Volume 6 Number 2 (2026)
July-December 2026
Page: 217-232

E-ISSN: 2797-0965
P-ISSN: 2809-9710
DOI: 10.37680/basica.v6i2.10639

BASICA Journal of Primary Education

Smart Education and Practical Learning Effectiveness in Tourism: Testing Tool-Course Fit and Teacher Digital Competence

Song Zan[1], Ketut Agustini[2], Ketut Suma[3]
[123] Universitas Pendidikan Ganesha; Indonesia
Correspondence Email ; 415497480@qq.com

Submitted: 03/09/2026 Revised: 25/09/2026 Accepted: 08/10/2026 Published: 08/11/2026

Abstract

This study examines how smart education tool utilisation, digital learning readiness, and student learning engagement shape practical learning effectiveness among tourism management students, while testing the moderating roles of tool-course fit and teacher digital competence. Using a positivist, explanatory, cross-sectional design, data were collected through an online questionnaire from 360 undergraduate students in tourism-related programmes in and around Singaraja, Bali, selected purposively from students with practical-course and smart-tool experience. The data were analysed using descriptive statistics and Pearson correlations in SPSS and partial least squares structural equation modelling in SmartPLS. Smart education tool utilisation ($\beta = 0.246$, $p < 0.001$), student learning engagement ($\beta = 0.228$, $p < 0.001$), and digital learning readiness ($\beta = 0.198$, $p < 0.001$) positively influenced practical learning effectiveness. Tool-course fit ($\beta = 0.174$, $p < 0.001$) and teacher digital competence ($\beta = 0.119$, $p = 0.003$) also had significant direct effects. However, neither tool-course fit ($\beta = 0.029$, $p = 0.456$) nor teacher digital competence ($\beta = -0.010$, $p = 0.790$) significantly moderated the smart-tool utilisation–effectiveness relationship. The model explained 46.1% of the variance in practical learning effectiveness and demonstrated predictive relevance (Q^2predict = 0.434). The findings indicate that effective technology-supported practical learning depends on the combined presence of tool use, learner readiness, engagement, pedagogical fit, and teacher competence, with the latter two functioning as direct environmental enablers rather than moderators.

Keywords

Digital Learning Readiness; Practical Learning Effectiveness; Smart Education Tools; Student Learning Engagement; Tourism Management.

© 2025 by the authors. Submitted for possible open access publication under the terms and conditions of the Creative Commons Attribution-NonCommercial 4.0 International License (CC BY NC) license (https://creativecommons.org/licenses/by-nc/4.0/).

INTRODUCTION

Tourism management education is increasingly shaped by digital transformation, with smart education tools becoming part of how students access information, practise decisions, and connect classroom knowledge with professional situations. This shift restructures learning through digital platforms and combines intelligent technologies, interactive environments, and flexible learning processes (Issakov et al., 2023; Yang et al., 2025). This development is especially relevant to tourism management because the discipline is practice-oriented: students are expected to move beyond conceptual understanding and demonstrate competencies in areas such as hospitality operations, destination planning, customer service, event management, and problem solving. Practical learning effectiveness therefore concerns the capacity to acquire, apply, and transfer knowledge and skills through authentic or experiential learning activities (Abdelghani & Ahmed, 2025; Radygina, 2023).

The use of digital and AI-supported tools provides new possibilities for such practice-oriented learning. Smart technologies can support simulations, virtual environments, collaborative projects, and other activities that approximate industry situations. Extended reality can support experiential learning in hospitality management, while innovative technology can contribute to vocational tourism education (Bahçelerli, 2023; Cunha et al., 2023). Smart education can also increase interactivity and personalisation, which are frequently associated with stronger participation and learning outcomes (Jangjarat et al., 2023). Evidence from other educational settings points in the same direction: AI-based media can support more tailored and engaging learning experiences (Rohmah, 2024), while interactive Canva-based media have been associated with higher learning motivation, academic performance, and creativity (Susanti et al., 2025). Although those studies were conducted in primary education, they reinforce the broader proposition that digital tools gain educational value when they support concrete learning processes. Yet the existence or frequency of technology use does not automatically guarantee that students develop practical competence. Digital tools need to be used in ways that correspond to the demands of learning tasks and the capacities of the people who use them.

