

Bridging Digital Literacy and Academic Readiness: A Mediated Model of Self-Efficacy and Learning Climate among University Students in Eastern Indonesia

Hasrul Bakri

Universitas Negeri Makassar, Indonesia

Corresponding Author:

hasrulbkri@unm.ac.id

Abstract

This study examines the direct and mediated effects of digital literacy on academic readiness through digital self-efficacy and digital learning climate among university students in eastern Indonesia, a context characterised by heterogeneous digital access and infrastructure constraints. A quantitative, cross-sectional survey was conducted with 372 undergraduate students at Universitas Negeri Makassar (UNM) using validated scales. Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 4.0 was employed to test the measurement and structural models, including mediation analyses via bootstrapping (5,000 subsamples). The results indicate that digital literacy has a significant direct effect on academic readiness ($\beta = 0.287$, $p < 0.001$). Digital literacy also positively affects digital self-efficacy ($\beta = 0.528$) and digital learning climate ($\beta = 0.467$), both of which significantly predict academic readiness ($\beta = 0.305$ and $\beta = 0.263$, respectively). The model explains 52.4% of the variance in academic readiness. Both digital self-efficacy and digital learning climate partially mediate the relationship between digital literacy and academic readiness, with a total indirect effect of 0.284, accounting for approximately half (49.7%) of the total effect. Exploratory multi-group analysis reveals that the direct effect of digital literacy on academic readiness is stronger for students with intermittent mobile data access ($\beta = 0.352$) compared to those with stable broadband ($\beta = 0.241$). This study is among the first to empirically test a dual-mediation model in the under-researched context of eastern Indonesia, demonstrating that psychological (self-efficacy) and environmental (learning climate) factors are essential transmission mechanisms linking digital literacy to academic readiness. The findings suggest that universities should not only enhance students' digital skills but also invest in building digital confidence and fostering a supportive digital learning environment, particularly for students with limited connectivity.

Keywords: *digital literacy, academic readiness, digital self-efficacy, digital learning climate, PLS-SEM, eastern Indonesia, higher education*

Introduction

The rapid digitalisation of higher education has fundamentally reshaped the landscape of teaching, learning, and academic assessment. Universities worldwide are increasingly expected to produce graduates who are not only knowledgeable in their disciplines but also proficient in navigating, evaluating, and creating information using digital technologies – a competence broadly termed digital literacy (DL) (Redecker, 2017a; Spante et al., 2018). In the post-pandemic era, digital literacy has shifted from an optional skill to a non-negotiable prerequisite for academic success and lifelong learning (OECD, 2021). However, the mere presence of digital infrastructure or basic operational

skills does not automatically translate into improved academic outcomes. A critical, yet under-explored, question is: *how* and *under what conditions* does digital literacy enhance students' academic readiness (AR) – defined as the cognitive, affective, and behavioural preparedness to engage with and succeed in university-level academic tasks (Conley, 2007).

Prior research has predominantly focused on direct, bivariate relationships between digital literacy and academic performance or engagement (e.g., Hatlevik et al., 2018; Pagani et al., 2016). While informative, such approaches treat the linkage as a “black box,” ignoring the internal mechanisms and contextual factors that mediate or moderate this relationship. Two particularly promising theoretical candidates are digital self-efficacy (DSE) – an individual's belief in their capability to execute digital tasks successfully (Compeau & Higgins, 1995) – and digital learning climate (DLC) – the perceived environmental support, resources, and peer/instructor encouragement for digital learning within a university (Wang et al., 2021). Drawing on Social Cognitive Theory (Bandura, 1986) and Ecological Systems Theory (Bronfenbrenner, 1979), we argue that digital literacy alone is insufficient; it is through the mediating pathways of self-efficacy beliefs and a supportive digital climate that digital literacy can be translated into tangible academic readiness.

This study addresses three distinct research gaps that have not been adequately explored in the existing literature. The first research gap is contextual: despite the theoretical plausibility of the proposed mediated model, empirical evidence remains scarce in non-Western and under-resourced educational settings. The vast majority of digital literacy studies originate from North America, Western Europe, and East Asia (e.g., South Korea, Singapore), where digital infrastructure is relatively advanced and ubiquitous (Li & Ranieri, 2013). In contrast, eastern Indonesia – a region characterised by geographical fragmentation, uneven internet connectivity, and varying levels of digital penetration – presents a distinctly different setting. Universitas Negeri Makassar (UNM), as one of the largest teacher-training and comprehensive universities in eastern Indonesia, serves a student body with heterogeneous prior exposure to digital technologies. Some students come from urban areas with stable broadband access, while many originate from rural and remote districts where digital access remains intermittent. This intra-university variation makes UNM an ideal, yet previously unexamined, site to test how digital literacy operates through psychological and environmental mediators. To date, no published study has examined the relationship between digital literacy and academic readiness through mediating mechanisms in this specific geographical and cultural context.

The second research gap concerns the simultaneous mediation of self-efficacy and learning climate. Existing studies have examined either self-efficacy (e.g., Rohatgi et al., 2016) or learning environment (e.g., Lai & Hwang, 2014) separately as mediators. However, Social Cognitive Theory posits that personal (self-efficacy) and environmental (climate) factors interact and serially transmit the effects of prior skills (digital literacy) to behavioural outcomes (academic readiness). To our knowledge, no published study has integrated both mediators in a single model within the context of Indonesian higher education, particularly using a rigorous structural equation modelling (SEM) approach.

