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The Influence of Digital Readiness and Learning Styles on Self-Directed Learning and Student Learning Outcomes in Technology-Based Learning

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ABSTRACT

Technology-enhanced learning and flipped classroom approaches have become increasingly important in higher education. However, limited research has examined the integrated relationships among digital readiness, learning styles, self-directed learning, and learning outcomes within a single analytical model. This study aims to analyze the relationships among digital readiness, learning styles based on Kolb's Experiential Learning Theory, self-directed learning, and student learning outcomes in a flipped classroom learning environment. A quantitative approach with an explanatory correlational design was employed. The sample consisted of 90 fifth-semester students in the Informatics Engineering Education program selected through purposive sampling. Data were collected using a five-point Likert-scale questionnaire and academic achievement records and analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 4. The results showed that digital readiness significantly influenced self-directed learning (β = 0.45, $p < 0.001$), while learning styles also positively affected self-directed learning (β = 0.32, $p < 0.001$). Self-directed learning emerged as the strongest predictor of learning outcomes (β = 0.51, $p < 0.001$) and significantly mediated the relationships between digital readiness and learning outcomes (β = 0.278, $p < 0.001$) and between learning styles and learning outcomes (β = 0.164, p = 0.003). The model demonstrated substantial explanatory power (R^2 = 0.620 for self-directed learning; R^2 = 0.680 for learning outcomes). The findings suggest that technology integration is most effective when accompanied by strong self-directed learning skills. This study contributes to constructivist learning theory and provides practical implications for technology-enhanced and flipped classroom learning in higher education.

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1. INTRODUCTION

The rapid development of digital technology over the past decade has brought significant changes to the field of education, particularly in how students access, manage, and construct knowledge. Globally, the integration of technology in education has become a necessity rather than a complementary tool. A report by [1] indicates that more than 70% of higher education institutions worldwide have adopted digital or hybrid learning models. Similarly, the Organisation for Economic Co-operation and Development [2] emphasized that digital transformation in higher education has accelerated significantly following the COVID-19 pandemic, reshaping instructional practices and learner engagement. However, increased access to technology does not necessarily lead to improved learning outcomes, especially in terms of self-directed learning and critical thinking skills [3], [4].

In Indonesia, this phenomenon is also evident. Data from the Ministry of Education, Culture, Research, and Technology [5] shows that although 65% of higher education institutions have adopted Learning Management Systems (LMS) has reached 65% in higher education institutions, there remains a gap in the effective use of technology to support meaningful learning. Many students still demonstrate a high level of dependence on lecturers and lack initiative in independent learning. This indicates that digital transformation has not been fully accompanied by pedagogical transformation [6], [7].

One widely studied approach to addressing this issue is the flipped classroom model. This model emphasizes independent learning before class and active discussion during face-to-face sessions, aiming to enhance student engagement and conceptual understanding. Research by [8] shows that flipped classrooms significantly improve cognitive learning outcomes and student engagement compared to traditional methods. Similar findings were reported by [9], who identified increased learner autonomy and participation in flipped learning environments. In addition, [10] found that flipped classrooms positively affect academic achievement, motivation, and student interaction. However, its implementation does not always produce consistent results across different contexts [11], [12].

Within the constructivist learning framework, the flipped classroom aligns with active learning principles, where students construct knowledge through experience and interaction. Constructivist theory, as proposed by Piaget and Vygotsky, emphasizes active engagement in the learning process. Social interaction, collaborative inquiry, and reflective learning are considered central components in knowledge construction [13]. A study by [14] found that integrating flipped classrooms with constructivist approaches significantly enhances students' critical thinking skills. Likewise, [15] reported that constructivist-oriented flipped classrooms improve higher-order thinking skills and learner autonomy. Nevertheless, such studies are still limited in scope and have not extensively examined the simultaneous relationship between self-directed learning and learning outcomes [16].

In addition, students' digital readiness is a crucial factor influencing the success of technology-based learning. Digital readiness refers to an individual's capability and preparedness to effectively use digital technologies for learning purposes, including digital literacy, technological self-efficacy, and information management skills [17], [18]. Students with a high level of digital readiness are generally better able to navigate digital learning environments, access relevant information, and use technological tools to support their learning. Previous research by [17] found that digital readiness directly affects the effectiveness of online learning. Similar findings by [18] demonstrated that digital literacy and technological self-efficacy significantly influence self-regulated learning behavior. Students with higher digital readiness are better able to manage their learning independently. However, previous studies have not sufficiently explored how digital readiness interacts with learning styles in influencing learning outcomes [19], [20].

