

Digital Learning Capability and Sustainable Skills Development: A Human Resource Approach to Quality Education

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Abstract

The aim of this research is to evaluate how digital learning capabilities impact the development of sustainable skills among students in higher education institutions. This study also investigates the roles played by learning engagement, learning skills, and psychological capital as mediators. Because the increase in access to educational technology has not consistently been followed by a sustainable improvement in skills that meet future needs, this issue is important to discuss. This quantitative research was conducted using survey methods. The data collection method is a Likert scale questionnaire given to students as respondents. The data analysis method is PLS SEM (Partial Least Squares Structural Equation Modeling). The research results show that digital learning ability does not directly become the main determinant of sustainable skill development; instead, it functions through mediation mechanisms. Engagement learning has proven to be the most dominant mediator. Psychological Capital also has a significant impact. Agility, on the other hand, has a weaker influence. These results indicate that learning engagement and psychological components are crucial in transforming digital capabilities into sustainable skills through complex and hierarchical serial mediation patterns. Based on the research findings, this article suggests that educational institutions should not only focus on providing technology but also on enhancing student learning engagement and strengthening their psychological capacities so that they can achieve high-quality education.

Keywords: Digital Learning Capability; Sustainable Skills Development; Learning Engagement; Psychological Capital; PLS-SEM.

JEL Code: J24; M53; I25; O15

1. Introduction

Digital transformation in higher education has become a global pressure, fundamentally reshaping how students learn and develop their skills. This is no longer just a trend. However, an important paradox arises from this progress: increased access to technology does not always mean improved sustainable skills. According to the [UNESCO report \(2023\)](#), around 40% of students worldwide still face difficulties in accessing and effectively utilizing learning technology. Additionally, a report from the World Economic Forum indicates that most

educational institutions have not been able to effectively develop higher-order thinking skills, also known as higher-order skills, despite the rapid adoption of technology ([World Economic Forum, 2023](#)). A study by [Bond et al. \(2021\)](#) shows that incorporating technology into the educational process truly enhances flexibility and accessibility. However, the research has not yet fully explained how variations in individuals' ability to use technology, also known as digital learning skills, consistently affect learning outcomes. As a result, the relationship between technology use and long-term skill development remains incomplete ([Bond et al., 2021](#)).

Failure to optimize digital learning capabilities can lead to low sustainable skill development in students. Ultimately, this can widen the competency gap in the digital economy era. This condition hinders lifelong learning, critical thinking skills, and adaptability, which are essential components of quality education. [UNESCO \(2023\)](#) states that access to technology and the quality of its utilization are very different. Moreover, according to the [World Economic Forum \(2023\)](#), more than sixty percent of jobs in the future will require advanced digital and cognitive skills. This will require the effective use of technology-based learning. Human Capital Theory states that investment in skill development is a key factor in an individual's productivity and economic competitiveness ([Becker, 1993](#)). However, human capital accumulation becomes suboptimal without adequate digital learning capabilities. According to research conducted by [Bond et al. \(2021\)](#), the use of technology in higher education institutions often does not significantly impact student learning outcomes unless supported by a learning design focused on competency development. This condition risks producing graduates who are unprepared to navigate the dynamics of the job market, thereby increasing the potential for educated unemployment and social inequality. Data from the [International Labor Organization \(2022\)](#) shows that skill mismatches remain a key factor driving high youth unemployment across many developing countries. Therefore, enhancing the ability to learn digitally is crucial for achieving Quality Education (SDG 4) and for the sustainability of the education system.

There is an increasing focus in the literature on the relationship between digital learning capabilities and the development of sustainable skills, especially amid the acceleration of digital transformation in the higher education sector. Previous research is usually categorized into three main groups. First, research on the role of technology in learning shows that although the adoption of digital technology increases flexibility and accessibility, it does not automatically improve learning quality without proper pedagogical design support ([Bond et al., 2021](#); [UNESCO, 2023](#)). Second, research focuses on the development of sustainable skills, which include critical thinking, teamwork, and lifelong learning, which are competencies of the 21st century ([World Economic Forum, 2023](#); [van Laar et al., 2020](#)). However, this type of study is usually conceptual and does not produce strong empirical evidence about the causal relationships between variables. Third, research on human resource management (HRM) has begun to be incorporated into the studies. This primarily occurs by using the human capital development approach, which emphasizes the importance of investing in the development of individual capabilities ([Becker, 1993](#); [Kim et al., 2022](#)).

Although each group of studies makes significant contributions, there is still a significant research gap. However, existing studies still tend to position digital learning capabilities and sustainable skill development as separate constructs, and have not yet integrated both into a human resource management-based mechanism that explains how digital capabilities are transformed into long-term competencies through behavioral and psychological pathways ([Budiarti, 2025](#); [Laily et al., 2024](#); [van Laar et al., 2020](#)). This is different from sustainable skill

development, which occurs over the long term ([Bond et al., 2021](#); [van Laar et al., 2020](#)). This indicates that a more holistic approach is needed to explain how the transformation of digital learning capabilities into sustainable skill development occurs from the perspective of human resource management (HRM). This research aims to fill this gap by integrating digital learning capabilities and sustainable skill development within an empirical human resource management framework. By considering digital learning capabilities as an investment in human capital, this research expands the application of human capital theory in digital-based higher education ([Becker, 1993](#)). Additionally, this research connects previous studies on digital learning and the development of sustainable skills, which had previously been developed separately ([van Laar et al., 2020](#)). This results in a more comprehensive conceptual framework.