One important student-level condition is digital learning readiness. In this study, digital learning readiness refers to students' preparedness, confidence, self-efficacy, and willingness to engage with technology-supported learning. Online learning readiness is an important condition for effective participation in digitally mediated learning and is also connected with technological skills and employability outcomes among hospitality graduates (Elshaer et al., 2025; Reyes-Millán et al.,

2023). Students who feel capable of navigating digital environments are more likely to engage with unfamiliar tools, regulate their own learning, and use technological resources productively. This makes readiness particularly important when practical tourism learning requires students to interact with simulations, online systems, AI tools, and digital planning resources.

Student learning engagement constitutes a second learner-related condition. Engagement covers cognitive, emotional, and behavioural involvement in learning, including persistence, enthusiasm, meaningful participation, and immersion in study activities (Xu et al., 2023). Technology can provide opportunities for active learning, but these opportunities only become educationally valuable when students invest attention and effort in the learning process. Learning engagement is structurally connected with professional identity, academic self-efficacy, and university support among tourism students (Chen et al., 2023). In another educational setting, a multimodal learning ecosystem can similarly increase learning engagement and shift learners from passive recipients toward more active learning agents (Supaat et al., 2026). Thus, the effectiveness of smart education should be examined not only through access to technology but also through the extent to which learners are ready and actively engaged.

The learning environment introduces two further conditions: tool-course fit and teacher digital competence. Tool-course fit refers to the degree to which the selected technology matches course objectives, learning activities, and practical requirements. This idea is consistent with the broader task-technology fit argument that technological usefulness depends on alignment between technological capabilities and task requirements (Yu & Yu, 2010). Within tourism education, a tool that supports realistic destination planning, hotel operations, or service scenarios may provide greater pedagogical value than a generic digital platform that is poorly aligned with practical competencies. Teacher digital competence, meanwhile, concerns educators' ability to manage digital resources, organise technology-supported learning, assist students, and integrate ICT into pedagogy (Nguyen et al., 2022; Revuelta-Domínguez et al., 2022). Digital competence is likewise necessary for successful pedagogical practice in the digital age (Kiryakova & Kozhuharova, 2024). BASICA studies provide additional support for this environmental dimension: Latifah, 2024) found that teachers' digital-literacy integration is shaped by self-efficacy and facilitating conditions, while Roudhoh et al. (2026) reported a significant contribution of teacher digital competence to the effectiveness of digital learning media.

These relationships are framed through Social Cognitive Theory (SCT). SCT explains learning through reciprocal interaction among personal, behavioural, and environmental factors. In technology-supported education, digital learning readiness represents an important personal condition; student learning engagement represents behavioural involvement; and the learning environment includes technological and instructional conditions such as smart tool utilisation, tool-course fit, and teacher competence. Triadic reciprocal determinism therefore provides a useful explanation for why learning effectiveness may depend on multiple interacting conditions rather than on technology alone (Chai & Ye, 2024; Firmansyah & Saepuloh, 2022). From this perspective, smart education tools create learning opportunities, but students' readiness and engagement influence how those opportunities are used, while pedagogical fit and teacher competence shape the environment in which technology is implemented.

Previous research provides evidence for individual parts of this model but leaves an empirical gap when they are considered together in practice-oriented tourism education. ICT advantages, compatibility, usefulness, virtual self-efficacy, and related factors contribute to e-learning effectiveness among tourism and hospitality students (Amin et al., 2022). Studies of smart education similarly report positive relationships with engagement and learning outcomes (Jangjarat et al., 2023), while research on digital competence suggests that teachers' technological capabilities can influence the quality of technology integration (Kiryakova & Kozhuharova, 2024). At the implementation level, Nisak & Rofi'ah (2023) documented that digital learning media may remain underused when teachers have difficulty operating digital media and when supporting facilities are limited. However, the thesis underpinning this article identified limited attention to whether the alignment of tools with course requirements and teachers' digital competence actually change the strength of the relationship between smart tool use and practical learning effectiveness. This issue is important because a moderator is conceptually different from a direct predictor: a variable may improve learning in its own right without necessarily strengthening the effect of technology use.

The novelty of this study lies in integrating smart education tool utilisation, digital learning readiness, student learning engagement, tool-course fit, and teacher digital competence within a single Social Cognitive Theory-based model of practical tourism learning, while simultaneously distinguishing the direct environmental effects of tool-course fit and teacher digital competence from their proposed moderating roles. This distinction extends prior tourism-education research, which has largely examined technology adoption, readiness, engagement, or digital competence

separately, by testing whether pedagogical fit and teacher competence operate as direct enablers rather than boundary conditions of smart-tool effectiveness. This study therefore examines practical learning effectiveness among tourism management students in and around Singaraja, Bali, Indonesia. It tests the direct effects of smart education tool utilisation, digital learning readiness, and student learning engagement on practical learning effectiveness; evaluates whether tool-course fit and teacher digital competence moderate the smart-tool utilisation–effectiveness relationship; and assesses the overall explanatory and predictive capability of the model. The study contributes theoretically by applying SCT to a practice-oriented digital learning setting and empirically by distinguishing direct environmental contributions from true moderation effects. Practically, the results can inform technology selection, teacher professional development, and student readiness and engagement programmes in tourism education.