Learning style refers to an individual's preferred way of perceiving, processing, and organizing information during learning activities. This study adopts Kolb's Experiential Learning Theory, which categorizes learners into four learning styles: diverging, assimilating, converging, and accommodating [21]. Although the predictive value of learning styles remains debated in contemporary educational research, Kolb's framework continues to provide a useful perspective for understanding individual differences in learning processes by emphasizing how learners interact with experiences and transform information into knowledge. Rather than viewing learning styles as fixed learner categories, this framework highlights the dynamic ways individuals engage with and interpret learning experiences. In technology-based learning environments, these differences may influence students' engagement, learning strategies, ability to participate in independent learning activities, and capacity to regulate their own learning behavior.

Another study by [22] found that students' learning styles play a moderating role in the success of digital learning implementation. Students with active and reflective learning styles tend to achieve better outcomes in flipped classroom environments. Furthermore, research by [23] indicated that students with collaborative and experiential learning preferences demonstrate stronger engagement in active learning settings. However, these studies were primarily descriptive in nature and did not employ inferential quantitative approaches to comprehensively examine the structural relationships among learning styles, self-directed learning, and learning outcomes [24], [25].

Self-directed learning is defined as the ability of learners to take responsibility for planning, monitoring, and evaluating their own learning activities [26]. It reflects students' capacity to set learning goals, manage learning resources, monitor their progress, and evaluate learning outcomes independently. In technology-based learning environments, self-directed learning becomes increasingly important because students are often required to regulate their learning processes with reduced direct supervision from instructors. Previous studies have consistently demonstrated that self-directed learning positively influences academic achievement, learning persistence, and student engagement in online and blended learning settings [27], [28]. Consequently, self-directed learning is considered a critical mechanism through which digital readiness and learning styles may contribute to improved learning outcomes.

Furthermore, [29] highlighted that student engagement is a key factor in the success of technology-based learning. However, engagement is highly influenced by instructional design and individual student characteristics. [30] also emphasized that active interaction and collaborative learning activities significantly contribute to learner engagement in online and blended learning environments. A limitation of previous studies is the lack of an integrative model that connects digital readiness, learning styles, self-directed learning, and learning outcomes within a unified analytical framework [31], [32], [33].

Based on this literature review, a research gap can be identified: the lack of empirical studies examining the simultaneous relationships among digital readiness, learning styles, and self-directed learning in predicting student learning outcomes within a flipped classroom context, particularly in higher education in Indonesia. Most previous studies remain partial and have not integrated these variables into a comprehensive quantitative model.

Moreover, prior studies have generally focused on direct relationships among variables without examining mediating mechanisms that explain how self-directed learning contributes to learning outcomes in technology-enhanced learning environments [12]; [17]. Therefore, this study aims to analyze the influence of digital readiness and learning styles on self-directed learning and their implications for student learning outcomes. Specifically, this study examines both direct and indirect relationships among variables using a quantitative approach.

Based on the theoretical framework and previous empirical findings, five hypotheses were proposed. H1: Digital readiness positively influences self-directed learning. H2: Learning styles positively influence self-directed learning. H3: Self-directed learning positively influences learning outcomes. H4: Self-directed learning mediates the relationship between digital readiness and learning outcomes. H5: Self-directed learning mediates the relationship between learning styles and learning outcomes. This study is expected to contribute theoretically to the development of constructivist-based learning models and, practically, to the improvement of instructional strategies in higher education.

2. METHOD

This study employed a quantitative approach with an explanatory correlational design to examine the predictive relationships among digital readiness, learning styles, self-directed learning, and student learning outcomes. This design was selected because it allows researchers to analyze both direct and indirect relationships among variables within a structural model. Explanatory research is widely used to investigate predictive relationships and associations among latent variables in educational research. [34]; [35]. The quantitative approach is considered appropriate, as the study focuses on the objective measurement of variables and on statistical analysis to test the proposed hypotheses [36]. The data used in this study were primary data collected directly from respondents through the distribution of research instruments.