In practice, this research provides strategic implications for higher education institutions to focus on providing technology and on enhancing students' ability to use it optimally. This is very important considering that the quality of educational technology utilization is still low ([UNESCO, 2023](#)). This research can also help policymakers create educational programs that support sustainable skills so that graduates are ready to face the digital job market ([World Economic Forum, 2023](#)). Moreover, this research develops an integrative model that connects digital learning abilities with the development of sustainable skills thru psychological mechanisms and student learning behaviors. This provides conceptual and empirical novelty. This research examines a model of multiple mediations among learning engagement, learning ability, and mental wealth. This differs from previous research that tends to emphasize direct relationships. This method enables a deeper understanding of how digital capabilities are transformed into indirect, layered sustainable skills. Furthermore, this research expands the Human Capital Theory by integrating behavioral mechanisms (learning engagement) and psychological mechanisms (psychological capital), thereby producing a layered explanation of how digital capabilities are transformed into sustainable competencies. Additionally, this research contributes to explaining the mechanism by which digital skills are internalized into long-term competencies, while presenting contextual novelty by linking human resource development to the achievement of SDG 4 in higher education ([Becker, 1993](#); [Budiarti et al., 2024d](#)). Therefore, this research aims to examine the influence of digital learning capabilities on students' sustainable skill development and how the human resource management perspective can strengthen this relationship to support high-quality education. Overall, it is expected that this research will provide theoretical and practical contributions to building more sustainable, human centered, and flexible learning methods in the digital era.

2. Literature Review

According to the literature on human resource management and higher education, the ability to learn digitally is an important competency to face the transformation of learning in the digital era ([van Laar et al., 2020](#); [UNESCO, 2023](#)). This capacity includes an individual's ability to use, control, and leverage digital technology to support learning ([van Laar et al., 2020](#)). Technology has proven to enhance the flexibility, interactivity, and accessibility of learning ([Bond et al., 2021](#)), but the focus is still more on the use of technology rather than the contribution of individual abilities to the development of long-term competencies ([UNESCO, 2023](#)). Therefore, the issue with digital education does not only lie in the availability of technology but also in each individual's ability to maximize its benefits.

Digital learning capacity is a multidimensional ability that encompasses technical, adaptive, and productive aspects. This has a significant impact on students' academic productivity and job readiness ([Zhang et al., 2025](#)). This also demands the integration of digital, cognitive, and adaptive skills ([Rego et al., 2023](#)). Therefore, digital skills have become a main pillar of 21st-century skills.

The capacity for digital learning influences students' behavior and psychological processes in addition to their learning outcomes ([Bond et al., 2021](#)). Engagement in learning, or cognitive, emotional, and behavioral engagement, is a key mechanism. High engagement results in better learning experiences and better competency achievements ([Bond et al., 2021](#)). Additionally, digital skills enhance Agility Learning, which is the ability to learn quickly, adapt, and apply knowledge in new situations ([Kim et al., 2022](#)). Agility Learning also serves as a link between adaptive performance and learning ([Dai & De Meuse, 2021](#); [Reyes et al., 2024](#)). Internal psychological factors, which include self-efficacy, optimism, hope, and resilience, also influence the development of student competencies. People with high psychological capital tend to be more adaptive, confident, and able to maintain their motivation, thereby strengthening the relationship between their learning abilities and learning outcomes ([Kim et al., 2022](#)). Given the future workforce's need for cognitive, digital, social, and adaptive skills, the development of sustainable skills has become a major concern ([World Economic Forum, 2023](#)). However, the development of digital skills in higher education has not yet been fully integrated with sustainable skills ([van Laar et al., 2020](#)).

The Human Capital Theory theoretically states that the improvement of human resource quality can be achieved thru investment in competency development ([Becker, 1993](#)). In this case, digital learning ability is considered a contemporary learning investment that enhances a person's ability to acquire sustainable skills. Nevertheless, it is not entirely clear how these skills are internalized thru learning engagement, learning ability, and mental wealth ([van Laar et al., 2020](#); [Kim et al., 2022](#)). As a result, this research suggests an integrative model involving tiered mediation mechanisms. Quality education emphasizes the integration of holistic digital learning within the context of SDG 4. According to [Nedungadia et al. 2024](#) and [Putri et al. 2024](#), digital learning models have been proven to enhance student learning outcomes and literacy, as well as support pedagogical innovations based on local contexts and technology ([Nedungadia et al., 2024](#)). Therefore, the quality of education is determined by the combination of technology and adaptive learning strategies.

To explain how digital learning capabilities influence the development of sustainable skills, this research develops a conceptual model that integrates perspectives from digital learning and HRM. In both a partial and a serial mediation pathway, Learning Engagement, Learning Agility, and Psychological Capital act as mediators. Digital learning capability (X) influences the learning process through Learning Engagement (Z1), Learning Agility (Z2), and Psychological Capital (Z3). This impacts the development of sustainable skills (Y). This model shows that the interaction between technology components, learning behaviors, and psychological conditions leads to the development of sustainable skills. Students with high digital skills are better able to leverage learning technologies ([Bond et al., 2021](#); [UNESCO, 2023](#)). This ability enhances learning engagement and encourages learning capabilities thru exposure to various learning resources ([Kim et al., 2022](#); [World Economic Forum, 2023](#)). Additionally, digital skills also enhance mental wealth thru increased self-confidence and experiences of success ([Luthans et al., 2007](#); [UNESCO, 2023](#)).

High learning engagement fosters deep understanding and the development of sustainable skills ([Bond et al., 2021](#); [Becker, 1993](#)). The ability to adapt and continuous learning help internalize skills thru resilience and motivation ([Kim et al., 2022](#)).