METHOD

The study employed a positivist, explanatory quantitative design with a cross-sectional survey. The target population comprised undergraduate students enrolled in tourism management or related tourism programmes at higher education institutions in and around Singaraja, Buleleng, Bali, Indonesia. Purposive sampling was used because the study required participants who had sufficient exposure to theoretical and practical tourism learning as well as experience using smart educational tools. Eligibility focused on students in advanced semesters who had undertaken practical tourism courses, had experience with smart education tools, voluntarily agreed to participate, and provided informed consent. A G*Power analysis identified 119 participants as the minimum required sample for the proposed structural model; the final dataset contained 360 eligible respondents, providing a larger basis for PLS-SEM estimation.

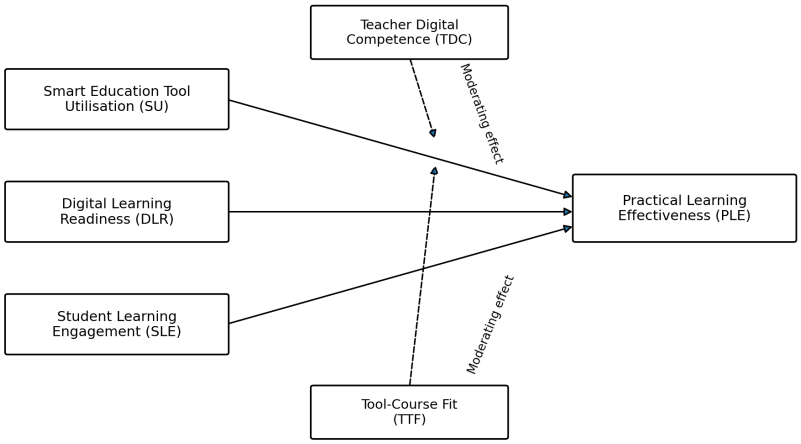


Figure 1. Conceptual Framework
Source: Adapted from the thesis conceptual framework (2026)

Data were collected through an online structured questionnaire distributed through university networks and educational platforms. The instrument contained demographic questions and six research constructs. Smart Education Tool Utilisation (SU) was measured with seven items adapted from Elmourad et al. (2026); Digital Learning Readiness (DLR) used six items based on Elshaer et al. (2025); Student Learning Engagement (SLE) used eight items adapted from Chen et al. (2023); Teacher Digital Competence (TDC) used three items from the adapted instrument reported in the thesis; Tool-Course Fit (TTF) consisted of six items adapted from Yu and Yu (2010); and Practical Learning Effectiveness (PLE) contained four items adapted from Amitani et al. (2021). The questionnaire presented a five-point response scale coded from 1 to 5. Existing measures were contextualised for undergraduate tourism management and smart education, and the thesis specified expert evaluation and pilot testing before the main survey.

Data analysis combined SPSS and SmartPLS. SPSS was used for demographic description, means, standard deviations, skewness, kurtosis, and Pearson correlations. The PLS-SEM analysis assessed construct reliability through Cronbach's alpha and composite reliability, convergent validity through average variance extracted (AVE), and discriminant validity through HTMT and the Fornell-Larcker criterion. The structural model was evaluated using variance inflation factors (VIF), standardised path coefficients, bootstrapped t statistics and p values, coefficient of determination (R^2), effect size (f^2), predictive relevance (Q^2predict), and standardised root mean square residual (SRMR). The thesis adopted $p < 0.05$ and $t > 1.96$ as significance criteria and used SRMR < 0.08 as the principal model-fit threshold (Subhaktiyasa, 2024). Moderation was assessed

from the significance of the interaction terms TTF × SU and TDC × SU.

Participation was voluntary. Respondents received information about the purpose and procedures of the study and provided informed consent electronically. No names or student identification numbers were collected, responses were anonymised, and the data were intended solely for academic use. These procedures were designed to protect confidentiality and participant autonomy throughout the survey process.

