banking services. Venkatesh et al. (2003) noted that women are generally more influenced by social factors than by performance outcomes. In addition, Chang et al. (2019) demonstrated that in hotel online bookings, the relationship between expectancy and behavioral intention was greater for men than for women. Similarly, Alharbi et al. (2022) found an association between performance expectancy and use of technology to be significantly moderated by gender among schoolteachers utilizing a learning management system. Hence, we formulate hypothesis H12: Gender moderates the relationship between performance expectancy and behavioral intention to use digital technology in TVET curriculum delivery.

Conversely, Alshahrani and Walker (2017) revisited the UTAUT model and found that gender did not significantly moderate the relationship between effort expectancy and behavioral intention. Given these findings, we propose hypothesis H13: Gender moderates the relationship between effort expectancy and behavioral intention to use digital technology in TVET curriculum delivery.

Chang et al. (2019) demonstrated that gender moderates the impact of key constructs such as social influence on use intention, highlighting its importance in shaping behavioral responses. Similarly, Ghalandari (2012) demonstrated the significant moderating role of gender between the relationship of social influence and behavioral intention. These insights underscore the need to assess whether gender meaningfully influences how social expectations shape behavioral intention in TVET contexts. Therefore, we propose hypothesis H14: Gender moderates the relationship between social influence and behavioral intention to use digital technology in TVET curriculum delivery.

Moderating Role of Experience

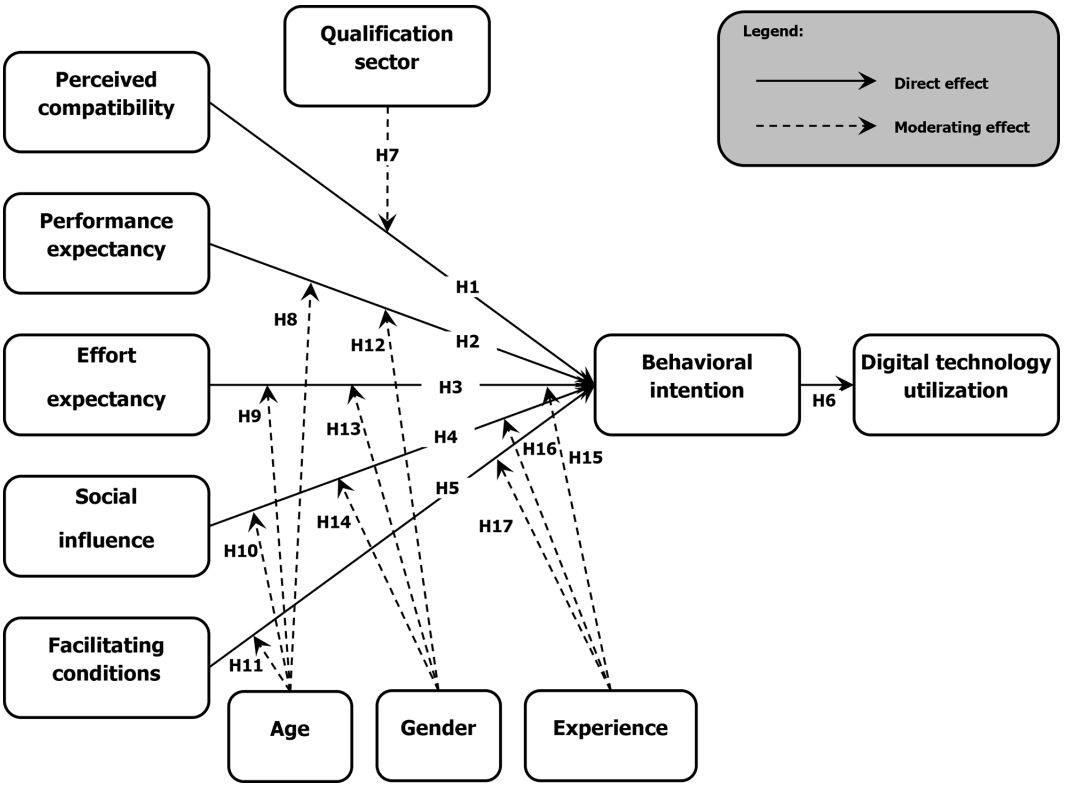
In this study, experience refers to the duration of trainers' engagement with digital technology in teaching, such as computers and the Internet. It is tested as a moderator in the relationship between effort expectancy and behavioral intention. Experience plays a pivotal role in shaping the relationship between effort expectancy and behavioral intention. Venkatesh et al. (2003) theorized that experience is a significant moderating factor in technology adoption, noting that as users accumulate familiarity with a technology, the influence of effort expectancy on behavioral intention diminishes over time. This result is supported by evidence from Sinha and Singh (2023), who found that perceived experience functions as both a moderating and mediating variable in determining behavioral intention to use technology, underscoring its critical role in shaping adoption dynamics. Conversely, Sitar-Tăut (2021) demonstrated that hedonic motivation mediates the relationship between effort-related perceptions and behavioral intention in mobile learning contexts, suggesting that motivational factors can amplify or buffer the role of perceived ease of use. Maduku (2017), in the context of mobile banking, found that the moderating effects of use experience on behavioral intention factors were largely nonsignificant, suggesting that the moderating role of experience is context-dependent rather than universal. Considering these factors, we formulate hypothesis H15: Experience moderates the relationship between effort expectancy and behavioral intention to use digital technology in TVET curriculum delivery.

Experience significantly influences how social influence impacts behavioral intention. Izkair and Lakulu (2021) confirmed that experience moderates the relationship between social influence and behavioral intention in mobile learning, demonstrating that the level of experience shapes how social influence affects users' intention to adopt technology. Sitar-Tăut (2021) found that novice trainers are more likely to rely on peer recommendations when adopting technology. In addition, Alsarayrah and Ali (2025) demonstrated that internal experience does not influence the adoption of technology. Based on these insights, we propose hypothesis H16: Experience moderates the relationship between social influence and behavioral intention to use digital technology in TVET curriculum delivery.

Sitar-Tăut (2021) found that experienced trainers capitalize on available resources, leading to increased behavioral intention to use the technology. Similarly, Alsarayrah and Ali (2025) highlighted that experienced users subsequently secure enhanced managerial backing, resources, and training for the integration of technology. Conversely, Alkawsi et al. (2021) found that experience did not moderate the effect of facilitating conditions on behavioral intentions of smart meter consumers. Therefore, we formulate hypothesis H17: Experience moderates the relationship between facilitating conditions and behavioral intention to use digital technology in TVET curriculum delivery.

Taking these discussions into account, this study proposes the modified UTAUT framework depicted in Figure 2.

Figure 2. Proposed Modified Unified Theory of Acceptance and Use of Technology (m-UTAUT)



Note. Abbreviations H1 to H17 refer to hypothesis numbers.

METHODS

In this section, the results of PLS-SEM analysis are presented, employing WarpPLS 8.0, a specialized tool for analyzing relationships among variables. The analysis considers both the measurement model and the structural model. The measurement model analysis scrutinizes the relationships between observed variables and latent constructs to evaluate the reliability and validity of the measurement model. In contrast, the structural model analysis investigates the relationships between latent constructs, thus providing insights into the underlying associations among constructs within the model. Together, these analyses offer a comprehensive understanding of the interplay between variables in the study.

Instrument

A structured research instrument, which is detailed in Table A1 of the Appendix, was adopted from measures validated in previous studies for each construct. All constructs, except for digital technology utilization, consisted of multiple items based on a 5-point Likert scale ranging from 1 = *strongly disagree* to 5 = *strongly agree*. The five items under digital technology utilization were based on TESDA trainers' core competencies (TESDA, 2024). These items ask the participants to rate their frequency of using digital technology—such as computers, the Internet, and other technologies—for teaching or training purposes using a 5-point Likert scale ranging from 1 = *never* to 5 = *always*. Perceived compatibility, performance expectancy, effort expectancy, social influence, facilitating conditions, and behavioral intention had five construct measurement indicators (Chau & Hu, 2001; Moore & Benbasat, 1991; Venkatesh et al., 2003).

Sampling and Data Collection

The data collection in this study focused on TVET trainers in the Zamboanga Peninsula, under the supervision of TESDA Region IX in Pagadian City, Zamboanga City, in the southern Philippines. The provincial training centers in the region are distributed across Zamboanga City in the towns of Sindangan, Buug, and Pagadian City. The study also included two TESDA-administered technical institutions: Zamboanga Sibugay Polytechnic Institute in Kabasalan and the Dipolog School of Fisheries. These centers play a crucial role in providing technical-vocational education and training to the region's workforce. The Zamboanga Peninsula is known for its emphasis on education and workforce development, with institutions offering programs in agriculture, sciences, education, and technical-vocational fields. The presence of TESDA-accredited training centers, universities, and specialized institutions like Zamboanga Peninsula Polytechnic State University supports the region's goal of producing a skilled workforce aligned with the demands of evolving industries.