Data were collected using a questionnaire based on a five-point Likert scale, developed according to the indicators of each variable [37]. Digital readiness was measured through indicators of digital literacy, technological self-efficacy, and information access skills. Learning styles were based on Kolb’s classification, while self-directed learning was measured using indicators such as learning initiative, time management, and self-evaluation. Learning outcomes were measured using students’ academic performance obtained from official course assessment records. The construct was operationalized through three indicators: assignment scores (LO1), midterm examination scores (LO2), and final examination scores (LO3). These indicators were treated as reflective measures representing students' overall academic achievement in the course. The scores ranged from 0 to 100 and were derived from standardized assessments consisting of assignments, project work, mid-term examinations, and final examinations. The same assessment criteria were applied to all students to ensure comparability. The use of questionnaires as the primary instrument is supported by previous studies demonstrating their effectiveness in measuring students' perceptions and learning characteristics [38], [39]. Furthermore, self-directed learning constructs have been widely operationalized using self-report instruments in higher education research [26]; [27].

The study population consisted of all fifth-semester students in the Informatics Engineering Education program at a higher education institution in Indonesia, totaling 120 students. The inclusion criteria required students to have completed at least one semester of technology-enhanced learning and to have participated in flipped classroom instruction for at least one academic semester. This criterion was established to ensure that participants had sufficient experience with digital learning environments and independent pre-class learning activities [34]. Purposive sampling is considered appropriate when researchers aim to select participants with specific characteristics relevant to the research objectives [40]. Based on these criteria, a sample of 90 respondents was obtained. This sample size is considered adequate for analysis using Partial Least Squares Structural Equation Modeling (PLS-SEM), which does not require large sample sizes compared to covariance-based SEM [36], [41]. In addition, the sample size exceeded the minimum requirement suggested by the "10-times rule" commonly used in PLS-SEM analysis [42].

Table 1. Measurement Instruments

Variable	Items	Example Indicator	Source
Digital Readiness	4	Ability to access digital resources	Tang et al.[17]
Learning Styles	3	Preference for experiential learning	Kolb [21]
Self-Directed Learning	4	Learning initiative	Garrison [26]
Learning Outcomes	3	Assignment score, midterm examination score, and final examination score	Course Assessment

The questionnaire consisted of 14 items measured using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). Digital readiness was measured using four items adapted from Tang et al. (2021), learning styles were measured using three items derived from Kolb's experiential learning framework, and self-directed learning was measured using four items adapted from [26]. Learning outcomes were represented by academic achievement indicators obtained from course assessment records.

The research instrument was tested for validity and reliability prior to its wider use. Validity testing included content validity through expert judgment and construct validity using confirmatory factor analysis in SmartPLS 4. Indicators were considered valid if they had outer loading values greater than 0.70 and an Average Variance Extracted (AVE) greater than 0.50. Discriminant validity was also assessed using the Fornell-Larcker Criterion and Heterotrait-Monotrait Ratio (HTMT) to ensure adequate construct distinction [43]. Reliability testing was conducted using Cronbach's Alpha and Composite Reliability, with

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a minimum threshold of 0.70 [44], [45]; [36]. These procedures ensured that the instrument consistently measured the intended constructs.

Data analysis techniques included both descriptive and inferential statistical analyses. Descriptive analysis was used to describe respondent characteristics and data distribution, such as mean values and percentages. Inferential analysis was conducted using PLS-SEM with SmartPLS 4 to examine relationships among variables in the structural model [46], [47]. PLS-SEM was selected because it is suitable for predictive research models, exploratory causal analysis, and complex structural relationships involving latent variables [48]. In addition, PLS-SEM is considered robust for relatively small sample sizes and non-normal data distributions [49], [50].

Hypothesis testing was conducted using the bootstrapping procedure with 5,000 subsamples and a two-tailed significance test at the 95% confidence interval. This procedure was employed to estimate the significance of path coefficients and indirect effects without assuming normal data distribution. Bootstrapping is widely recommended in PLS-SEM because it provides stable parameter estimates and does not require normally distributed data [36], [51].

The adequacy of the sample size was assessed using both the 10-times rule and statistical power analysis. Using G*Power with a medium effect size (f^2 = 0.15), a significance level of α = 0.05, statistical power of 0.80, and three predictor variables, the minimum required sample size was 77 respondents. Therefore, the sample of 90 respondents was considered adequate for detecting meaningful relationships among the constructs.

The structural model was evaluated using the coefficient of determination (R^2), effect size (f^2), and predictive relevance (Q^2) to assess the model's explanatory and predictive capabilities [52], [53]. The significance level adopted in this study was 5% (α = 0.05). PLS-SEM was selected because it is suitable for analyzing complex relationships among latent variables simultaneously and is robust to non-normal data distributions [36], [50].