FINDINGS AND DISCUSSION

Findings

The final sample consisted of 360 respondents. Gender representation was relatively balanced, with 49.2% male and 46.9% female students, while 3.9% preferred not to state gender. The largest age group was 21–23 years (39.7%), followed by 18–20 years (30.0%). Respondents came from Tourism Management, Hospitality Management, Hotel Management, Travel and Tourism, and other related programmes. Smart education tool use was already common: 47.8% reported using the tools often and 26.4% very frequently. More than half of respondents (56.9%) had received formal training in smart education technologies, and most reported daily use of one to four hours. Table 1 provides the detailed demographic and smart-technology-use profile of the respondents, allowing the sample composition and level of prior exposure to smart education to be read directly alongside the narrative description.

Table 1. Respondent Characteristics

Characteristic	Category	n (%)
Gender	Male	177 (49.2%)
	Female	169 (46.9%)
	Prefer not to say	14 (3.9%)
Age	18–20 years	108 (30.0%)
	21–23 years	143 (39.7%)
	24–25 years	80 (22.2%)
	26 years and above	29 (8.1%)
Programme	Tourism Management	101 (28.1%)
	Hospitality Management	80 (22.2%)
	Hotel Management	79 (21.9%)
	Travel and Tourism	80 (22.2%)
	Others	20 (5.6%)
Smart tool use	Never	20 (5.6%)
	Rarely	73 (20.3%)
	Often	172 (47.8%)

	Very frequently	95 (26.4%)
Formal training	Yes	205 (56.9%)
	No	155 (43.1%)
Daily smart-tool time	1–2 hours	167 (46.4%)
	3–4 hours	141 (39.2%)
	More than 5 hours	52 (14.4%)
Semester	Semester 5	85 (23.6%)
	Semester 6	88 (24.4%)
	Semester 7	90 (25.0%)
	Semester 8	78 (21.7%)
	Others	19 (5.3%)

Source: Authors' analysis (2026)

Descriptive statistics show moderate perceptions across all constructs, with mean values clustered around 3.00. Tool-Course Fit recorded the highest mean (M = 3.092, SD = 0.968), while Digital Learning Readiness recorded the lowest (M = 2.963, SD = 0.936). Practical Learning Effectiveness had a mean of 3.033 (SD = 1.022). Pearson correlations were positive and significant for all constructs in relation to PLE. Smart Education Tool Utilisation had the strongest bivariate association with PLE ($r = 0.557$, $p < 0.001$), followed by Student Learning Engagement ($r = 0.524$, $p < 0.001$) and Digital Learning Readiness ($r = 0.478$, $p < 0.001$). Table 2 summarises the central tendency of each construct and its bivariate association with practical learning effectiveness, showing how the descriptive pattern corresponds with the subsequent structural analysis.

Table 2. Descriptive Statistics and Correlations with Practical Learning Effectiveness

Construct	Mean	SD	r with PLE	p
SU	3.012	0.974	0.557	<0.001
DLR	2.963	0.936	0.478	<0.001
SLE	2.994	0.905	0.524	<0.001
TDC	3.043	1.015	0.295	<0.001
TTF	3.092	0.968	0.410	<0.001
PLE	3.033	1.022	1.000	—

Source: Authors' analysis (2026)

The measurement model met the reliability and validity criteria used in the thesis. Cronbach's alpha ranged from 0.732 to 0.895, composite reliability (rho_c) ranged from 0.848 to 0.918, and all AVE values exceeded 0.50. HTMT values ranged from 0.017 to 0.645, remaining below the 0.85 threshold, and the Fornell-Larcker criterion was also satisfied. These results indicate acceptable internal consistency, convergent validity, and discriminant validity before interpretation of the structural paths. Table 3 presents the reliability and convergent-validity indices for each construct and confirms that the measurement model was adequate before testing the structural relationships.

Table 3. Measurement Model Assessment

Construct	Cronbach α	rho_a	rho_c	AVE
DLR	0.865	0.870	0.899	0.599
PLE	0.832	0.835	0.888	0.665
SLE	0.889	0.893	0.911	0.563
SU	0.895	0.901	0.918	0.615
TDC	0.732	0.733	0.848	0.650
TTF	0.882	0.890	0.911	0.630

Source: Authors' analysis (2026)

The structural model showed no problematic multicollinearity: VIF values ranged from 1.030 to 1.695. Model fit was satisfactory with SRMR = 0.047. The model explained 46.1% of the variance in Practical Learning Effectiveness (R^2 = 0.461; adjusted R^2 = 0.451). Q^2predict was 0.434, with RMSE = 0.757 and MAE = 0.604, supporting predictive relevance. Effect sizes for the significant direct predictors were small, ranging from f^2 = 0.024 to 0.066, while the interaction effects were negligible (f^2 = 0.000–0.002). Table 4 consolidates the structural-model diagnostics, including collinearity, model fit, explanatory power, and predictive relevance, to provide a concise assessment of overall model adequacy.