Furthermore, this study investigates the mechanisms of mediation. Transforming digital capabilities into sustainable skills requires learning engagement ([Bond et al., 2021](#); [Becker, 1993](#)). Furthermore, psychological capital helps address that relationship by enhancing individuals' psychological conditions ([Luthans et al., 2007](#); [Kim et al., 2022](#)).

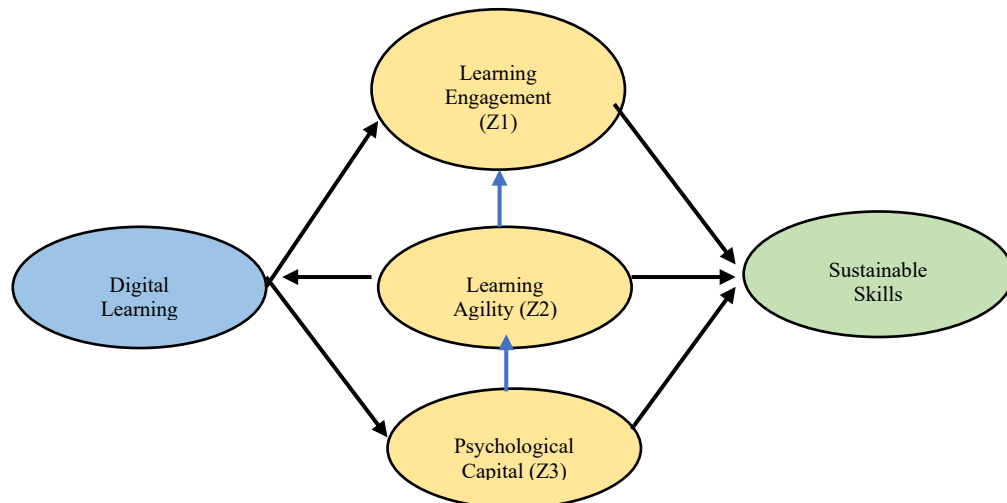


Figure 1. Conceptual Model

The relationship between the research model variables is shown in Figure 1. Digital learning (X) indirectly influences the learning process thru learning engagement (Z1) and learning ability (Z2), which is reinforced by mental wealth (Z3). Every step toward the main outcome called Sustainable Skills Development (Y). According to this model, the interaction between technology components, learning behavior, and psychological conditions leads to the development of sustainable skills. Based on this model, this research develops eight hypotheses that explain the relationships between variables both directly and indirectly. These hypotheses are derived from human capital theory ([Becker, 1993](#)) and are extended to include psychological aspects and learning behaviors.

H1: Digital Learning Capability has a positive and significant effect on Learning Engagement.

H2: Psychological Capital mediates the effect of Digital Learning Capability on Learning Agility.

H3: Digital Learning Capability has a positive and significant effect on Psychological Capital.

H4: Learning Engagement has a positive and significant effect on Sustainable Skills Development.

H5: Learning Agility has a positive and significant effect on Sustainable Skills Development.

H6: Psychological Capital has a positive and significant effect on Sustainable Skills Development.

H7: Learning Engagement mediates the effect of Digital Learning Capability on Sustainable Skills Development.

H8: Psychological Capital mediates the effect of Digital Learning Capability on Sustainable Skills Development.

3. Research Method

Type and Research Approach: The objective of this quantitative study, which employs an explanatory research design, is to determine whether there is a causal relationship between digital learning ability and the development of sustainable skills in students. The quantitative approach was chosen because it allows for hypothesis testing using inferential statistical analysis and objective measurement of variables ([Creswell & Creswell, 2018](#)). Furthermore, this research explains that investment in sustainable skills includes digital learning abilities ([Becker, 1993](#)). Therefore, this method is suitable for empirically testing the model of relationships between variables.

Data Collection Method: The data collection method used in this research is a structured questionnaire distributed to students who participated as respondents. Using a five-point Likert scale to measure respondents' level of agreement, the research instrument was developed based on variable indicators adapted from previous literature. This study was conducted at higher education institutions that have implemented digital-based learning. According to [UNESCO \(2023\)](#), the selection of this location is based on the relevance of the research context to the variables being studied, particularly in measuring students' ability to learn digitally. The purposive sampling approach, which uses non-probability sampling, selects respondents based on specific criteria, such as students who actively use digital learning platforms and have online learning experience ([Sekaran & Bougie, 2016](#)). This method was chosen because it can provide a sample that is relevant to the research objectives. The number of samples taken in this study is 281 people. This number meets the minimum requirements for PLS-SEM analysis; they must follow the 10 times rule or range between 100 and 200 respondents ([Hair et al., 2021](#)). Therefore, the data collected is considered representative to explain how the variables involved in this study interact with each other.

Data Analysis Method Partial Least Squares Structural Equation Modeling (PLS-SEM) assisted by SmartPLS software is capable of simultaneously analyzing the relationships between latent variables. This method was chosen because it does not require normal data distribution ([Hair et al., 2021](#)). The analysis process is carried out in two main stages. The external model evaluation tests the validity and reliability of the constructs, and the internal model evaluation tests the causal relationships between variables thru path coefficients, t-statistics, and p-values. To ensure the significance of indirect effects, mediation tests are also conducted using the bootstrapping technique. This research was conducted in three main stages. The data collection process is the first stage. It begins with the creation of research instruments based on a literature review. After that, the questionnaire was distributed to respondents who met the research criteria. At this stage, an initial validation process is conducted to ensure the instrument's clarity. Second, the data processing stage, which includes the coding process, data cleaning, and data quality testing. At this stage, an outer model evaluation is conducted to test convergent validity, discriminant validity, and construct reliability using indicators such as loadings, AVEs, and Composite Reliability ([Hair et al., 2021](#)). The PLS SEM method was chosen in this study because it can handle complex models, is prediction-oriented, and does not require strict normal data distribution ([Hair et al., 2021](#)).