A total of 278 trainers were purposively selected from various training centers, schools, and institutions. Of these, 241 trainers responded to the survey. These participants possess the most relevant perceptions and experiences regarding digital technology usage in TVET curriculum delivery. During the data gathering period, which spanned from April to May 2024, they were fully informed about all aspects of the study through a comprehensive orientation session, during which the purpose, objectives, and procedures of the study were explained in detail. Their rights as participants, including the right to withdraw at any time without any repercussions, were clearly communicated. Only after they demonstrated a clear understanding of the process and agreed to participate voluntarily was their informed consent obtained. Data collection was carried out over eight weeks. The research team utilized structured questionnaires to collect the data, which were subsequently organized and analyzed for the study.

The minimum sample size requirement, as outlined by Barclay et al. (1995), is determined by whichever is greater: (a) 10 times the highest number of formative indicators for any single construct or (b) 10 times the greatest number of structural paths pointing to any one construct in the model. As further supported by Hair et al. (2011) and Marcoulides and Chin (2013), this requirement translates to a minimum of 10 times the highest count of arrowheads directed at any latent variable within the PLS path model. Furthermore, Hair, Hult, et al. (2014) introduced the minimum R^2 method as an alternative to the 10-times rule. This method is built upon Cohen's (1977, 1992) power table for least squares regression. In this demonstrative case, five independent variables in the measurement models would require 70 observations to achieve a statistical power of 80% for detecting R^2 values of at least 0.25 (with a 5% probability of error). Given the two criteria and the available data, the 241 valid responses collected from TVET trainers are deemed adequate for the present study.

Profile of the Participants

The demographic profile of the participants, presented in Table 1, provides valuable insights into their age, gender, experience, and specialization.

Table 1. Profile of Participants

Attributes	Values	*f*	%
Age	≤25	11	5
	26–35	42	17
	36–45	99	41
	46–55	74	31
	≥56	15	6
Gender	Male	187	78
	Female	54	22
Length of experience	<2 years	6	2
	2–5 years	98	41
	>5 years	137	57
Qualification sector	Construction	57	24
	Auto and land transport	38	16
	Metals and engineering	28	12
	Agriculture and fishery	32	13
	ICT	13	5
	Tourism	32	13
	Electrical and electronics	19	8
	Other qualification	22	9

Note. ICT = information and communications technology.

Demographically, the participants were predominantly male (78%), with the largest group (41%) aged between 36–45 years. Furthermore, most of the participants (57%) reported having more than five years of experience with digital tools, while 41% had between two and five years of experience. The participants also represented diverse qualification sectors, with the construction sector being the largest at 24%, followed by auto and land transport (16%), agriculture and fishery (13%), and metals and engineering (12%). Other sectors included tourism (13%), electrical and electronics (8%), and information and communications technology (5%), with 9% in other specializations.

Data Analysis Results

This study employs SEM as its primary analytical framework, offering a robust multivariate approach for examining complex structural relationships among variables. PLS-SEM has gained considerable traction across information systems research and various other disciplines, particularly with smaller sample sizes and multivariate data structures; for example, Eroa et al. (2026) reported a relatively small sample size despite a larger population. A key advantage of PLS lies in its capacity to simultaneously assess both measurement and structural models, thereby accommodating more sophisticated research designs that incorporate moderating and mediating effects (Hair, Sarstedt, et al., 2014). To evaluate the reliability and validity of the data, the analysis employs several diagnostic measures: Cronbach's alpha, convergent validity, average variance extracted (AVE), and composite reliability (CR).

Measurement Model Assessment

Measurement model analysis in SEM is fundamental for evaluating the validity and reliability of the measurement model. This typically involves assessing indicator loadings that measure the strength of the relationship between observed variables and latent constructs. Factor loadings, indicating the correlation between observed variables and latent constructs, should ideally be 0.7 or higher. Convergent validity and reliability tests are also conducted to ensure the measurement model accurately represents the underlying constructs. This process is described in studies by Chin (2010) and Hair et al. (2011). In the measurement model, the composite reliability and Cronbach's alpha coefficients should be larger than or equal to 0.7 to be conservative (Fornell & Larcker, 1981). CR, similar to Cronbach's alpha, should also be 0.7 or higher, with values above 0.6 acceptable in exploratory studies (Hair et al., 2011). Additionally, AVE, which reflects the variance explained by a construct relative to measurement error, should be at least 0.5, indicating that the construct captures a significant portion of the variance of its indicators (Hair et al., 2011).

Table 2 provides a comprehensive overview of the indicator loadings, convergent validity, and reliability tests for all constructs.

Table 2. Measurement Model Assessment Results

Construct	Item	Factor loading	Cronbach's α	CR	AVE
Perceived Compatibility	PC1	0.749	0.797	0.860	0.552
	PC2	0.744			
	PC3	0.752			
	PC4	0.733			
	PC5	0.736			
Performance Expectancy	PE1	0.836	0.873	0.908	0.663
	PE2	0.776			
	PE3	0.823			
	PE4	0.815			
	PE5	0.821			
Effort Expectancy	EE2	0.614	0.742	0.839	0.569
	EE3	0.828			
	EE4	0.811			
	EE5	0.744			
Social Influence	SI1	0.671	0.718	0.826	0.543
	SI2	0.798			
	SI4	0.745			
	SI5	0.728			
Facilitating Conditions	FC1	0.748	0.763	0.841	0.516
	FC2	0.646			
	FC3	0.672			
	FC4	0.805			
	FC5	0.709			

continued on following page

Table 2. Continued

Construct	Item	Factor loading	Cronbach's α	CR	AVE
Behavioral Intention	BI1	0.832	0.881	0.913	0.679
	BI2	0.766			
	BI3	0.790			
	BI4	0.878			
	BI5	0.847			
Digital Technology Utilization	DTU1	0.836	0.901	0.927	0.716
	DTU2	0.803			
	DTU3	0.868			
	DTU4	0.869			
	DTU5	0.854			

Note. CR = composite reliability; AVE = average variance extracted.

The Perceived Compatibility (PC) construct, comprising five items (PC1 to PC5), demonstrates factor loadings ranging from 0.733 to 0.752, a Cronbach's alpha of 0.797, a CR of 0.860, and an AVE of 0.552, indicating satisfactory reliability and convergent validity. Similarly, the Performance Expectancy (PE) construct, represented by five items (PE1 to PE5), shows high factor loadings between 0.776 and 0.836, a Cronbach's alpha of 0.873, a CR of 0.908, and an AVE of 0.663, reflecting strong internal consistency and convergent validity. The Effort Expectancy (EE) construct, evaluated through four items (EE2 to EE5), exhibits factor loadings from 0.614 to 0.828, a Cronbach's alpha of 0.742, a CR of 0.839, and an AVE of 0.569, indicating acceptable reliability and convergent validity. For the Social Influence (SI) construct, comprising four items (SI1 to SI5), factor loadings range from 0.671 to 0.798, with a Cronbach's alpha of 0.718, a CR of 0.826, and an AVE of 0.543, suggesting satisfactory internal consistency and convergent validity. Based on the initial findings and established criteria, two measurements were removed, namely SI3 (0.543) and EE1 (0.582), indicating inadequate correlation with their constructs and potential measurement issues.

Facilitating Conditions (FC), represented by five items (FC1 to FC5), demonstrates factor loadings between 0.646 and 0.805, a Cronbach's alpha of 0.763, a CR of 0.841, and an AVE of 0.516, indicating good reliability and convergent validity. The Behavioral Intention (BI) construct, comprising five items (BI1 to BI5), shows high factor loadings from 0.766 to 0.878, a Cronbach's alpha of 0.881, a CR of 0.913, and an AVE of 0.679, reflecting excellent reliability and convergent validity. Lastly, Digital Technology Utilization (DTU), assessed through five items (DTU1 to DTU5), demonstrates factor loadings between 0.803 and 0.869, a Cronbach's alpha of 0.901, a CR of 0.927, and an AVE of 0.716, indicating strong reliability and convergent validity for the construct.

Consequently, all factor loadings exceed 0.60, which indicates strong correlations between items and their respective constructs. All constructs have Cronbach's alpha values above 0.7, thus demonstrating good internal consistency. CR values for all constructs indicate high reliability, with values above 0.8. AVE values are above 0.5 for all constructs, which confirm adequate convergent validity. These results demonstrate strong reliability and a high level of variance explained, which show excellent convergent validity for the construct.

The discriminant validity of the measurement model is presented in Table 3. As defined by Chin (2010) and Hair, Hult, et al. (2014), discriminant validity refers to the degree to which a construct is distinctly differentiated from other constructs within the same model. This is evaluated by comparing each AVE of the construct against its highest squared correlation with any other construct in the model, or by

comparing an indicator's loading on its associated construct against its loadings on other constructs (Chin, 2010; Fornell & Larcker, 1981; Hair et al., 2011).

Table 3. Fornell and Larcker Criterion Results

Construct	PC	PE	EE	SI	FC	BI	DTU
PC	**0.743**						
PE	0.602	**0.814**					
EE	0.295	0.281	**0.754**				
SI	0.027	0.217	0.517	**0.737**			
FC	0.320	0.550	0.150	0.082	**0.718**		
BI	0.466	0.722	0.409	0.372	0.508	**0.824**	
DTU	0.654	0.569	0.308	0.049	0.295	0.598	**0.846**

Note. Diagonal values in bold are the square root of AVE; interconstruct correlation is shown off the diagonal. PC = Perceived Compatibility; PE = Performance Expectancy; EE = Effort Expectancy; SI = Social Influence; FC = Facilitating Conditions; BI = Behavioral Intention; DTU = Digital Technology Utilization.