Table 4. Structural Model Evaluation

Indicator	Value	Interpretation
VIF range	1.030–1.695	No multicollinearity concern
SRMR	0.047	Satisfactory fit
R^2 PLE	0.461	46.1% variance explained
Adjusted R^2	0.451	Stable explanatory power
Q^2predict PLE	0.434	Predictive relevance
RMSE	0.757	Prediction error indicator
MAE	0.604	Prediction error indicator

Source: Authors' analysis (2026)

The path analysis provides the main evidence for the study objectives. SU, DLR, and SLE each had significant positive effects on PLE. TTF and TDC also demonstrated significant direct effects on PLE. In contrast, the two interaction terms were not significant. Consequently, the statistical evidence supports H1–H3, while H4 and H5 are not supported. The overall model-level expectation that the principal predictors jointly explain meaningful variance in PLE is supported by the R^2 and Q^2predict results. Table 5 reports the direct and interaction paths together with the corresponding hypothesis decisions, providing the empirical basis for the discussion of each proposed relationship.

Table 5. Path Coefficients and Hypothesis Decisions

Path	β	t	p	f^2	Decision
H1: SU → PLE	0.246	4.502	<0.001	0.066	Supported
H2: DLR → PLE	0.198	4.055	<0.001	0.052	Supported
H3: SLE → PLE	0.228	4.867	<0.001	0.062	Supported
TTF → PLE	0.174	3.680	<0.001	0.046	Significant direct effect
TDC → PLE	0.119	2.965	0.003	0.024	Significant direct effect
H4: TTF × SU → PLE	0.029	0.745	0.456	0.002	Not supported
H5: TDC × SU → PLE	-0.010	0.267	0.790	0.000	Not supported

Source: Authors' analysis (2026)

Discussion

H1 is supported, the first major finding is that smart education tool utilisation positively influences practical learning effectiveness. Smart education can enhance performance through interactivity and personalisation, while ICT advantage, compatibility, ease of use, and usefulness can contribute to e-learning effectiveness among tourism education students (Amin et al., 2022; Jangjarat et al., 2023). Findings from BASICA also indicate that AI-based media can foster engaging learning experiences (Rohmah, 2024) and that interactive digital media such as Canva can support motivation, performance, and creativity (Susanti et al., 2025), although those studies were conducted at the primary-education level. In tourism management, where learning frequently requires decision making, service simulation, destination planning, and other applied activities, smart tools can provide opportunities to rehearse professional situations that are difficult to reproduce through conventional classroom explanation alone. The finding also aligns with Aggarwal et al. (2023) and Cunha et al. (2023), who position AI-supported and extended-reality technologies as resources for more experiential forms of education. From an SCT perspective, smart tools are environmental resources that create opportunities for observation, practice, feedback, and application. Their value therefore depends less on mere availability than on how effectively they support meaningful professional learning activities.

H2 is supported, digital learning readiness has a positive effect on practical learning effectiveness. The result indicates that access to technology is insufficient if students are not confident and prepared to use it. Readiness in this study reflects self-efficacy, confidence, expertise in accessing smart tools, and willingness to engage in digital learning. Readiness and self-efficacy are important in online learning, while e-learning readiness is also connected with technological skills and employability among hospitality graduates (Elshaer et al., 2025; Reyes-Millán et al., 2023).

Viewed through SCT, readiness represents a personal factor that influences how students interpret and respond to technological opportunities in the learning environment. Students with stronger readiness are more capable of navigating digital systems, persisting when technical demands arise, and translating digital experiences into practical learning outcomes. SCT explains readiness as a personal factor within reciprocal determinism. Students who believe they can manage digital demands are more likely to explore unfamiliar tools, persist through technical difficulties, and transform digital activities into practical competence.