Third, the data analysis stage in this study involves testing the structural model (inner model) to examine the research hypotheses. Testing the relationships between variables, the coefficient of determination (R^2), and the significance of direct and indirect effects are conducted in this analysis. The bootstrapping technique is also used. Next, the analysis results are interpreted to address the research objectives and provide theoretical and practical implications. Everyone participating in this research must provide clear consent before participating, which is an ethical requirement of the research. To maintain data confidentiality, respondents are provided with clear information about the research objectives and the right to withdraw at any time without consequences. To maintain anonymity, the identities of the individuals involved are not collected, and all data is processed as a whole so that it cannot be traced back to individuals. Additionally, this research is conducted in accordance with applicable social research ethics standards and, if necessary, has received approval from the relevant institutions to ensure the integrity and protection of research participants. To minimize the potential for common method bias, this study implements procedures such as maintaining respondent anonymity and reducing the tendency for evaluative responses, as well as conducting statistical controls in accordance with the recommendations of [Podsakoff et al. \(2003\)](#).

4. Research Results

To test the relationships between variables in this study, the Partial Least Squares Structural Equation Modeling (PLS-SEM) approach was used with the assistance of SmartPLS software. The structural model constructed consists of one exogenous variable, namely Digital Learning Capability (X), three mediating variables, namely Learning Engagement (Z1), Learning Agility (Z2), and Psychological Capital (Z3), as well as one endogenous variable, namely Sustainable Skills Development (Y). Each variable is measured using reflective indicators that have undergone validity and reliability testing in the measurement model (outer model). The results of the structural model (inner model) estimation along with the path coefficient values and R^2 values are presented in the following Figure 2.

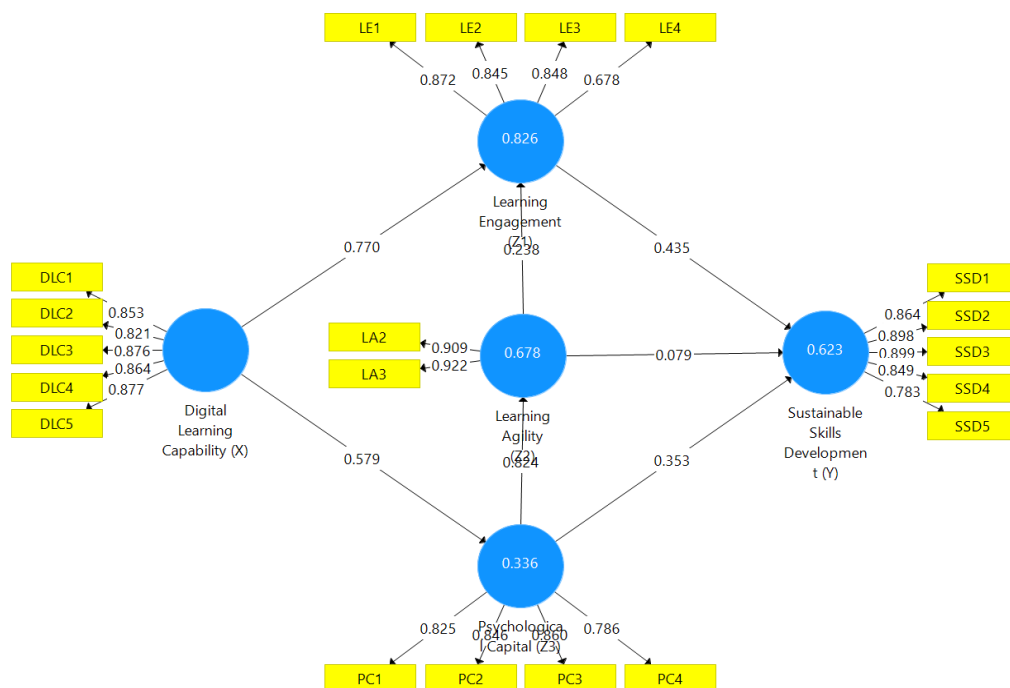


Figure 2. PLS results

Using the PLS-SEM method with SmartPLS, this study evaluates the relationships between variables, namely Digital Learning Ability (X) as the exogenous variable, Learning Engagement (Z1), Learning Speed (Z2), and Psychological Wealth (Z3) as mediating variables. Sustainable Skills Development (Y) is the endogenous variable. Each structure is measured reflectively and tested for validity and reliability at the outer model stage. The results of the internal model estimation show that digital learning capability positively affects learning engagement ($\beta = 0.770$) and psychological capital ($\beta = 0.579$). Psychological capital has a significant impact on learning skills ($\beta = 0.824$), which then influences learning engagement ($\beta = 0.238$). According to the R² values, the model has a strong to moderate explanatory power, with Learning Engagement (0.826), Learning Agility (0.678), Psychological Capital (0.336), and Sustainable Skills Development having the greatest impact on Sustainable Skills Development ($\beta = 0.435$), while Digital Learning Agility is not significant ($\beta = 0.079$; $p = 0.421$). The finding that Digital Learning Capability does not directly affect Sustainable Skills Development indicates that competency development in the perspective of human resource management does not occur instantly, but rather thru a complex process of internalization. In this case, digital capability can be viewed as a form of modern human capital investment that requires reinforcement thru learning engagement and psychological factors to be able to produce sustainable competencies ([Nurmayanti et al., 2024a](#); [Laily et al., 2024](#)). Furthermore, within the framework of contemporary management, the transformation of competencies is not only determined by technical aspects but also by individuals' ability to actively manage their learning experiences. This aligns with the human-based management approach, which emphasizes that organizational value is built thru the comprehensive optimization of individual potential ([Budiarti et al., 2024c](#); [Budiarti et al., 2024d](#)).