The square roots of all AVE values surpass the required threshold, confirming that the AVE square root for each construct serves as a reliable indicator of discriminant validity in the measurement model. Thus, the measurement model results affirm that the questionnaires are both trustworthy and valid for measuring the nine components examined in this study.

The results for discriminant validity using the heterotrait-monotrait (HTMT) ratio of correlations are presented in Table 4. HTMT is the ratio of the between-trait correlations to the within-trait correlations (Henseler et al., 2015).

Table 4. Discriminant Validity Using HTMT Ratio of Correlations

Construct	PC	EE	SI	FC	BI	DTU
PE	0.721					
EE	0.402	0.358				
SI	0.210	0.317	0.720			
FC	0.414	0.674	0.283	0.175		
BI	0.559	0.826	0.517	0.471	0.619	
DTU	0.775	0.640	0.387	0.128	0.360	0.673

Note. HTMT = heterotrait-monotrait; PC = Perceived Compatibility; PE = Performance Expectancy; EE = Effort Expectancy; SI = Social Influence; FC = Facilitating Conditions; BI = Behavioral Intention; DTU = Digital Technology Utilization. The HTMT ratios are all significant, that is, $p < .05$ (one-tailed). The values are within the lower and upper limits of the 90% confidence intervals.

The HTMT ratios are all significant at $p < .05$ (one-tailed) and fall within the lower and upper limits of the 90% confidence intervals, indicating discriminant validity. The HTMT values range between 0.128 and 0.721, supporting its distinctiveness. Overall, the required conditions for reliability and validity of the measurement model were met.

Table 5 presents various model fit and quality indices used to assess the goodness of fit of structural equation models.

Table 5. Model Fit and Quality Indices

Index name	Values	Criterion
APC	0.123, $p = .013$	$p < .05$
ARS	0.514, $p < .001$	$p < .05$
AARS	0.499, $p < .001$	$p < .05$
AVIF	2.225	Acceptable if ≤ 5, ideally ≤ 3.3
AFVIF	1.866	Acceptable if ≤ 5, ideally ≤ 3.3
Tenenhaus GoF	0.670	Small ≥ 0.1; medium ≥ 0.25; large ≥ 0.36
SPR	0.765	Acceptable if ≥ 0.7, ideally = 1
RSCR	0.953	Acceptable if ≥ 0.9, ideally = 1
SSR	1.000	Acceptable if ≥ 0.7
NLBCDR	0.735	Acceptable if ≥ 0.7

Note. APC = average path coefficient; ARS = average R^2; AARS = average adjusted R^2; AVIF = average block variance inflation factor; GoF = goodness of fit; AFVIF = average collinearity variance inflation factor; SPR = Sympson's paradox ratio; RSCR = R^2 contribution ratio; SSR = statistical suppression ratio; NLBCDR = nonlinear bivariate causality direction ratio.

The benchmarks for interpreting the indices in Table 5 have been established by Davcik (2014); Hair, Hult, et al. (2014); Hazen et al. (2015); and Schreiber et al. (2006). The average path coefficient (APC), average R-squared (ARS), and average adjusted R-squared (AARS) show values of 0.123 ($p = .013$), 0.514 ($p < .001$), and 0.499 ($p < .001$), respectively, meeting the required threshold. In addition, the average block variance inflation factor (AVIF) and average collinearity variance inflation factor (AFVIF) are 2.225 and 1.866, respectively, which fall within the ideal range of $\leq$ 3.3. The Tenenhaus goodness of fit (GoF) is 0.670, indicating a large effect size, which is above the threshold of 0.36 for a large effect. The Sympson's paradox ratio (SPR) is 0.765, meeting the criterion of ≥ 0.7. The R-squared contribution ratio (RSCR) is 0.953, exceeding the criterion of ≥ 0.9. The statistical suppression ratio (SSR) is 1.000, which exceeds the acceptable threshold of greater than 0.7. Lastly, the nonlinear bivariate causality direction ratio (NLBCDR) is 0.735, which meets the criterion of ≥ 0.7. Overall, these results indicate a good model fit and quality, with most indices meeting or exceeding their respective criteria.

Structural Model Assessment

The criteria utilized in SEM for hypothesis testing, including standardized path coefficients (β -values), p-values, and f^2 values, are essential for assessing the significance and strength of relationships between constructs in the model. Standardized path coefficients indicate the direction and strength of these relationships, while p-values determine their statistical significance, with values below the significance level (at $\alpha = 0.05$) indicating significance. The f^2 values denote the effect size of each predictor on the endogenous variable, with values of 0.02, 0.15, and 0.35 representing small, medium, and large effect sizes, respectively (Hair et al., 2016).

In Table 6, the results of hypothesis testing for direct relationships and moderating effects are presented.

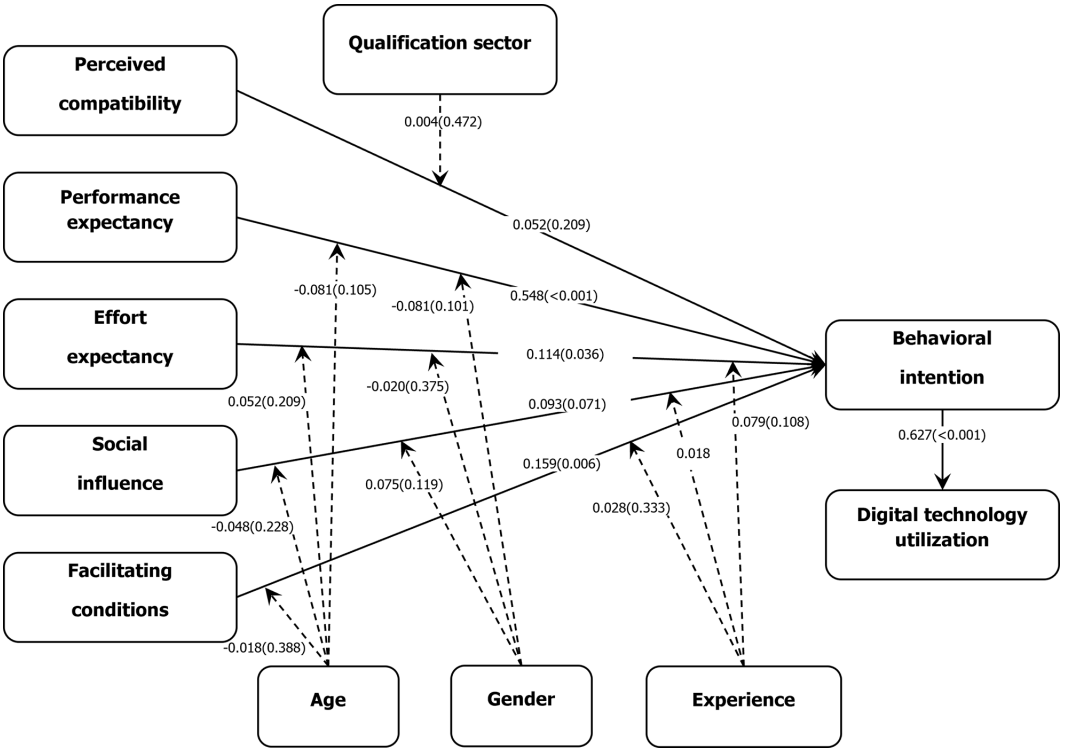
Table 6. Results of Hypothesis Testing

Hypothesis	Path	β	*p*	f^2	Decision	Effect size
Direct relationship						
H1	PC → BI	.052	.209	0.025	Not supported	Small
H2	PE → BI	.548	<.001	0.404	**Supported**	Large
H3	EE → BI	.114	.036	0.051	**Supported**	Small
H4	SI → BI	.093	.071	0.035	Not supported	Small
H5	FC → BI	.159	.006	0.081	**Supported**	Small
H6	BI → DTU	.627	<.001	0.394	**Supported**	Large
Moderating effect						
H7	QS × PC → BI	.004	.472	0.000	Not supported	Small
H8	Age × PE → BI	−.081	.105	0.030	Not supported	Small
H9	Age × EE → BI	.052	.209	0.006	Not supported	Small
H10	Age × SI → BI	−.048	.228	0.007	Not supported	Small
H11	Age × FC → BI	−.018	.388	0.004	Not supported	Small
H12	Gender × PE → BI	−.081	.101	0.036	Not supported	Small
H13	Gender × EE → BI	−.020	.375	0.006	Not supported	Small
H14	Gender × SI → BI	.075	.119	0.028	Not supported	Small
H15	Exp × EE → BI	.079	.108	0.018	Not supported	Small
H16	Exp × SI → BI	.018	.388	0.003	Not supported	Small
H17	Exp × FC → BI	.028	.333	0.005	Not supported	Small

Note. PC = Perceived Compatibility; PE = Performance Expectancy; EE = Effort Expectancy; SI = Social Influence; FC = Facilitating Condition; BI = Behavioral Intention; DTU = Digital Technology Utilization; QS = Qualification Sector; Exp = Experience.