H3 is supported, student learning engagement provides the second strongest principal direct effect. This finding reinforces the behavioural dimension of SCT: learning technologies do not create practical competence independently of active student involvement. Cognitive, emotional, and behavioural engagement is associated with learning outcomes and is intertwined with professional identity, self-efficacy, and university support among tourism students (Chen et al., 2023; Xu et al., 2023). An activating, multimodal learning ecosystem can likewise increase engagement and encourage more active learner agency (Supaat et al., 2026). The present result suggests that smart tools function most productively when learners are mentally resilient, energetic, enthusiastic, and immersed in study activities. In SCT, engagement represents the behavioural pathway through which personal readiness and environmental opportunities become learning performance. Smart technology can provide resources and simulations, but students still need attention, persistence, collaboration, and problem-solving activity for those opportunities to produce practical competence.

The most distinctive result concerns tool-course fit and teacher digital competence. Both variables have significant direct effects on practical learning effectiveness but neither significantly moderates the relationship between smart education tool utilisation and PLE. H4 and H5 is not supported, the TTF × SU interaction is small and non-significant, and the TDC × SU interaction is also non-significant. This means that better course alignment and stronger teacher competence are associated with higher practical learning effectiveness in their own right, but they do not systematically increase or decrease the marginal effect of smart-tool utilisation. The direct contribution of TDC is consistent with Roudhoh et al. (2026), who found teacher digital competence to be a significant predictor of digital learning-media effectiveness, and with (Latifah, 2024), who linked digital integration with teacher self-efficacy and facilitating conditions. Theoretically, this distinction matters because it separates a direct environmental contribution from a true boundary condition. Task-technology alignment should therefore be treated as a basic requirement of

instructional design rather than as a factor that only becomes important when technology use increases. In SCT terms, teacher competence therefore contributes directly to environmental quality, while student technology use remains a separate behavioural pathway to learning effectiveness.

The model as a whole explains 46.1% of the variance in practical learning effectiveness and produces Q^2predict = 0.434, indicating that the combination of personal, behavioural, technological, and environmental factors has meaningful explanatory and predictive value. At the same time, the small f^2 values show that no single predictor dominates practical learning effectiveness. This pattern is compatible with SCT because the theory does not treat learning as the product of one isolated factor; rather, learning develops through reciprocal relationships among personal characteristics, behaviour, and environmental conditions (Chai & Ye, 2024). The findings therefore support a multidimensional view of digital practical learning in which technology utilisation, learner readiness, learner engagement, pedagogical alignment, and teacher capability each make distinct contributions.

Theoretically, the direct TTF finding remains consistent with the task-technology fit logic developed by Yu and Yu (2010): technology is more useful when its capabilities correspond with learning tasks. In the present setting, students who perceive digital systems as relevant to course objectives, practical tasks, and learning activities also report higher practical learning effectiveness. However, the non-significant moderation result suggests that this alignment does not change the strength of the SU–PLE relationship across students. A similar interpretation applies to teacher digital competence. The importance of digitally competent teachers for educational quality has been emphasised in previous research, and the significant direct TDC path in this study supports that position (Kiryakova & Kozhuharova, 2024; Revuelta-Domínguez et al., 2022). Yet the interaction result indicates that teacher competence contributes to the broader learning environment rather than amplifying the effect of each additional increase in student smart-tool use. This result differs from contingency-oriented expectations in studies such as Yaskevich et al. (2022) and Yi et al. (2025), which provide arguments for contextual or facilitating conditions that can alter technology-related effects.

These findings have practical implications for tourism education institutions. Investments in smart education should not be limited to purchasing or providing access to digital platforms. Institutions should simultaneously strengthen student readiness through orientation, digital literacy activities, self-efficacy support, and peer learning; design tasks that require active use of technology

in realistic tourism scenarios; and provide continuous professional development so that teachers can integrate digital resources pedagogically. Tool selection should also be reviewed against course objectives and practical competencies before implementation. The absence of moderation does not make tool-course fit or teacher competence unimportant; rather, their significant direct effects suggest that both should be treated as core components of instructional quality.

CONCLUSION

Practical learning effectiveness in tourism management is best understood as the outcome of several complementary conditions rather than technology use alone. Smart education tool utilisation, digital learning readiness, and student learning engagement each make significant positive contributions, while tool-course fit and teacher digital competence also provide direct environmental support. The model's explanatory and predictive results reinforce the Social Cognitive Theory perspective that effective learning emerges from the combined operation of personal, behavioural, technological, and environmental factors. Importantly, tool-course fit and teacher digital competence do not significantly moderate the smart-tool utilisation–effectiveness relationship; in this sample they function more convincingly as direct enablers of practical learning. Theoretically, these results refine SCT in technology-supported practical education by showing that environmental conditions can improve learning directly without necessarily moderating the effect of technology utilisation.