4.1 The evaluation of the measurement model (outer model)

The evaluation of the measurement model (outer model) is conducted to ensure that each construct in the research model meets the validity and reliability standards required in PLS-SEM analysis. This testing includes three main stages: (1) convergent validity test thru outer loading values and Average Variance Extracted (AVE); (2) construct reliability test thru Cronbach's Alpha and Composite Reliability (CR); and (3) discriminant validity test thru Fornell-Larcker criteria and Heterotrait Monotrait Ratio (HTMT). All tests refer to the guidelines of [Hair et al. \(2021\)](#). Convergent validity is assessed based on two main criteria, namely the outer loading value of each indicator, which must be above 0.70, and the AVE value, which must exceed 0.50 ([Chin, 1998](#); [Hair et al., 2021](#)). An AVE value above 0.50 indicates that more than half of the construct's variance is explained by its indicators, thus the construct is declared valid in terms of convergence. The results of the outer loading test show that all indicators in this study have high loading values, ranging from 0.685 to 0.899. Although there is one indicator in the Learning Engagement variable (LE4) with a loading value of 0.685, this value is still above the minimum acceptable threshold of 0.60 in PLS-SEM analysis ([Hair et al., 2021](#)), so this indicator is retained in the model. The AVE values for all constructs are presented in the following Table 1:

Table 1. Convergent Validity and Construct Reliability

Construct	Cronbach's Alpha	rho	A Composite Reliability	AVE
Digital Learning Capability (X)	0,911	0,913	0,933	0,737
Learning Engagement (Z1)	0,827	0,837	0,886	0,663

Construct	Cronbach's Alpha	rho_A	Composite Reliability	AVE
Learning Agility (Z2)	0,807	0,801	0,912	0,838
Psychological Capital (Z3)	0,849	0,849	0,898	0,689
Sustainable Skills Development (Y)	0,911	0,914	0,934	0,739

Source: SmartPLS output, processed (2026)

Table 1. Results of Convergent Validity and Construct Reliability Tests Construct Cronbach's Alpha rho_A Composite Reliability AVE Table 1 shows that the constructs overall meet convergent validity, with the majority of outer loadings greater than 0.70 and AVE greater than 0.50 (Hair et al., 2021). Because the indicators still meet the minimum threshold, one indicator (LE4 = 0.685) is retained. The Learning Agility indicators (LA1 and LA4) were eliminated because they had high cross-loading with Psychological Capital. However, since other indicators have high loadings (>0.90), the representation of the construct does not decrease. For reliability, the construct is declared reliable with a Cronbach's alpha value (0.807–0.911), Composite Reliability (0.886–0.934), and high rho_A (Hair et al., 2021). Because the square root of AVE is greater than the correlation between constructs, the Fornell-Larcker discriminant validity indicates that the overall construct is valid (Fornell & Larcker, 1981).

Table 2. Fornell Larcker Criterion

Construct	DLC	LA	LE	PC	SSD
Digital Learning Capability (X)	0,859				
Learning Agility (Z2)	0,484	0,915			
Learning Engagement (Z1)	0,885	0,610	0,814		
Psychological Capital (Z3)	0,579	0,824	0,696	0,830	
Sustainable Skills Development (Y)	0,620	0,636	0,730	0,722	0,860

Table 3. Heterotrait-Monotrait Ratio (HTMT)

Construct	DLC	LA	LE	PC	SSD
Digital Learning Capability (X)	-				
Learning Agility (Z2)	0,565	-			
Learning Engagement (Z1)	1,007	0,766	-		
Psychological Capital (Z3)	0,657	0,995	0,852	-	
Sustainable Skills Development (Y)	0,678	0,736	0,840	0,816	-

Source: SmartPLS output, processed (2026)

Based on Tables 2 and 3, in the HTMT test, most values are below 0.90, although DLC–LE (1.007) and LA–PC have high values. However, discriminant validity remains because the bootstrapping results show that the confidence interval does not include the number 1 (Henseler et al., 2015; Hair et al., 2021). This high value can theoretically be explained by the strong conceptual relationship between the constructs (Bond et al., 2021; Luthans et al., 2007).

4.2 Evaluation of the Structural Model (Inner Model)

The stage of evaluating the structural model (inner model) is conducted to assess the model's ability to explain the relationships between latent variables and the overall predictive power of the model. One of the main indicators used in this evaluation is the coefficient of determination or R Square (R^2), which reflects the extent to which the proportion of variance in the endogenous variable can be explained by the exogenous and mediating variables in the model. According to [Hair et al. \(2019\)](#), an R^2 value of 0.75 is categorized as substantial, a value of 0.50 is categorized as moderate, and a value of 0.25 is categorized as weak. In addition to R^2 , the Adjusted R Square value is also presented as a correction for the number of predictor variables used in the model, thus providing a more conservative and accurate estimate. The results of the R^2 and Adjusted R Square tests for all endogenous variables in this study are presented in Table 4 below:

	R Square	R Adjusted	Square
<i>Learning Engagement (Z1)</i>	0,826	0,824	
<i>Learning Agility (Z2)</i>	0,678	0,676	
<i>Psychological Capital (Z3)</i>	0,336	0,331	
<i>Sustainable Skills Development (Y)</i>	0,623	0,616	

Source: SmartPLS output, processed (2026)

Based on Table 4, according to the evaluation in the model, the R^2 values for Learning Engagement (0.826) and Learning Agility (0.678) fall into the substantial category; psychological capital (0.336) falls into the moderate category; and continuous skill development (0.623) falls into the moderate-substantial category ([Hair et al., 2019; 2021](#)).