The results reveal four direct relationships as significant: H2, H3, H5, and H6. Meanwhile, not all hypothesized moderating effects were supported. In this study, results show that PE has a large effect on BI ($f^2 = 0.404$) and BI also has a large effect on DTU ($f^2 = 0.394$). On the other hand, paths with small effects are as follows: PC to BI ($f^2 = 0.025$), EE to BI ($f^2 = 0.051$), SI to BI ($f^2 = 0.035$), and FC has a small effect on BI ($f^2 = 0.081$). The moderating paths also have minor effects, which are QS × PC → BI with $f^2 = 0.000$, Age × PE → BI with $f^2 = 0.030$, Age × EE → BI with $f^2 = 0.006$, Age × SI → BI with $f^2 = 0.007$, Age × FC → BI with $f^2 = 0.004$, Gender × PE → BI with $f^2 = 0.036$, Gender × EE → BI with $f^2 = 0.006$, Gender × SI → BI with $f^2 = 0.028$, Exp × EE → BI with $f^2 = 0.018$, Exp × SI → B with $f^2 = 0.003$, Exp × FC → BI with $f^2 = 0.005$. The results of the structural model are illustrated in Figure 3.

Figure 3. Structural Model Assessment



In addition, Table 7 provides key metrics for assessing the model's performance for each construct.

Table 7. Values of Stone-Geisser's Q^2 and Coefficient of Determination R^2

Endogenous construct	R^2	Full collinearity VIF	Q^2
Behavioral Intention (BI)	0.633	3.243	0.665
Digital Technology Utilization (DTU)	0.394	2.643	0.391

Note. VIF = variance inflation factor.

The coefficient of determination (R^2) for BI is 0.633, indicating that 63.3% of the variance in BI is explained by the model. This suggests a strong relationship between the predictors and BI. For DTU, the R^2 is 0.394, explaining 39.4% of the variance in DTU, indicating a moderate relationship. The full collinearity VIF values are 3.243 for BI and 2.643 for DTU, both below the threshold of 5, indicating acceptable levels of collinearity. Lastly, the Q^2 values are 0.665 for BI and 0.391 for DTU, suggesting that the model has good predictive power for both constructs, with values above 0 indicating predictive relevance.

DISCUSSION AND INSIGHTS

This section presents discussions and insights from results derived from the analysis through PLS-SEM. First, the findings reveal that PC does not significantly associate with BI in using digital technology in TVET curriculum delivery ($\beta = .052$, $p = .209$). This result diverges from several studies, such as those by Wang et al. (2017) and Oluyinka et al. (2021), which highlighted compatibility's role in facilitating task performance and promoting technology adoption. In contrast, the findings align with research by Kishore and McLean (2007), which demonstrated the insignificant relationship of compatibility with technology infusion behavior. The insignificant relationship between compatibility and behavioral intention supports alternative perspectives that prioritize factors such as perceived usefulness and ease of use. One possible explanation is that trainers may view digital tools as inherently disruptive rather than compatible with hands-on vocational tasks. Moreover, the findings suggest that TVET institutions integrating digital technologies should shift their focus to demonstrating tangible benefits rather than framing adoption around how well new tools fit trainers' existing curriculum delivery. School administrators should incorporate design strategies that emphasize usability, performance improvements, and ease of use to encourage technological adoption among trainers through annual performance evaluation with institution-level incentives. Investment in training programs by TESDA that build confidence in using digital tools and demonstrate their practical advantages may be deemed essential.

Second, the significant relationship between PE and BI was supported ($\beta = .548$, $p < .001$). This result confirms that PE is a critical factor motivating TESDA trainers to adopt digital technology in TVET curriculum delivery. Trainers perceive that digital tools improve teaching efficiency, streamline processes, and enhance curriculum delivery outcomes. These perceptions position PE as one of the most important predictors of trainers' intention to adopt digital tools in TVET institutions. The results align with studies emphasizing PE as a key predictor of technology adoption, particularly when users believe that the digital tools improve teaching outcomes (Mbazu et al., 2024; Nikolopoulou et al., 2021). This reinforces PE as a foundational construct within UTAUT. For TESDA, this result emphasizes the importance of demonstrating the performance-enhancing benefits of digital technologies. Practical strategies such as workshops, case studies, and peer testimonials can build confidence among trainers and encourage higher adoption rates. Also, TESDA can present success stories of TVET institutions who successfully adopted digital tools in their delivery to other institutions because testimonials that came from their peers within the same institutional context may provide more credibility. By focusing on the direct impact of digital tools on job performance, TESDA can ensure greater integration of technology into teaching practices, which can ultimately enhance learning outcomes in TVET institutions.

Third, H3, which suggests that EE significantly associates with BI, was supported by the empirical data ($\beta = .114$, $p = .036$). This finding highlights that ease of use is a meaningful determinant of TESDA trainers' intention to adopt digital technology. Trainers appreciate user-friendly digital tools that simplify processes and make technological integration more accessible. These results validate the role of EE in fostering trainers' confidence to adopt digital tools for curriculum delivery. The results align with the seminal work of Venkatesh et al. (2003), who found EE to be crucial in encouraging behavioral intention for technology use. Conversely, this result disagrees with Nikolopoulou et al. (2021), where in cases that require quick adaptation, EE does not influence BI. Given this result, TESDA should prioritize investing in training programs and digital tools that emphasize usability and intuitive design. They may provide a minimum usability standard or endorse digital platforms with simplified interfaces, support of local languages, and offline functionality suited to institutions with inconsistent Internet connectivity. This strategy may address barriers related to EE that are rooted in the regions' infrastructure constraints, rather than treating usability as purely an issue of software design. Simplifying user interfaces and providing accessible training materials can significantly improve trainers' confidence with adopting new technologies.

Fourth, SI is not significantly associated with BI ($\beta = .093$, $p = .071$). This result suggests that external pressures such as peer encouragement or expectations from administrators play a limited role in shaping TESDA trainers' intention to adopt digital technology. Trainers in TESDA appear to prioritize intrinsic motivators, such as perceived performance benefits and ease of use, over external social influences. The findings of this study do not conform with the results of studies affirming the significant relationship between SI and BI, such as Menon and Shilpa (2023) and Williams et al. (2015). In contrast, the findings align with studies that challenge SI's role as a universal determinant of BI, such as the results from Abbad (2021) in the context of e-learning systems. Given these results, TVET administrators may depart from campaigns centered on leveraging social influence to promote adoption of technology. Instead, TVET institutions may consider redirecting their resources from top-down promotional campaigns, such as memoranda from the administration encouraging adoption, into directly observable benefits for the trainers, consistent with the discussed PE and EE findings. For instance, instead of issuing an institution-wide campaign to adopt digital technology, school administrators could allow trainers to opt into a pilot program where they experience the tools' efficiencies firsthand before the wider rollout. Feedback from trainers during the pilot program may also be documented and utilized in decisions involving the procurement of digital tools to cater to trainers' needs and comfort. By shifting attention from external pressures to internal motivators, TVET institutions can better align their strategies with trainers' priorities.

Fifth, H5 was supported in this study, which proposes the positive association between FC and BI ($\beta = .159$, $p = .006$). This result emphasizes the importance of providing adequate resources, technical support, and infrastructure to encourage TESDA trainers to adopt digital technology. Trainers' behavioral intention increases when they perceive sufficient support systems (e.g., TESDA-led digital literacy programs, industry partnerships for infrastructure, or continuous professional development for trainers) to reduce barriers and ensure successful integration into teaching practices. The results align with Abbad et al. (2021), who highlighted that FC significantly impacts technology integration. Hence, with this result, TVET institutions should prioritize investments in infrastructure such as reliable Internet access, updated devices, and accessible technical support. Establishing dedicated support teams and help desks to assist trainers can further reduce barriers. Clear communication about available resources and how to access them is equally critical for ensuring widespread utilization. Providing trainers with hands-on demonstrations, troubleshooting assistance, and access to updated systems can enhance their confidence with using digital tools. TESDA could also help the institutions by ensuring equitable access to resources across all regions to bridge potential gaps.

Sixth, the hypothesis that BI is significantly associated with DTU was supported by the study ($\beta = .627$, $p < .001$). This result confirms that trainers with strong intentions to use digital tools are more likely to integrate them into their teaching practices, validating the strong link between motivation and action. The findings align with Venkatesh et al. (2003), who identified BI as the most direct predictor of actual technology use. Raman et al. (2022) also reinforced that BI strongly predicts educators' adoption of digital tools. Thus, TVET administrators should focus on fostering trainers' BI through targeted communication, success stories, and motivational programs. Emphasizing the tangible benefits of digital tools and ensuring that trainers see value in adoption can strengthen their intentions. Additionally, removing barriers to DTU such as resource shortages can bridge the gap between intention and action. In addition, TVET institutions may organize workshops showcasing successful use cases of digital tools in teaching. Providing trainers with opportunities to see the direct benefits of technology in improving teaching efficiency can strengthen their intention to adopt these tools.