Ethical considerations were observed throughout the research process. Participation was voluntary, and all respondents provided informed consent prior to completing the questionnaire. Participants were informed about the study's objectives and assured that their responses would remain confidential and be used solely for research purposes. Permission to access and analyze students' academic scores was obtained from the relevant academic authorities, and all data were anonymized before analysis.

3. RESULTS AND DISCUSSION

3.1. Result

Based on a descriptive analysis of 90 respondents, the findings indicate that students' digital readiness is high, with a mean score of 4.12 (SD = 0.56). Learning styles show moderate variation with a mean of 3.85 (SD = 0.62), while self-directed learning is categorized as relatively high with a mean of 4.05 (SD = 0.58). Student learning outcomes, measured by academic scores, have a mean of 82.4 (SD = 6.75), which falls within the good range. These findings suggest that, in general, students possess a sufficient foundation to support digital-based learning.

Table 2. Descriptive Statistics of Research Variables

Variable	Mean	Standard Deviation	Category
Digital Readiness	4.12	0.56	High
Learning Styles	3.85	0.62	Moderate
Self-Directed Learning	4.05	0.58	High
Learning Outcomes	82.4	6.75	Good

The measurement model (outer model) was evaluated by examining indicator reliability, convergent validity, and internal consistency reliability. As shown in Table 3, all indicators exhibited outer loadings above the recommended threshold of 0.70, ranging from 0.78 to 0.89. These results indicate that all indicators adequately represent their respective constructs and satisfy the criterion for indicator reliability.

Table 3. Outer Loading Values

Construct	Indicator	Loading
Digital Readiness	DR1	0.82
Digital Readiness	DR2	0.85
Digital Readiness	DR3	0.88
Digital Readiness	DR4	0.81
Learning Styles	LS1	0.78
Learning Styles	LS2	0.86
Learning Styles	LS3	0.81
Self-Directed Learning	SDL1	0.87
Self-Directed Learning	SDL2	0.86
Self-Directed Learning	SDL3	0.84
Self-Directed Learning	SDL4	0.82
Learning Outcomes	LO1	0.83
Learning Outcomes	LO2	0.89
Learning Outcomes	LO3	0.85

Further assessment of convergent validity and reliability was conducted using Average Variance Extracted (AVE), Composite Reliability (CR), and Cronbach's Alpha. As shown in Table 4, the AVE values ranged from 0.667 to 0.741, exceeding the recommended threshold of 0.50. Likewise, Composite Reliability values ranged from 0.857 to 0.920, and Cronbach's Alpha values ranged from 0.750 to 0.884, all surpassing the minimum criterion of 0.70.

Table 4. Convergent Validity and Reliability Assessment

Construct	AVE	Composite Reliability	Cronbach's Alpha
Digital Readiness	0.705	0.905	0.861
Learning Styles	0.667	0.857	0.750
Self-Directed Learning	0.741	0.920	0.884
Learning Outcomes	0.733	0.891	0.818

The results presented in Tables 3 and 4 confirm that all constructs demonstrate satisfactory convergent validity and internal consistency reliability. Therefore, the measurement model is considered adequate for subsequent structural model evaluation.

Table 5. Heterotrait-Monotrait Ratio (HTMT)

Construct	DR	LS	SDL	LO
DR	-			
LS	0.621	-		
SDL	0.734	0.548	-	
LO	0.685	0.497	0.781	-

All HTMT values were below 0.85, indicating satisfactory discriminant validity among the constructs.

The structural model (inner model) analysis shows that the R-square for self-directed learning is 0.62, indicating that 62% of its variance in self-directed learning can be explained by digital readiness and learning styles. The R-square value for learning outcomes indicates that 68% of the variance in learning outcomes is explained collectively by self-directed learning and the indirect contribution of digital readiness and learning styles through the proposed structural model. These values suggest that the model has good predictive power.

Table 6. Fornell-Larcker Criterion

Construct	DR	LS	SDL	LO
DR	0.840			
LS	0.521	0.817		
SDL	0.651	0.473	0.861	
LO	0.604	0.418	0.732	0.856

The diagonal values represent the square roots of the AVEs and exceed the inter-construct correlations, confirming discriminant validity.

Table 7. Coefficient of Determination

Endogenous Variable	R^2	Adjusted R^2
Self-Directed Learning	0.620	0.611
Learning Outcomes	0.680	0.669

The results of hypothesis testing indicate that all proposed hypotheses were supported. Digital readiness significantly influenced self-directed learning ($\beta = 0.45$, $p < 0.001$), supporting H1. Learning styles also had a significant positive effect on self-directed learning ($\beta = 0.32$, $p < 0.001$), supporting H2. Furthermore, self-directed learning significantly influenced learning outcomes ($\beta = 0.51$, $p < 0.001$), supporting H3.