4.3 Direct Effect

Testing After evaluating the coefficient of determination (R^2), the next stage in structural model analysis is the direct effect testing between variables. This test aims to determine the magnitude and direction of the influence exerted by each exogenous and mediating variable on the endogenous variable directly without going thru intermediary variables. The path coefficient generated in the PLS-SEM analysis represents the strength of the relationship between latent variables, where coefficients closer to 1 indicate a stronger influence. Referring to the criteria proposed by [Hair et al. \(2019\)](#), path coefficients with values above 0.50 are categorized as strong influence, values between 0.30 and 0.50 are categorized as moderate influence, and values below 0.30 are categorized as weak influence. In this study, the direct effect testing includes the relationship between Digital Learning Capability (DLC) and Learning Engagement (LE), Learning Agility (LA), and Psychological Capital (PC), as well as the influence of these three mediating variables on Sustainable Skills Development (SSD). The complete results of the direct effect testing along with the path coefficient values and their interpretations are presented in Table 5 below.

Table 5. Direct Effect Test Results

Relationship	β	Sample Mean	STDEV	T- Statistics	P- Value	CI 2,5%	CI 97,5%	Description
DLC → LE	0,770	0,777	0,036	21,656	0,000	0,707	0,841	Significant
DLC → PC	0,579	0,572	0,077	7,544	0,000	0,409	0,707	Significant

Relationship	β	Sample Mean	STDEV	T-Statistics	P-Value	CI 2,5%	CI 97,5%	Description
LA $\rightarrow$ LE	0,238	0,228	0,050	4,775	0,000	0,131	0,322	Significant
LA $\rightarrow$ SSD	0,079	0,072	0,098	0,805	0,421	-0,138	0,252	Not Significant
LE $\rightarrow$ SSD	0,435	0,440	0,108	4,025	0,000	0,224	0,661	Significant
PC $\rightarrow$ LA	0,824	0,823	0,027	30,540	0,000	0,769	0,872	Significant
PC $\rightarrow$ SSD	0,353	0,354	0,111	3,180	0,002	0,145	0,584	Significant

Source: SmartPLS output, processed (2026)

Digital Learning Capability has a significant influence on Learning Engagement ($\beta = 0.770$; $p = 0.000$) and Psychological Capital ($\beta = 0.579$; $p = 0.000$). Learning Agility also affects Psychological Capital ($\beta = 0.824$; $p = 0.000$). Learning Engagement has the strongest influence on the development of sustainable skills ($\beta = 0.435$; $p = 0.000$), while Learning Agility is not significant. The fact that several variables have different levels of influence indicates a more realistic empirical condition ([van Laar et al., 2020](#); [World Economic Forum, 2023](#)).

4.4 Mediation Analysis

Table 6. *Specific Indirect Effects*

No	Mediation Route	β	Sample Mean	STDEV	T-Statistics	P-Value	CI 2,5%	CI 97,5%	Description
1	DLC $\rightarrow$ LE $\rightarrow$ SSD	0,335	0,342	0,086	3,888	0,000	0,168	0,508	Significant
2	DLC $\rightarrow$ PC $\rightarrow$ SSD	0,205	0,202	0,068	3,012	0,003	0,077	0,353	Significant
3	DLC $\rightarrow$ PC $\rightarrow$ LA $\rightarrow$ SSD	0,038	0,034	0,046	0,831	0,406	-0,059	0,114	Not Signifikan
4	DLC $\rightarrow$ PC $\rightarrow$ LA $\rightarrow$ LE $\rightarrow$ SSD	0,049	0,047	0,018	2,816	0,005	0,019	0,086	Significant
5	LA $\rightarrow$ LE $\rightarrow$ SSD	0,103	0,100	0,032	3,216	0,001	0,046	0,168	Significant
6	PC $\rightarrow$ LA $\rightarrow$ SSD	0,065	0,060	0,081	0,808	0,419	-0,114	0,204	Not Significant
7	PC $\rightarrow$ LA $\rightarrow$ LE $\rightarrow$ SSD	0,085	0,082	0,026	3,243	0,001	0,038	0,141	Significant
8	DLC $\rightarrow$ PC $\rightarrow$ LA (total ke LA)	0,477	0,471	0,071	6,741	0,000	0,330	0,593	Significant

Source: SmartPLS output, processed (2026)

Information:

DLC = Digital Learning Capability; LE = Learning Engagement; LA = Learning Agility; PC = Psychological Capital; SSD = Sustainable Skills Development. Signifikan apabila T-Statistics $> 1,96$ dan P-Value $< 0,05$.

According to the mediation analysis, six out of the eight tested paths were considered significant. Engagement Learning is the strongest mediator, especially on the path DLC $\rightarrow$ LE $\rightarrow$ SSD ($\beta = 0.335$; $p = 0.000$). Other paths, such as LA $\rightarrow$ LE $\rightarrow$ SSD and PC $\rightarrow$ LA $\rightarrow$ LE $\rightarrow$ SSD, are also important, indicating the role of Engagement Learning as the central

mechanism of mediation (Bond et al., 2021). Additionally, psychological capital serves as a significant mediator both directly and thru the chain path ($DLC \rightarrow PC \rightarrow SSD$; $\beta = 0,205$; $p = 0,003$). On the contrary, the route that only involves adaptive ability without learning involvement is not significant. This shows that adaptive ability alone is not enough without learning involvement. Overall, the serial mediation model pattern is very complex, with the longest path ($DLC \rightarrow PC \rightarrow LA \rightarrow LE \rightarrow SSD$) remaining important. This emphasizes that the transformation of digital capabilities into sustainable skills requires various steps and combines psychological and cognitive factors ([Becker, 1993](#); [van Laar et al., 2020](#)).