The moderating effects of qualification sector (QS), age, gender, and experience are found to be insignificant in this study. The hypothesis that QS moderates the relationship between PC and BI was not supported ($\beta = .004$, $p = .472$). This suggests that sector-specific factors do not significantly influence the relationship between PC and BI. The findings contrast with those of Malahay (2021), who emphasized that subject-specific needs influence trainers' perceptions of compatibility,

suggesting specialization enhances the perceived fit of digital tools in teaching practices. Furthermore, age does not moderate the relationship between PE and BI ($\beta = -.081$, $p = .105$), EE and BI ($\beta = -.052$, $p = .209$), SI and BI ($\beta = -.048$, $p = .228$), and FC and BI ($\beta = -.018$, $p = .388$). These results contradict those of Ghalandari (2012), Alharbi et al. (2022), and Chang et al. (2019). Similarly, gender also does not moderate the relationship between PE and BI ($\beta = -.081$, $p = .101$), EE and BI ($\beta = -.020$, $p = .375$), and SI and BI ($\beta = .075$, $p = .119$). This suggests that male and female trainers perceive PE, EE, and SI similarly. These findings challenge those of Ghalandari (2012), Chang et al. (2019), and Alharbi et al. (2022). Lastly, the results do not support the moderating role of experience toward the relationship between EE and BI ($\beta = .079$, $p = .108$), SI and BI ($\beta = .018$, $p = .388$), and FC and BI ($\beta = .028$, $p = .333$). These findings contradict those of Sinha and Singh (2023) and Izkair and Lakulu (2021).

CONCLUSION AND FUTURE WORK

To meet the demands of the technology-intensive labor market, evolving digital culture, and distance-learning environment, TVET institutions have been encouraged to integrate digital tools into their curricula. Digital technologies have expanded instructional possibilities within TVET by strengthening digital literacy, improving learning outcomes, and supporting the development of competencies essential for industry readiness. However, despite these recognized benefits, there are few studies in the literature that have explored technology adoption in TVET institutions. Moreover, trainers' perceived compatibility of digital technology is particularly critical in this regard, as it, together with their attitudes and intentions, can explain how effectively digital tools can be embedded into vocational curriculum delivery. To address this gap, this study assessed the influence of perceived compatibility alongside the core UTAUT constructs—performance expectancy, effort expectancy, social influence, and facilitating conditions—on TVET trainers' behavioral intention to adopt digital technology in curriculum delivery. These constructs were synthesized into a theoretical model, and the relationships among them were empirically validated using PLS-SEM.

The findings of this study emphasize the critical role of trainers' perceptions in successfully integrating digital technology into TVET curriculum training. The study demonstrated the coefficients of determination of behavioral intention ($R^2 = 0.633$) and digital technology utilization ($R^2 = 0.394$), which point to the need for designing initiatives that enhance trainers' behavioral intentions, such as showcasing the tangible benefits of technology in improving teaching efficiency. On the other hand, the results support the direct influence of performance expectancy, effort expectancy, and facilitating conditions toward behavioral intention, while behavioral intention also has a direct relationship with digital technology utilization. Meanwhile, significant relationships of perceived compatibility and social influence toward behavioral intention are not supported. In addition, the moderating roles of age, gender, and experience are found to be insignificant.

Despite the significant contributions of this study, several limitations are acknowledged, which can be a starting point for future work. First, considering that the data collected in this study are exclusive to the Zamboanga Peninsula, the findings may primarily reflect the conditions of TVET institutions in this context. Thus, the generalization of the results operating under different conditions may be limited. Second, the study was based on a sample size of 241 respondents, constrained by the limited number of trainers available across TVET institutions in the study area. This relatively small sample size may have affected the statistical power of the model, and caution should be exercised when interpreting the results. Third, future studies should explore additional constructs such as institutional support, digital literacy, and organizational culture to refine the model further and address the unique challenges of TVET institutions. Investigating these constructs would provide a deeper understanding of the factors influencing technology adoption, particularly in vocational education contexts. Fourth, future work might examine interplay between demographic factors such as age and experience and technology-related perceptions to identify strategies for personalized interventions. Fifth, expanding

the model to include external factors like policy support and technological advancements could also provide valuable insights into fostering sustainable digital technology integration within TVET institutions. These efforts could enhance the robustness of the theoretical framework and ensure its applicability in diverse educational settings. Sixth, future research might consider digital technology utilization as a formative construct, considering the different activities that it represents, such as planning, facilitation of training, supervision of practical work, and competency assessments. Lastly, a cross-regional comparison of digital tool adoption might also be conducted using a longitudinal study design.

COMPETING INTERESTS

The authors of this publication declare there are no competing interests.

FUNDING

No funding was received for this work.

CORRESPONDING AUTHOR

Correspondence concerning this article should be addressed to Lanndon Ocampo: lanndonocampo@gmail.com.

REFERENCES

Abbad, M. M. M. (2021). Using the UTAUT model to understand students' usage of e-learning systems in developing countries. *Education and Information Technologies*, *26*(6), 7205–7224. DOI: 10.1007/s10639-021-10573-5 PMID: 34025204

Ajigini, O. A. (2023). Adoption of Internet of Things in the higher educational institutions: Perspectives from South Africa. *International Journal of Emerging Technologies in Learning*, *18*(16), 165–181. DOI: 10.3991/ijet.v18i16.42317

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, *50*(2), 179–211. DOI: 10.1016/0749-5978(91)90020-T

Ajzen, I. (2020). The theory of planned behavior: Frequently asked questions. *Human Behavior and Emerging Technologies*, *2*(4), 314–324. DOI: 10.1002/hbe2.195

Al-Rahmi, W. M., Yahaya, N., Alamri, M. M., Alyoussef, I. Y., Al-Rahmi, A. M., & Kamin, Y. B. (2021). Integrating innovation diffusion theory with technology acceptance model: Supporting students' attitude towards using a massive open online courses (MOOCs) systems. *Interactive Learning Environments*, *29*(8), 1380–1392. DOI: 10.1080/10494820.2019.1629599

Alamri, M. M., Almaiah, M. A., & Al-Rahmi, W. M. (2020). The role of compatibility and task-technology fit (TTF): On social networking applications (SNAs) usage as sustainability in higher education. *IEEE Access : Practical Innovations, Open Solutions*, *8*, 161668–161681. DOI: 10.1109/ACCESS.2020.3021944

Alea, L. A., Fabrea, M. F., Roldan, R. D. A., & Farooqi, A. Z. (2020). Teachers' COVID-19 awareness, distance learning education experiences and perceptions towards institutional readiness and challenges. *International Journal of Learning*. *Teaching and Educational Research*, *19*(6), 127–144.

Alghazi, S. S., Kamsin, A., Almaiah, M. A., Wong, S. Y., & Shuib, L. (2021). For sustainable application of mobile learning: An extended UTAUT model to examine the effect of technical factors on the usage of mobile devices as a learning tool. *Sustainability (Basel)*, *13*(4), 1856. DOI: 10.3390/su13041856

Alharbi, H., Ab Jalil, H., Omar, M. K., & Puad, M. H. M. (2022). The roles of mediators and moderators in the adoption of Madrasati (M) LMS among teachers in Riyadh. *International Journal of Learning*. *Teaching and Educational Research*, *21*(9), 95–119.

Alkawsi, G., Ali, N., & Baashar, Y. (2021). The moderating role of personal innovativeness and users experience in accepting the smart meter technology. *Applied Sciences (Basel, Switzerland)*, *11*(8), 3297. DOI: 10.3390/app11083297

Alsarayrah, T., & Ali, B. J. A. (2025). The moderating role of auditor experience on determinants of computer-assisted auditing tools and techniques. *Journal of Risk and Financial Management*, *18*(4), 206. DOI: 10.3390/jrfm18040206

Alshahrani, H. A., & Walker, D. A. (2017). Validity, reliability, predictors, moderation: The UTAUT model revisited. *General Linear Model Journal*, *43*(2), 23–34. DOI: 10.31523/glmj.043002.003

Antonietti, C., Cattaneo, A., & Amenduni, F. (2022). Can teachers' digital competence influence technology acceptance in vocational education? *Computers in Human Behavior*, *132*, 107266. DOI: 10.1016/j.chb.2022.107266

Aruppala, D. N., Gunawardene, K. D., & Razi, M. J. M. (2026). Digitalization and organizational productivity: The mediating role of employee change management—A theoretical framework. *International Journal of Sociotechnology and Knowledge Development*, *18*(1), 1–20. DOI: 10.4018/IJSKD.400105

Ayanwale, M. A., Molefi, R. R., & Matsie, N. (2023). Modelling secondary school students' attitudes toward TVET subjects using social cognitive and planned behavior theories. *Social Sciences & Humanities Open*, *8*(1), 100478. DOI: 10.1016/j.ssaho.2023.100478

Babalola, E., Adeyoola, I. A., & Omolafe, E. V. (2023). Virtual learning as a determinant of students' academic performance in University of Ilorin during COVID-19 pandemic. *Journal of Digital Learning and Education*, *3*(3), 243–253. DOI: 10.52562/jdle.v3i3.593

Baker, J. (2012). The technology–organization–environment framework. In Y. Dwivedi, M. Wade, & S. Schneberger (Eds.), *Information systems theory* (pp. 231–245). Springer. DOI: 10.1007/978-1-4419-6108-2_12

Bandura, A. (1977). Self-efficacy: Toward a unifying theory of behavioral change. *Psychological Review*, *84*(2), 191–215. DOI: 10.1037/0033-295X.84.2.191 PMID: 847061

Bandura, A. (1986). *Social foundations of thought and action*. Prentice-Hall, Inc.