The mediation analysis further revealed that self-directed learning significantly mediated the relationship between digital readiness and learning outcomes ($\beta = 0.278$, $p < 0.001$), supporting H4. Likewise, self-directed learning significantly mediated the relationship between learning styles and learning outcomes ($\beta = 0.164$, $p = 0.003$), supporting H5. These findings indicate that self-directed learning plays a crucial role in translating students' digital readiness and learning styles into improved learning outcomes.

Table 8. Hypothesis Testing Results

Hypothesis	Variable Relationship	β	t-value	p-value	Decision
H1	Digital readiness → Self-Directed Learning	0.45	5.21	<0.001	Accepted
H2	Learning Styles → Self-Directed Learning	0.32	3.87	<0.001	Accepted
H3	Self-Directed Learning → Learning Outcomes	0.51	6.14	<0.001	Accepted
H4	Digital readiness → Self-Directed Learning → Learning Outcomes	0.278	4.521	0.000	Accepted
H5	Learning Styles → Self-Directed Learning → Learning Outcomes	0.164	2.988	0.003	Accepted

In addition, the indirect effect analysis shows that digital readiness and learning styles have significant effects on learning outcomes through self-directed learning ($p < 0.05$). This indicates that self-directed learning acts as a mediating variable in these relationships. Thus, all hypotheses in this study are accepted, indicating that the proposed model has strong empirical support.

Table 9. Specific Indirect Effects

Indirect Path	β	t-value	p-value	95% CI LL	95% Ci UL	Mediation Type
DR → SDL → LO	0.278	4.521	0.000	0.157	0.392	Significant Mediation
LS → SDL → LO	0.164	2.988	0.003	0.073	0.268	Significant Mediation

The indirect effects analysis confirmed that self-directed learning significantly mediated the relationships between digital readiness and learning outcomes ($\beta = 0.278$, $p < 0.001$) and between learning styles and learning outcomes ($\beta = 0.164$, $p = 0.003$).

Table 10. Effect Size (f^2)

Relationship	f^2	Interpretation
DR → SDL	0.352	Large
LS → SDL	0.187	Medium
SDL → LO	0.421	Large

Self-directed learning demonstrated the largest effect on learning outcomes ($f^2 = 0.421$), indicating its substantial role within the structural model.

Table 11. Predictive Relevance (Q^2)

Endogenous Variable	Q^2
Self-Directed Learning	0.431
Learning Outcomes	0.487

Both Q^2 values were greater than zero, indicating that the model possesses satisfactory predictive relevance.

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3.2 Discussion

The findings indicate that digital readiness significantly predicts self-directed learning ($\beta = 0.45$, $p < 0.001$), supporting H1. This result is consistent with previous studies suggesting that students who possess stronger digital literacy, technological self-efficacy, and information management skills are better equipped to navigate technology-enhanced learning environments [17], [18]. From a constructivist perspective, digital readiness enables learners to access, evaluate, and utilize information independently, thereby facilitating the development of self-directed learning behaviors. The present finding reinforces previous evidence that digital readiness serves as an important prerequisite for effective participation in technology-based learning.

The results also demonstrate that learning styles significantly influence self-directed learning ($\beta = 0.32$, $p < 0.001$), supporting H2. However, this finding should not be interpreted as evidence that instructional practices must be fully aligned with individual learning styles. Rather, the results suggest that students' learning preferences influence how they approach independent learning tasks, organize learning resources, and regulate their learning processes. Consistent with Kolb's experiential learning framework, students who exhibit active, reflective, and experiential learning tendencies may be more likely to engage in self-directed learning activities. This interpretation aligns with previous studies indicating that learning styles shape learning behaviors and strategies rather than directly determining academic performance.

Among all relationships examined in this study, self-directed learning emerged as the strongest predictor of learning outcomes ($\beta = 0.51$, $p < 0.001$), with the largest effect size ($f^2 = 0.421$). This finding deserves particular attention because it suggests that access to technology alone is insufficient to improve academic achievement. While digital technologies provide students with learning resources and information, meaningful learning outcomes depend on how effectively students utilize those resources. Students who can plan, monitor, and evaluate their learning activities are more likely to transform available information into meaningful knowledge. This finding may explain why self-directed learning demonstrates a stronger predictive relationship with learning outcomes than digital readiness itself. In technology-enhanced learning environments, learning success appears to be driven more by students' self-regulatory capacity than by access to technology alone.