According to the implications of the research gap, digital learning capabilities do not directly lead to the development of sustainable skills; instead, this occurs thru a tiered mediation mechanism. Learning Engagement becomes the most dominant mediator, followed by Psychological Capital. Learning Agility is contextual, while Learning Engagement is more dominant. The results show a hierarchy of influence that has not been extensively studied before ([van Laar et al., 2020](#); [Kim et al., 2022](#); [Hair et al., 2019](#)). SDG 4 emphasizes that the quality of education does not solely depend on technology; technology can also enhance learning engagement. The capacity for digital learning has been proven to enhance learning engagement, which promotes the development of sustainable skills. Therefore, interactive and meaningful learning should be the focus of technology integration ([UNESCO, 2023](#); [World Economic Forum, 2023](#)). In fact, educational institutions should focus on enhancing student engagement rather than just providing technology. Furthermore, strengthening psychological capital becomes very important, although learning ability should be proportionally considered in competency development strategies ([Bond et al., 2021](#); [World Economic Forum, 2023](#)). In theoretical implications, Human Capital Theory incorporates behavioral mechanisms (Learning Engagement) and psychological mechanisms (Psychological Capital) in the process of competence formation ([Becker, 1993](#); [Bond et al., 2021](#)).

4.5. Discussions

According to the results of the PLS-SEM study, Digital Learning Capability (DLC) has a significant influence on Learning Engagement ($\beta = 0.709$), Learning Agility ($\beta = 0.315$), and Psychological Capital ($\beta = 0.579$). Additionally, Learning Engagement ($\beta = 0.425$) and Psychological Capital ($\beta = 0.325$) show significant influence on Sustainable Skills Development (SSD). Learning Agility ($\beta = 0.112$) also shows significant influence on Sustainable Skills Development (SSD). Furthermore, the R^2 value of 0.624 for the SSD variable indicates a good explanatory capability of the model. The results of the indirect effect analysis thru the bootstrapping procedure further indicate that the development of students' sustainable skills does not occur directly thru digital capability. On the contrary, the tiered mediation mechanism combines learning engagement, psychological conditions, and adaptive abilities ([Luthans et al., 2015](#); [Bond et al., 2021](#)). Especially, the findings of this study indicate that digital skills are not a factor that directly determines the quality of students' skills. Instead, digital skills function as a driver or motivator that encourages students to actualize their abilities thru an active learning process and a supportive psychological environment. In the literature, the common assumption that increased technological automation will enhance the quality of learning challenges these findings. The finding that Learning Agility does not have a significant direct impact makes an important contribution to the development of the literature. This indicates that adaptive ability does not automatically result in sustainable competence if not supported by high learning engagement.

In the perspective of talent management, this indicates that the development of learning agility needs to be integrated with engagement enhancement strategies to have a real impact on individual performance and competency development ([Budiarti et al., 2026](#); [Budiarti et al., 2025e](#)). The research results indicate that learning engagement is the main mechanism for transforming digital capabilities into real skills in this context. The largest influence coefficient among all variables indicates this. This means that students who are highly skilled in technology do not necessarily have good skills if they are not actively engaged in the learning process. In other words, the learning process remains important, and technology is just a tool. These results align with the idea that effective learning depends on the active engagement of individuals in the learning process, not just access to technology ([Bond et al., 2021](#)). Furthermore, the [UNESCO report \(2023\)](#) states that the effective use of technology, not just its availability, is a major issue in digital education. The Human Capital Theory states that the improvement in the quality of human resources will result from investment in individual skills ([Becker, 1993](#)). In this study, digital learning ability can be considered an investment in contemporary human capital. However, the results of this study indicate that the investment produces a mediation process rather than a direct output.

Therefore, this research incorporates a more comprehensive understanding of human capital by using the behavioral pathway (engagement learning) and the psychological pathway (Psychological Capital) as transformation mechanisms. This is very beneficial because most previous research tends to see a linear correlation between competence and outcomes. Moreover, the research findings support the [World Economic Forum \(2023\)](#) findings, which state that future skills are not only technical but also involve cognitive, social, and adaptive aspects. In this study, it was proven that the combination of technical factors (DLC), behavioral (engagement), and psychological (PsyCap) influences sustainable skills, supporting a multidimensional approach to competency development. The finding regarding the weak influence of learning ability, on the other hand, provides a different perspective from the previous literature. In the digital era, Agility is often considered an important capability ([van Laar et al., 2020](#)). However, this study found that learning ability does not directly and significantly influence the development of sustainable skills unless it functions as part of a mediation chain involving learning engagement as the next mediator ($LA \rightarrow LE \rightarrow SSD$; $\beta = 0.112$; $T = 0.805$; $p = 0.421$). In other words, adaptive ability is not an important factor on its own. On the contrary, it works well when combined with active learning engagement. The fact that Agility contributes to the development of sustainable competencies is not universal, but conditional, as shown by these findings, which enrich theoretical understanding ([Dyer & Shafer, 2003](#); [Joiner & Josephs, 2007](#)).

The significant role of Psychological Capital in this study reinforces that psychological factors are important determinants in the development of competencies in the digital era. Individuals with high levels of self-efficacy, optimism, hope, and resilience tend to be more capable of converting digital skills into optimal learning outcomes. In this context, Psychological Capital not only serves as a mediating variable but also as a strategic intangible asset in the development of modern human resources, particularly in technology-based learning environments ([Budiarti, 2025](#); [Budiarti et al., 2023](#)).