Bandura, A. (1997). *Self-efficacy: The exercise of control*. Freeman Lawrence.

Barclay, D., Higgins, C., & Thompson, R. (1995). The partial least squares (PLS) approach to causal modeling: Personal computer adoption and use as an illustration. *Technology Studies*, *2*(2), 285–309.

Batucan, G. B., Gonzales, G. G., Balbuena, M. G., Pasaol, K. R. B., Seno, D. N., & Gonzales, R. R. (2022). An extended UTAUT model to explain factors affecting online learning system amidst COVID-19 pandemic: The case of a developing economy. *Frontiers in Artificial Intelligence*, *5*, 768831. DOI: 10.3389/frai.2022.768831 PMID: 35573898

Bayaga, A., & du Plessis, A. (2024). Ramifications of the Unified Theory of Acceptance and Use of Technology (UTAUT) among developing countries' higher education staffs. *Education and Information Technologies*, *29*(8), 9689–9714. DOI: 10.1007/s10639-023-12194-6

Candra, S., Frederica, E., Putri, H. A., & Loang, O. K. (2025). The UTAUT approach to Indonesia's behavioral intention to use mobile health apps. *Journal of Science and Technology Policy Management*, *16*(5), 892–911. DOI: 10.1108/JSTPM-10-2022-0175

Casquejo, M. N., Himang, C., Ocampo, L., Ancheta, R.Jr, Himang, M., & Bongo, M. (2020). The way of expanding technology acceptance—Open innovation dynamics. *Journal of Open Innovation*, *6*(1), 8. DOI: 10.3390/joitmc6010008

Centillas, C.Jr, Lumbay, C., Wenceslao, C., Villarosa, R., & Ocampo, L. (2024). Einstein aggregators on picture fuzzy sets for evaluating competencies in blueprint reading. *International Journal of Sociotechnology and Knowledge Development*, *16*(1), 1–22. DOI: 10.4018/IJSKD.365289

Chang, C. M., Liu, L. W., Huang, H. C., & Hsieh, H. H. (2019). Factors influencing online hotel booking: Extending UTAUT2 with age, gender, and experience as moderators. *Information (Basel)*, *10*(9), 281. DOI: 10.3390/info10090281

Chau, P. Y. K., & Hu, P. J. H. (2001). Information technology acceptance by individual professionals: A model comparison approach. *Decision Sciences*, *32*(4), 699–719. DOI: 10.1111/j.1540-5915.2001.tb00978.x

Chen, J. L. (2011). The effects of education compatibility and technological expectancy on e-learning acceptance. *Computers & Education*, *57*(2), 1501–1511. DOI: 10.1016/j.compedu.2011.02.009

Chin, W. W. (2010). How to write up and report PLS analyses. In *Handbook of partial least squares: Concepts, methods and applications* (pp. 655–690). Springer Berlin Heidelberg. DOI: 10.1007/978-3-540-32827-8_29

Cohen, J. (1977). *Statistical power analysis for the behavioral sciences*. Lawrence Erlbaum.

Cohen, J. (1992). A power primer. *Psychological Bulletin*, *112*(1), 155–159. DOI: 10.1037/0033-2909.112.1.155 PMID: 19565683

Compeau, D. R., & Higgins, C. A. (1995). Computer self-efficacy: Development of a measure and initial test. *Management Information Systems Quarterly*, *19*(2), 189–211. DOI: 10.2307/249688

Darwish, H. Y., Farouk, M., & Abdelsalam, M. (2024). The mediation role of technology systems in the relationship between education technology antecedents on student satisfaction. *International Journal of Sociotechnology and Knowledge Development*, *16*(1), 1–18. DOI: 10.4018/IJSKD.339566

Davcik, N. S. (2014). The use and misuse of structural equation modeling in management research: A review and critique. *Journal of Advances in Management Research*, *11*(1), 47–81. DOI: 10.1108/JAMR-07-2013-0043

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *Management Information Systems Quarterly*, *13*(3), 319–340. DOI: 10.2307/249008

Demsash, A. W., Kalayou, M. H., & Walle, A. D. (2024). Health professionals' acceptance of mobile-based clinical guideline application in a resource-limited setting: Using a modified UTAUT model. *BMC Medical Education*, *24*(1), 689. DOI: 10.1186/s12909-024-05680-z PMID: 38918767

Eroa, M., Himang, C., Aro, J. L., & Ocampo, L. (2026). Toward sustainable business models for startups from a triple bottom line perspective. *Journal of Open Innovation*, *12*(2), 100802. DOI: 10.1016/j.joitmc.2026.100802

Fernández-Batanero, J. M., Román-Graván, P., Reyes-Rebollo, M. M., & Montenegro-Rueda, M. (2021). Impact of educational technology on teacher stress and anxiety: A literature review. *International Journal of Environmental Research and Public Health*, *18*(2), 548. DOI: 10.3390/ijerph18020548 PMID: 33440738

Fishbein, M., & Ajzen, I. (1975). *Belief, attitude, intention, and behavior: An introduction to theory and research*. Addison-Wesley.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *JMR, Journal of Marketing Research*, *18*(1), 39–50. DOI: 10.1177/002224378101800104

Fu, J., Omar, M., Kamaruzaman, F. M., & Kang, D. (2026). Work-integrated learning and students' employability competences in Chinese TVET: The mediating role of digital literacy and the moderating role of competition experience. *International Journal of Learning*. *Teaching and Educational Research*, *25*(3), 796–818. DOI: 10.26803/ijlter.25.3.34

Gartner. (2026, February 3). *Information technology (IT) spending worldwide from 2012 to 2026, by segment (in billion U.S. dollars)* [Graph]. Statista. Retrieved April 16, 2026, from https://www.statista.com/statistics/268938/global-it-spending-by-segment/

Ghalandari, K. (2012). The effect of performance expectancy, effort expectancy, social influence and facilitating conditions on acceptance of e-banking services in Iran: The moderating role of age and gender. *Middle East Journal of Scientific Research*, *12*(6), 801–807.

Hair, J. F.Jr, Hult, G. T. M., Ringle, C., & Sarstedt, M. (2016). *A primer on partial least squares structural equation modeling (PLS-SEM)* (2nd ed.). Sage Publications.

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2014). *A primer on partial least squares structural equation modeling (PLS-SEM)*. Sage Publications.

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed a silver bullet. *Journal of Marketing Theory and Practice*, *19*(2), 139–152. DOI: 10.2753/MTP1069-6679190202

Hair, J. F.Jr, Sarstedt, M., Hopkins, L., & Kuppelwieser, G., V. (. (2014). Partial least squares structural equation modeling (PLS-SEM): An emerging tool in business research. *European Business Review*, *26*(2), 106–121. DOI: 10.1108/EBR-10-2013-0128

Hazen, B. T., Overstreet, R. E., & Boone, C. A. (2015). Suggested reporting guidelines for structural equation modeling in supply chain management research. *International Journal of Logistics Management*, *26*(3), 627–641. DOI: 10.1108/IJLM-08-2014-0133

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115–135. DOI: 10.1007/s11747-014-0403-8

Himang, C. M., Beltran, H. U., Ocampo, L., Garcia, J. M. S.II, Ancheta, R. A.Jr, Himang, M. M., Selerio, E. F.Jr, & Luzano, E. J. I. (2020). Acceptability evaluation of a developed thermal infrared device for fire risk management using the unified theory of acceptance and use of technology (UTAUT) model. *International Journal of Sociotechnology and Knowledge Development*, *12*(3), 1–25. DOI: 10.4018/IJSKD.2020070101

Horova, V., Sverdlyk, Z., Syerov, Y., & Lesyk, L. (2024). In-depth examination of the effective use of social networks for communication in united territorial communities: Navigating the digital landscape. In Štarchoň, P., Fedushko, S., & Gubíniová, K. (Eds.), *Data-centric business and applications: Advancements in information and knowledge management* (*Vol. 1*, pp. 225–246). Springer. DOI: 10.1007/978-3-031-62213-7_11

Hu, S., Laxman, K., & Lee, K. (2020). Exploring factors affecting academics' adoption of emerging mobile technologies: An extended UTAUT perspective. *Education and Information Technologies*, *25*(5), 4615–4635. DOI: 10.1007/s10639-020-10171-x

Ismail, M. H., Ali, S. H. S., Husin, H. S., Hassan, S., & Ali, S. N. D. M. (2025). From adoption to continuance: Understanding self-efficacy's role in TVET digital learning. *Journal of Technical Education and Training*, *17*(2), 128–136.

Izkair, A. S., & Lakulu, M. M. (2021). Experience moderator effect on the variables that influence intention to use mobile learning. *Bulletin of Electrical Engineering and Informatics*, *10*(5), 2875–2883. DOI: 10.11591/eei.v10i5.3109

Jeyaraj, A. (2021). Rethinking the intention to behavior link in information technology use: Critical review and research directions. *International Journal of Information Management*, *59*, 102345. DOI: 10.1016/j.ijinfomgt.2021.102345

Keelson, S. A., Addo, J. O., Kwarteng, K., & Amoah, J. (2025). The role of innovation in fostering entrepreneurial mindset among TVET students. *African Journal of Applied Research*, *11*(1), 285–305. DOI: 10.26437/ajar.v11i1.849

Khan, W. A., & Abideen, Z. U. (2023). Effects of behavioural intention on usage behaviour of digital wallet: The mediating role of perceived risk and moderating role of perceived service quality and perceived trust. *Future Business Journal, 9*(1), Article 73.