For tourism education practice, the findings imply that institutions should integrate technology with learner preparation, active engagement, course-level pedagogical alignment, and continuous teacher development. The study is limited by its cross-sectional, self-reported design and its geographical focus on students in Singaraja and surrounding areas, so the results should not be treated as evidence of long-term causality or universal generalisability. Future research can test the model longitudinally, use qualitative or mixed-method approaches to explain the mechanisms behind the non-significant moderation effects, and replicate the model across different regions, disciplines, and types of smart technology such as AI, virtual reality, and learning management systems.

REFERENCES

Abdelghani, A. A. A., & Ahmed, H. A. M. (2025). Applied internships in Egyptian tourism education: Measuring experiential learning's impact on student self-efficacy and perceived effectiveness of academic materials. *Journal of Social and Scientific Education*, *2*(3), 284–304. https://doi.org/10.58230/josse.v2i3.417

Aggarwal, D., Sharma, D., & Saxena, A. B. (2023). Adoption of artificial intelligence (AI) for development of smart education as the future of a sustainable education system. *Journal of Artificial Intelligence, Machine Learning and Neural Network*, *3*(6), 23–28. https://doi.org/10.55529/jaimlnn.36.23.28

Amin, I., Yousaf, A., Walia, S., & Bashir, M. (2022). What shapes e-learning effectiveness among tourism education students? An empirical assessment during COVID-19. *Journal of Hospitality, Leisure, Sport & Tourism Education*, *30*, 100337. https://doi.org/10.1016/j.jhlste.2021.100337

Amitani, M., Amitani, H., Suzuki, H., Kawazu, S., Fukumoto, T., Yamaguchi, K., & Asakawa, A. (2021). Effective learning strategies for Japanese Kampo medicine using problem-based learning and simulator training for medical students: A questionnaire survey. *Traditional & Kampo Medicine*, *8*(2), 155–162. https://doi.org/10.1002/tkm2.1281

Bahçelerli, N. M. (2023). The role of innovative technology in multicultural vocational tourism education. *Frontiers in Psychology*, *14*, 1091881. https://doi.org/10.3389/fpsyg.2023.1091881

Chai, J., & Ye, J. H. (2024). A social network analysis of college students' online learning during the epidemic era: A triadic reciprocal determinism perspective. *Heliyon*, *10*(6). https://doi.org/10.1016/j.heliyon.2024.e28107

Chen, Q., Zhang, Q., Yu, F., & Hou, B. (2023). Investigating structural relationships between professional identity, learning engagement, academic self-efficacy, and university support: Evidence from tourism students in China. *Behavioral Sciences*, *14*(1), 26. https://doi.org/10.3390/bs14010026

Cunha, C. R., Martins, C., & Mendonça, V. (2023). Using extended reality in experiential learning for hospitality management education. *Procedia Computer Science*, *219*, 634–641. https://doi.org/10.1016/j.procs.2023.01.333

Elmourad, T., Hadjiphanis, L., Christofi, K., Chourides, P., & Kythreotis, A. (2026). AI adoption in K-12 education: A model of skills transformation, productivity, and institutional readiness. *Education Sciences*, *16*(2), 337. https://doi.org/10.3390/educsci16020337

Elshaer, I. A., Azazz, A. M., Mohammad, A. A., & Fayyad, S. (2025). Decoding success: The role of e-learning readiness in linking technological skills and employability in hospitality management graduates. *Information*, *16*(1), 47. https://doi.org/10.3390/info16010047

Firmansyah, D., & Saepuloh, D. (2022). Social learning theory: Cognitive and behavioral approaches. *Jurnal Ilmiah Pendidikan Holistik*, *1*(3), 297–324. https://doi.org/10.0.218.119/jiph.v1i3.2317

Issakov, Y., Aktymbayeva, B., Artemyev, A., Kubessova, G., Abdreyeva, S., Surina, A., & Dávid, L. D. (2023). Digital transformation reshaping tourism education: Investigating the influence of MOOCs on teaching tourism fundamentals and local lore. *GeoJournal of Tourism and Geosites*, *49*(3), 1015–1026. https://doi.org/10.30892/gtg.49317-1101

Jangjarat, K., Klayklung, P., Chocksathaporn, P., & Maskran, P. (2023). The impact of smart education on learning outcomes in the digital era: A systematic review. *Advance Knowledge for Executives*, *2*(2), 1–9. https://ssrn.com/abstract=4424676