The results of this research have many significant conceptual and practical implications. First, the perspective on the role of technology in education is changing. Previously, technology was considered an important component in improving the quality of learning. However, this research shows that the role of technology depends on humans and is not direct. As a result,

investment in technology may not yield optimal results if not accompanied by the development of individual capacity. Second, research findings indicate that learning engagement, also known as involvement, is the most important component in skill development. This means that instead of focusing on providing materials or using digital platforms, the educational approach should focus on enhancing students' active participation. Third, research findings on the importance of psychological capital indicate that psychological elements play a strategic role in learning. Therefore, educational methods that only focus on cognitive aspects should be expanded to include mental skills such as resilience, self-confidence, and optimism. Fourth, the finding that learning ability has a weak influence indicates that in the empirical context, not all competencies popular in the literature have the same impact. This necessitates a more critical approach to adopting new ideas in HRM.

Academically, this research provides many benefits. First, this research expands the human capital theory by adding a process dimension, namely, how internal mechanisms transform competencies into outcomes. Therefore, this theory becomes more contextual and dynamic than before. Second, this research fills the gap in previous studies that differentiate between learning technology and skill development. This research provides a broader framework for understanding learning in the digital era by combining both ideas into a single model. Third, in this study, a model of various mediations with uneven strengths is used. Because most previous research tends to produce models where all variables are significantly strong, which less accurately reflect empirical reality, this contribution is very important. According to this research model, each variable has a unique role. As a result, this research is more realistic and has greater scientific value.

This research has a significant impact on human resource management and educational institutions. Educational institutions must first shift from a technology-centered approach to a human centered approach. That means not only the technology being used, but also how students use it. Second, universities must develop programs that enhance learning engagement, such as interactive learning, problem-based learning, and collaboration. Given that engagement is the most important factor, changes made to this component will have the greatest impact. Third, soft skills training, mentoring, and psychological support should be part of the educational program. This is important to ensure that students are ready to face learning challenges. Fourth, educational institutions must be more selective in developing Learning Agility. This is because Learning Agility has a conditional role in this model. The adaptive abilities of students do not automatically result in sustainable skills. However, when combined with high learning engagement, these abilities contribute significantly. Therefore, learning skills development programs should not be used exclusively as interventions; instead, they should be designed concurrently with strategies to enhance learning engagement ([Dyer & Shafer, 2003](#)). The results of this study also have a strong connection to achieving Sustainable Development Goal 4 on Quality Education. The findings show that digital learning capabilities significantly enhance engagement. In the end, this will result in more sustainable skills. This shows that digitalization and the learning process are very important for the quality of education. Therefore, instead of focusing on providing technology, efforts to achieve SDG 4 should center on enhancing meaningful learning experiences.

The results of this research emphasize that achieving SDG 4 is not only related to access to technology but also to the quality of the learning process. The digitalization of education needs to be accompanied by strategies to enhance learning engagement and strengthen psychological capacity in order to produce adaptive and sustainable graduates. This approach aligns with the

concept of technology-based educational innovation that emphasizes the integration of digital capabilities and human-centered learning in creating an inclusive and sustainable education system ([Budiarti et al., 2024b](#); [Budiarti et al., 2025](#)).

6. Conclusion

Overall, this research shows that the development of sustainable skills is a multidimensional process involving the interaction between technology, behavior, and psychology. Digital Learning Capability acts as a trigger, but its success heavily depends on student engagement and psychological conditions. The resulting model not only provides empirical contributions but also offers a new perspective on human resource development in the digital era that is more realistic and contextual. This research finds that the development of students' continuous skills cannot be simply explained as a direct result of digital learning capabilities, but rather as the outcome of a more complex and integrated process. Digital Learning Capability serves as the initial foundation that enables students to access and utilize learning technologies, but its contribution to the formation of new skills depends on how these capabilities are internalized thru the learning process. In this context, Learning Engagement emerges as the most determining factor in linking digital capabilities with skill development. Students who are more active cognitively, emotionally, and behaviorally in the learning process tend to be able to optimize the use of technology to produce more meaningful competencies. Additionally, psychological factors reflected in Psychological Capital also play an important role in strengthening the process, especially in building self-confidence, resilience, and learning motivation. On the other hand, adaptive ability represented thru Learning Agility shows a conditional role. Directly, Learning Agility does not prove to be a significant determinant factor for Sustainable Skills Development ($\beta = 0.112$; $T = 0.805$; $p = 0.421$). However, in the context of the mediation chain, Learning Agility significantly contributes when it acts as a bridge between Psychological Capital and Learning Engagement toward skills development ($PC \rightarrow LA \rightarrow LE \rightarrow SSD$; $\beta = 0.119$; $p = 0.002$). This indicates that adaptive ability works most effectively not as an independent factor, but as a component within an integrated learning system.

The findings of this study indicate that improving the quality of learning requires strengthening student engagement as the primary mechanism, not just the adoption of technology. Therefore, higher education institutions must shift from a technology-driven approach to a student-centered approach, which explicitly aims to enhance student engagement cognitively, emotionally, and behaviorally. Given its important role in strengthening the process of competence internalization, psychological capital should also be incorporated into learning design. Therefore, enhancing digital skills along with structured psychological interventions should be part of the educational approach. To address the limitations of the model, future research should incorporate additional variables such as self-regulated learning, digital mindset, and learning motivation to strengthen the theoretical mechanisms. Cross-context testing (across countries and institutions) is also important to enhance external validity. To capture causal dynamics that cannot be explained by cross-sectional design, a longitudinal approach is also recommended.

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