Khater, A. H. O., Omer, M. S., Khatarna, A. A. A., Osman, M. E. M. I., & Osman, I. Y. I. (2020). Customers intention to use internet banking: Age as a moderator variable. *International Journal of Scientific & Technology Research*, *9*(3), 6541–6548.

Kishore, R., & McLean, E. R. (2007). Reconceptualizing innovation compatibility as organizational alignment in secondary IT adoption contexts: An investigation of software reuse infusion. *IEEE Transactions on Engineering Management*, *54*(4), 756–775. DOI: 10.1109/TEM.2007.906849

Li, Z., Islam, A. A., & Spector, J. M. (2022). Unpacking mobile learning in higher vocational education during the COVID-19 pandemic. *International Journal of Mobile Communications*, *20*(2), 129–149. DOI: 10.1504/IJMC.2022.121465

Liaw, S. S., Hatala, M., & Huang, H. M. (2010). Investigating acceptance toward mobile learning to assist individual knowledge management: Based on activity theory approach. *Computers & Education*, *54*(2), 446–454. DOI: 10.1016/j.compedu.2009.08.029

Limayem, M., Hirt, S. G., & Cheung, C. M. K. (2007). How habit limits the predictive power of intention: The case of information systems continuance. *Management Information Systems Quarterly*, *31*(4), 705–737. DOI: 10.2307/25148817

Maduku, D. K. (2017). Customer acceptance of mobile banking services: Use experience as moderator. *Social Behavior and Personality*, *45*(6), 893–900. DOI: 10.2224/sbp.5871

Malahay, R. S. (2021). Area of specialization and teaching performance of the secondary science teachers in Negros Oriental, Philippines. *Journal of Scientific Research and Reports*, *27*(11), 97–103. DOI: 10.9734/jsrr/2021/v27i1130461

Marcoulides, G. A., & Chin, W. W. (2013). You write, but others read: Common methodological misunderstandings in PLS and related methods. In *New perspectives in partial least squares and related methods* (pp. 31–64). Springer New York. DOI: 10.1007/978-1-4614-8283-3_2

Mbatha, K. (2024). Meaningful learning experience using digital technologies in TVET: Towards innovative digital pedagogy. In *Technical and Vocational Teaching in South Africa: Practice, Pedagogy and Digitalisation* (pp. 247–262). Springer Nature Switzerland.

Mbazu, E. C., Oladokun, B. D., & Mohammed, J. D. (2024). Awareness, adoption and perception of lecturers toward the use of information and communication technology (ICT) in Nigeria. *The Howard Journal of Communications*, *35*(4), 412–428. DOI: 10.1080/10646175.2023.2291120

Menon, D., & Shilpa, K. (2023). "Chatting with ChatGPT": Analyzing the factors influencing users' intention to use the Open AI's ChatGPT using the UTAUT model. *Heliyon*, *9*(11), e20962. DOI: 10.1016/j.heliyon.2023.e20962 PMID: 37928033

Mensah, I. K., & Khan, M. K. (2024). Unified theory of acceptance and use of technology (UTAUT) model: Factors influencing mobile banking services' adoption in China. *SAGE Open*, *14*(1). DOI: 10.1177/21582440241234230

Mishra, P., & Koehler, M. J. (2006). Technological pedagogical content knowledge: A framework for teacher knowledge. *Teachers College Record*, *108*(6), 1017–1054. DOI: 10.1111/j.1467-9620.2006.00684.x

Momani, A. M. (2020). The unified theory of acceptance and use of technology: A new approach in technology acceptance. *International Journal of Sociotechnology and Knowledge Development*, *12*(3), 79–98. DOI: 10.4018/IJSKD.2020070105

Moore, G. C., & Benbasat, I. (1991). Development of an instrument to measure the perceptions of adopting an information technology innovation. *Information Systems Research*, *2*(3), 192–222. DOI: 10.1287/isre.2.3.192

Nikolopoulou, K., Gialamas, V., & Lavidas, K. (2021). Habit, hedonic motivation, performance expectancy and technological pedagogical knowledge affect teachers' intention to use mobile internet. *Computers and Education Open*, *2*, 100041. DOI: 10.1016/j.caeo.2021.100041

Oluyinka, S., Endozo, A. N., & Cusipag, M. N. (2021). Integrating trialability and compatibility with UTAUT to assess canvas usage during COVID-19 quarantine period. *Asia-Pacific Social Science Review*, *21*(2), 31–47. DOI: 10.59588/2350-8329.1366

Onaolapo, S., & Oyewole, O. (2018). Performance expectancy, effort expectancy, and facilitating conditions as factors influencing smart phones use for mobile learning by postgraduate students of the University of Ibadan, Nigeria. *Interdisciplinary Journal of e-Skills and Lifelong Learning, 14*, 95–115.

Othman, N., Omar, M., & Abd Majid, M. Z. (2025). Challenges of digitalisation in TVET: A recent comprehensive structured review. *International Journal of Learning*. *Teaching and Educational Research*, *24*(10), 210–229.

Palapa, A., Handoko, W., & Wanto, K. (2026). The impact of digital learning and digital capability on digital engagement and performance in TVET higher education: A mediation analysis. *Multidisciplinary Science Journal, 8*(8), Article 2026533.

Qatanani, N. O., Alghababsheh, M., Aburayya, A., & Nasaj, M. (2026). Factors influencing m-government adoption in the developing world: A UTAUT-based model integrating trust, risk and trendiness. *VINE Journal of Information and Knowledge Management Systems*, *56*(3), 797–828. DOI: 10.1108/VJIKMS-10-2023-0255

Rahi, S., & Ghani, M. A. (2018). The role of UTAUT, DOI, perceived technology security and game elements in internet banking adoption. *World Journal of Science, Technology and Sustainable Development*, *15*(4), 338–356.

Raman, A., Thannimalai, R., Rathakrishnan, M., & Ismail, S. N. (2022). Investigating the influence of intrinsic motivation on behavioral intention and actual use of technology in Moodle platforms. *International Journal of Instruction*, *15*(1), 1003–1024. DOI: 10.29333/iji.2022.15157a

Rambe, P., Mbeo, M. A., & Meda, L. (2022). Using the technology-organization-environment framework to explore research and innovation strategies and manage academic resistance at a university of technology. *The International Journal of Learning in Higher Education*, *30*(2), 29–45. DOI: 10.18848/2327-7955/CGP/v30i02/29-45

Regassa, M. S., & Desissa, T. D. (2025). Technology integration status in TVET colleges: Evidence from Sheger City, Ethiopia. *Discover Education*, *4*(1), 507. DOI: 10.1007/s44217-025-00949-x

Rogers, E. M. (1995). *Diffusion of innovations*. The Free Press.

Ronchi, A. M. (2019). E-learning: How teaching and training methods changed in the last 20 years. In *e-Services: Toward a New Model of (Inter) active Community* (pp. 69–113). Springer International Publishing.

Schreiber, J. B., Nora, A., Stage, F. K., Barlow, E. A., & King, J. (2006). Reporting structural equation modeling and confirmatory factor analysis results: A review. *The Journal of Educational Research*, *99*(6), 323–338. DOI: 10.3200/JOER.99.6.323-338

Sharma, A., Sharma, A., Singh, R. K., & Bhatia, T. (2023). Blockchain adoption in agri-food supply chain management: An empirical study of the main drivers using extended UTAUT. *Business Process Management Journal*, *29*(3), 737–756. DOI: 10.1108/BPMJ-10-2022-0543

Singh, N., Sinha, N., & Liébana-Cabanillas, F. J. (2020). Determining factors in the adoption and recommendation of mobile wallet services in India: Analysis of the effect of innovativeness, stress to use and social influence. *International Journal of Information Management*, *50*, 191–205. DOI: 10.1016/j.ijinfomgt.2019.05.022

Sinha, N., & Singh, N. (2023). Moderating and mediating effect of perceived experience on merchant's behavioral intention to use mobile payments services. *Journal of Financial Services Marketing*, *28*(3), 448–465. DOI: 10.1057/s41264-022-00163-y

Sitar-Tăut, D. A. (2021). Mobile learning acceptance in social distancing during the COVID-19 outbreak: The mediation effect of hedonic motivation. *Human Behavior and Emerging Technologies*, *3*(3), 366–378. DOI: 10.1002/hbe2.261 PMID: 34222833

Sousa, M. M., Oliveira, B. F., Gonçalves, T. I., Alves, S., Carreira, C., & Barbosa, F. V. (2026). UTAUT-for-Industry: A novel model for assessing employee's acceptance of new technologies in the industrial context. *International Journal on Interactive Design and Manufacturing*, *20*(3), 1171–1195. DOI: 10.1007/s12008-025-02464-7

Technical Education and Skills Development Authority. (2021, December 10). *Omnibus guidelines on technical vocational education and training (TVET) program registration* (TESDA Circular No. 107, Series of 2021). https://intranet.tesda.gov.ph/RMIS/Serve/9BB28C20