Kiryakova, G., & Kozhuharova, D. (2024). The digital competences necessary for the successful

pedagogical practice of teachers in the digital age. *Education Sciences*, *14*(5), 507. https://doi.org/10.3390/educsci14050507

Latifah, K. (2024). Digital Literacy Integration and Teacher Belief in Public Elementary School: Examining Decomposed Theory of Planned Behavior. *BASICA*, *3*(1), 163–172. https://doi.org/10.37680/basica.v3i1.5263

Nguyen, L. T., Kanjug, I., Lowatcharin, G., Manakul, T., Poonpon, K., Sarakorn, W., & Tuamsuk, K. (2022). How teachers manage their classroom in the digital learning environment—Experiences from the University Smart Learning Project. *Heliyon*, *8*(10). https://doi.org/10.1016/j.heliyon.2022.e10817

Nidaur Rohmah, A. (2024). The Utilization of Artificial Intelligence (AI) Based Media In Enhancing The Learning Process At The Elementary School Level. *BASICA*, *4*(2), 29–36. https://doi.org/10.37680/basica.v4i2.6145

Nisak, R. K., & Rofi'ah, S. (2023). Problematika Guru dalam Penggunaan Media Pembelajaran Berbasis Digital. *BASICA*, *3*(1), 41–50. https://doi.org/10.37680/basica.v3i1.3623

Radygina, E. G. (2023). Practical training model for students in tourism and hospitality: Description of the elements of the practical training system at the university. *Human Resources Management and Services*, *5*(2), 3372. https://doi.org/10.18282/hrms.v5i2.3372

Revuelta-Domínguez, F. I., Guerra-Antequera, J., González-Pérez, A., Pedrera-Rodríguez, M. I., & González-Fernández, A. (2022). Digital teaching competence: A systematic review. *Sustainability*, *14*(11), 6428. https://doi.org/10.3390/su14116428

Reyes-Millán, M., Villareal-Rodríguez, M., Murrieta-Flores, M. E., Bedolla-Cornejo, L., Vázquez-Villegas, P., & Membrillo-Hernández, J. (2023). Evaluation of online learning readiness in the new distance learning normality. *Heliyon*, *9*(11). https://doi.org/10.1016/j.heliyon.2023.e22070

Roudhoh, Fachruddin, A., Hidayati, S., Astuti, R. N., & Murni, W. (2026). The Influence of Teachers' Resilience and Digital Competence on the Effectiveness of Digital Learning Media in Elementary Schools. *BASICA*, *5*(2), 23–37. https://doi.org/10.37680/basica.v5i2.9230

Supaat, S., Taufikin, T., & Lailatur Rizqi, F. N. (2026). Multiple Intelligences as a Pedagogical Activation System in Primary Education. *BASICA*, *5*(2), 53–69. https://ejournal.insuriponorogo.ac.id/index.php/basica/article/view/9288

Susanti, D. A., Sultonurohmah, N., & Purwitasari, E. D. (2025). The Effectiveness of Using Canva Application as A Science Learning Media in Elementary Schools. *BASICA*, *4*(2), 89–100. https://doi.org/10.37680/basica.v4i2.6393

Xu, X., Shi, Z., Bos, N. A., & Wu, H. (2023). Student engagement and learning outcomes: An empirical study applying a four-dimensional framework. *Medical Education Online*, *28*(1), 2268347. https://doi.org/10.1080/10872981.2023.2268347

Yang, J., Shi, G., Zhu, W., & Sun, Y. (2025). Intelligent technologies in smart education: A comprehensive review of transformative pillars and their impact on teaching and learning methods. *Humanities and Social Sciences Communications*, *12*(1), 1–15. https://doi.org/10.1057/s41599-025-05444-0

Yaskevich, V., Tagliabue, L. C., & Kuspangaliev, B. (2022). Smart campus as a core of project-based BIM education in AECO: Case study in Satbayev University, Kazakhstan. *EC3 Conference 2022*, *3*.

Yi, R., Liu, D., Sun, X., & Zhou, B. (2025). Exploring the link between AI usage intention and digital competence among college PE teachers: A moderated mediation model based on SCT and

UTAUT. *PLoS ONE*, *20*(11), e0334699. https://doi.org/10.1371/journal.pone.0334699

Yu, T. K., & Yu, T. Y. (2010). Modelling the factors that affect individuals' utilisation of online learning systems: An empirical study combining the task technology fit model with the theory of planned behaviour. *British Journal of Educational Technology*, *41*(6), 1003–1017. https://doi.org/10.1111/j.1467-8535.2010.01054.