The large effect size of self-directed learning ($f^2 = 0.421$) suggests that learner agency may play a more substantial role than technological access in determining academic achievement. This finding supports constructivist assumptions that meaningful learning emerges from active knowledge construction rather than mere exposure to digital resources.

The mediation analysis further revealed that self-directed learning significantly mediated the relationship between digital readiness and learning outcomes ($\beta = 0.278$, $p < 0.001$), supporting H4. Likewise, self-directed learning significantly mediated the relationship between learning styles and learning outcomes ($\beta = 0.164$, $p = 0.003$), supporting H5. These findings suggest that digital readiness and learning styles primarily influence learning outcomes through their effects on students' learning behaviors. Students with stronger digital readiness and learning preferences that support active engagement are more likely to develop self-directed learning skills, which, in turn, contribute to improved academic performance. Therefore, the findings should be interpreted as predictive associations rather than evidence of direct causal relationships.

The results are particularly relevant within the flipped classroom context adopted in this study. Flipped classroom learning requires students to engage with instructional materials before class and participate actively in collaborative problem-solving activities during face-to-face sessions. Such a learning environment places substantial responsibility on students to manage their own learning processes. Pre-class preparation requires students to independently access learning resources, identify key concepts, and monitor their understanding before participating in classroom discussions. Consequently, students with stronger self-directed learning skills are more likely to benefit from flipped classroom implementation. This finding supports previous research indicating that learner autonomy is a critical determinant of success in flipped learning environments.

Compared with previous studies on digital readiness, self-directed learning, and flipped classroom implementation, this study contributes by integrating these variables within a single PLS-SEM model. The present findings are consistent with [17], [18], and [14], who similarly reported that digital readiness and learner autonomy contribute substantially to learning effectiveness in technology-enhanced environments. While previous studies often examined partial relationships among variables, the present study demonstrates how self-directed learning functions as a central mechanism linking student characteristics and learning outcomes. The model's relatively strong explanatory power ($R^2 = 0.620$ for self-directed learning and $R^2 = 0.680$ for learning outcomes) further underscores the importance of considering these variables simultaneously when investigating the effectiveness of technology-based learning.

From a practical perspective, the findings suggest that higher education institutions should move beyond merely providing digital infrastructure. Universities should strengthen students' digital literacy through structured training programs, provide learning analytics feedback to support self-monitoring, and create learning environments that encourage self-regulation. Lecturers are encouraged to design self-directed learning tasks, incorporate reflective learning activities, and implement adaptive instructional strategies that accommodate diverse learning preferences. Such efforts may help students maximize the benefits of technology-enhanced learning and improve academic performance.

Several limitations should be acknowledged. First, the study was conducted within a single academic program, which may limit the generalizability of the findings. Second, purposive sampling was employed, potentially affecting the representativeness of the sample. Third, the use of self-reported questionnaires may introduce response bias and possible common method bias. Fourth, the cross-sectional design only allows the identification of predictive relationships among variables and does not permit causal conclusions. Finally, learning outcomes may also be influenced by factors not included in the present model, such as lecturer quality, prior academic achievement, learning motivation, course difficulty, and learning environment characteristics.

Future studies are encouraged to involve larger and more diverse samples across different academic disciplines and institutions. Additional variables such as learning motivation, engagement, academic self-efficacy, and instructional quality may also be incorporated to improve explanatory power. Furthermore, longitudinal research designs are recommended to examine changes in self-directed learning and learning outcomes over time and to provide stronger evidence regarding technology-based learning processes.

4. CONCLUSION

This study demonstrates that digital readiness and learning styles significantly predict self-directed learning, and that self-directed learning is the strongest predictor of learning outcomes. The structural model explains 62% of the variance in self-directed learning and 68% of the variance in learning outcomes. Furthermore, self-directed learning significantly mediates the relationships between digital readiness, learning styles, and learning outcomes. These findings suggest that technology integration may have a limited impact when it is not accompanied by students' capacity to regulate and direct their own learning. Higher education institutions should therefore strengthen digital literacy training, design self-directed learning activities, and utilize learning analytics to support student learning. Future studies are encouraged to involve larger, more diverse samples and to employ longitudinal designs to provide stronger evidence regarding technology-enhanced learning processes.

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