Technical Education and Skills Development Authority. (2024, November 13). *Approving the revisions to the Philippine TVET trainer's qualification framework (PTTQF)* (Resolution No. 2024-18). https://www.tesda.gov.ph/CMSFiles/TESDABoardResolution/2024/BR%20No,%202024-18%20w%20attach.pdf

Thompson, R. L., Higgins, C. A., & Howell, J. M. (1991). Personal computing: Toward a conceptual model of utilization. *Management Information Systems Quarterly*, *15*(1), 125–143. DOI: 10.2307/249443

Twum, K. K., & Yalley, A. A. (2025). Marketing analytics acceptance: Using the UTAUT, perceived trust, personal innovativeness in information technology and user attitude. *Journal of Science and Technology Policy Management*, *16*(7), 1271–1295. DOI: 10.1108/JSTPM-01-2022-0001

United Nations Educational, Scientific and Cultural Organization. (2023). *Global education monitoring report 2023: Technology in education—A tool on whose terms?* UNESCO. https://gem-report-2023.unesco.org/technology-in-education/

Utomo, P., Kurniasari, F., & Purnamaningsih, P. (2021). The effects of performance expectancy, effort expectancy, facilitating condition, and habit on behavior intention in using mobile healthcare application. *International Journal of Community Service & Engagement*, *2*(4), 183–197. DOI: 10.47747/ijcse.v2i4.529

Vargo, D., Zhu, L., Benwell, B., & Yan, Z. (2021). Digital technology use during COVID-19 pandemic: A rapid review. *Human Behavior and Emerging Technologies*, *3*(1), 13–24. DOI: 10.1002/hbe2.242

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *Management Information Systems Quarterly*, *27*(3), 425–478. DOI: 10.2307/30036540

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *Management Information Systems Quarterly*, *36*(1), 157–178. DOI: 10.2307/41410412

Wagino, A. A., Martias, Koto, R. D., Samala, A. D., & Criollo-C, S. (2025). Field-based insights into e-learning, PBL, and soft skills participation in TVET. In *E3S Web of Conferences, 622*, Article 04008. DOI: 10.1051/e3sconf/202562204008

Wang, M., Cho, S., & Denton, T. (2017). The impact of personalization and compatibility with past experience on e-banking usage. *International Journal of Bank Marketing*, *35*(1), 45–55. DOI: 10.1108/IJBM-04-2015-0046

Williams, M. D., Rana, N. P., & Dwivedi, Y. K. (2015). The unified theory of acceptance and use of technology (UTAUT): A literature review. *Journal of Enterprise Information Management*, *28*(3), 443–488. DOI: 10.1108/JEIM-09-2014-0088

Xue, L., Rashid, A. M., & Ouyang, S. (2024). The unified theory of acceptance and use of technology (UTAUT) in higher education: A systematic review. *SAGE Open*, *14*(1). DOI: 10.1177/21582440241229570

Yohanes, K., Junius, K., Saputra, Y., Sari, R., Lisanti, Y., & Luhukay, D. (2020, August). Unified Theory of Acceptance and Use of Technology (UTAUT) model perspective to enhance user acceptance of fintech application. In *2020 International Conference on Information Management and Technology* (pp. 643–648). IEEE. DOI: 10.1109/ICIMTech50083.2020.9211250

Zeebaree, M., Agoyi, M., & Aqel, M. (2022). Sustainable adoption of e-government from the UTAUT perspective. *Sustainability (Basel)*, *14*(9), 5370. DOI: 10.3390/su14095370

Zhou, M., Huang, J., Wu, K., Huang, X., Kong, N., & Campy, K. S. (2021). Characterizing Chinese consumers' intention to use live e-commerce shopping. *Technology in Society*, *67*, 101767. DOI: 10.1016/j.techsoc.2021.101767

APPENDIX

Table A1. Measurement Indicators

Construct	Items	References
Perceived Compatibility	Using digital technology is compatible with all aspects of my work as a trainer.	Moore and Benbasat (1991); Chau and Hu (2001)
	Digital technology is compatible with the instructions I currently use for training.	
	Using digital technology fits well with the way I like to work as a trainer.	
	Using digital technology fits with my workstyle as a trainer.	
	Digital technology is compatible with TVET curriculum delivery.	
Performance Expectancy	Digital technology is useful in my work as a TVET trainer.	Venkatesh et al. (2003)
	Using digital technology enables me to accomplish my tasks more quickly.	
	Using digital technology will increase my productivity as a trainer.	
	Using digital technology will enhance my effectiveness as a trainer.	
	Using digital technology will improve my overall performance as a trainer.	
Effort Expectancy	My interaction with digital technology is clear and understandable.	Venkatesh et al. (2003)
	It would be easy for me to become skillful at using digital technology.	
	I find digital technology easy to use.	
	Learning to operate digital technology is easy for me.	
	Utilizing digital technology for TVET curriculum is convenient for me as a trainer.	
Social Influence	People who influence my behavior believe that I should use digital technology in my teaching practices (e.g., co-trainer/teacher).	Venkatesh et al. (2003)
	People who are important to me think that I should use digital technology in teaching.	
	The administration has been helpful in the use of digital technology.	
	The institution has supported the use of digital technology.	
	In general, people in this institution influenced me to use digital technology for TVET curriculum delivery.	
Facilitating Conditions	I have the necessary resources to use digital technology in teaching.	Venkatesh et al. (2003)
	I have the knowledge necessary to use digital technology in teaching.	
	I have the necessary tools to use digital technical technology in teaching/training.	
	Technical assistance is accessible whenever support is needed.	
	Technical infrastructure is available to support the use of digital technology.	

continued on following page

Table A1. Continued

Construct	Items	References
Behavioral Intention	I intend to use digital technology in the next training period/semester.	Venkatesh et al. (2003); Chau and Hu (2001)
	I predict I would use digital technology in the next training period/ semester.	
	I plan to use digital technology in the next training period/semester.	
	I will continue using digital technology for TVET training delivery.	
	In general, I have the intention to integrate digital technology in the TVET curriculum.	
Digital Technology Utilization	I utilize digital technology to plan and prepare training sessions.	Technical Education and Skills Development Authority (2024)
	I utilize digital technology to conduct and facilitate training sessions.	
	I use digital technology to supervise/handle work-based learning/ practical training.	
	I utilize digital technology to conduct competency assessments.	
	In general, I use digital technology as a TVET trainer.	

Dr. Celbert M. Himang is a Full Professor at Cebu Technological University-Main Campus in the Philippines. He obtained his Bachelor's degree in Statistics in 1997 from Visayas State University, a Master's in Management focusing on Information Management in 1998 from the Consortium of Palompon Institute of Technology and Pangasinan State University, a Diploma in Mathematics Teaching in 2000 from UPOU and his PhD in Technology Management in 2001 from Cebu Technological University. He leads the Graduate School Research Area of CTU and chairs the Philosophy in Technology Management doctoral program, overseeing dissertations on technology acceptance, innovation, and adoption. Dr. Himang has authored books on Thesis and Dissertation Writing, Formula-Free Statistics using SPSS, and Participative Research Guide. His research papers on technology acceptance models, information system success, decision science, tourism management, and adult education have been published in SCOPUS and WOS-indexed journals. He has also contributed to the University's intellectual property assets, particularly food technology and electronic gadgets.

Joerabell Lourdes Aro received her M.S. degree in Industrial Engineering, major in Operations Research, from the University of the Philippines Diliman. She is currently a Science Research Assistant at the Center of Applied Mathematics and Operations Research, Cebu Technological University, Philippines. She has authored over 30 Scopus-indexed journal publications and holds a Scopus h-index of 11. She has also presented her research at international conferences. Her research interests include multicriteria decision making, optimization, and decision science.

Lanndon Ocampo is a Professor of Industrial Engineering and the Director of the Center for Applied Mathematics and Operations Research at Cebu Technological University. He obtained his Ph.D. in Logistics and Operational Research from the University of Portsmouth (UK). He also received his Ph.D. in Industrial Engineering from De La Salle University (Philippines) and his MEng and BSc (cum laude) degrees in Industrial Engineering, as well as an MSc in Mathematics, from the University of San Carlos (Philippines). He has authored over 200 international peer-reviewed journal papers (189 in Scopus, with a Google Scholar h-index of 38) and has presented papers at more than 30 research conferences. He is on the editorial boards of the International Journal of Management and Decision Making and Advances in Production Engineering and Management. His interests include soft operations research, decision science, and decision engineering. He served as Project Leader for seven externally funded research projects, supported by the Department of Science and Technology, the Commission on Higher Education, and the Department of Tourism. He was a 2017 Outstanding Young Scientist awardee by the National Academy of Science and Technology, Philippines (NAST PH). He was named one of 2018 THE ASIAN SCIENTIST 100 – an annual listing of the region's top researchers, academics, and innovators. He was conferred the 2019 Achievement Awardee by the National Research Council of the Philippines (NRCP) under the Division of Engineering and Industrial Research. Also, he received the 2025 PhilAAST Michael R.I. Purvis Award for Sustainability Research from the Philippine Association for the Advancement of Science and Technology (PhilAAST). Dr. Ocampo is listed in the 2020, 2021, 2022, 2023, 2024, and 2025 editions of the Top 2% of the world's researchers, based on composite citation metrics developed by a team of statisticians from Stanford University and Elsevier.