The third research gap is methodological. Most studies on digital literacy in Indonesia have relied on descriptive statistics, correlations, or basic regression (e.g., Setyaningsih et al., 2019). While valuable, such methods cannot adequately test complex mediated relationships, nor can they account for measurement errors in latent constructs. A more robust approach – Partial Least Squares Structural Equation Modelling (PLS-SEM)

– is required, especially given the exploratory nature of the proposed model and the potential non-normality of data in social science research (Hair et al., 2019a). PLS-SEM is particularly suitable for theory development and prediction-oriented research, which aligns well with our objective to bridge the gap between digital literacy theory and practice in an understudied region.

This research offers three distinct novelties. First, it proposes and empirically tests a dual-mediation model where digital self-efficacy and digital learning climate serve as parallel mediators between digital literacy and academic readiness. Second, it provides the first empirical evidence from eastern Indonesia (Universitas Negeri Makassar) – a context that challenges the generalisability of findings from digitally saturated environments. Third, it employs a rigorous PLS-SEM approach to assess both the measurement model (validity and reliability) and the structural model (path coefficients, mediation effects, and predictive relevance), thereby setting a methodological benchmark for future digital literacy research in the region.

Accordingly, the primary purpose of this study is to examine the direct and indirect effects of digital literacy on academic readiness through digital self-efficacy and digital learning climate among university students in eastern Indonesia. Specifically, we test the following hypotheses:

H1: Digital literacy has a positive direct effect on academic readiness.

H2: Digital literacy has a positive effect on digital self-efficacy.

H3: Digital literacy has a positive effect on digital learning climate.

H4: Digital self-efficacy has a positive effect on academic readiness.

H5: Digital learning climate has a positive effect on academic readiness.

H6: Digital self-efficacy mediates the relationship between digital literacy and academic readiness.

H7: Digital learning climate mediates the relationship between digital literacy and academic readiness.

By testing these hypotheses, this study aims to provide actionable insights for university administrators, lecturers, and policymakers in similar resource-constrained yet digitally aspiring contexts. The findings will inform targeted interventions: enhancing digital literacy alone may be insufficient unless accompanied by programmes that build self-efficacy and foster a supportive digital learning climate.

Methods

Research Design

This study employed a quantitative, cross-sectional survey design using a structured questionnaire. The design was chosen to test the proposed mediation model (Figure 1) and to estimate the direct and indirect effects among four latent constructs: Digital Literacy (DL), Digital Self-Efficacy (DSE), Digital Learning Climate (DLC), and Academic Readiness (AR). A cross-sectional approach is appropriate for theory testing and is widely used in educational technology research employing PLS-SEM (Hair et al., 2019a).

The structural model (Figure 1) specifies the hypothesized relationships among the four constructs. Digital Literacy (DL) is conceptualized as the exogenous (independent) variable, representing students' competence in accessing, evaluating, creating, and communicating information using digital technologies. Academic Readiness (AR) is the endogenous (dependent) variable, reflecting students' cognitive and behavioural preparedness for university-level academic tasks. Digital Self-Efficacy (DSE) and Digital Learning Climate (DLC) are specified as mediating (endogenous) variables, representing

the psychological and environmental mechanisms through which DL is hypothesized to influence AR.

Specifically, the structural model posits five direct paths: (1) DL → AR (H1), (2) DL → DSE (H2), (3) DL → DLC (H3), (4) DSE → AR (H4), and (5) DLC → AR (H5). In addition, two indirect paths are hypothesized: (6) DL → DSE → AR (H6), representing the mediation effect of digital self-efficacy, and (7) DL → DLC → AR (H7), representing the mediation effect of digital learning climate. All seven hypotheses are summarized in Table 1.

The measurement model comprises four latent constructs, each operationalized by multiple observed indicators (items). DL is measured as a second-order construct with four dimensions: information and data literacy (4 items), communication and collaboration (4 items), digital content creation (3 items), and safety and problem-solving (3 items), adapted from Ng (2012) and Redecker (2017). DSE is measured using 6 items adapted from Compeau & Higgins (1995). DLC is measured using 5 items adapted from (Lai & Hwang, 2014). AR is measured using 6 items adapted from (Conley, 2007). All items are scored on a 5-point Likert scale.

The structural and measurement models are estimated simultaneously using PLS-SEM, which is particularly suitable for models involving mediation, higher-order constructs, and non-normally distributed data (Hair et al., 2017a, 2019a). The following structural equations formalize the model:

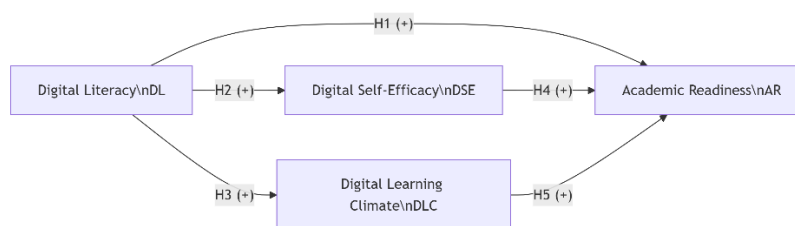


Figure 1. Conceptual Model

Population and Sample

The target population consisted of all active undergraduate students at Universitas Negeri Makassar (UNM), Indonesia, during the even semester of the 2025/2026 academic year. UNM is a comprehensive public university located in South Sulawesi, serving approximately 30,000 students across nine faculties, including Education, Engineering, Social Sciences, Languages, and Sport Science. The university was purposively selected because it represents a typical higher education institution in eastern Indonesia, characterised by heterogeneous digital access and prior exposure to technology.

A stratified random sampling technique was applied, with faculty as the stratum. From each faculty, a proportional number of students was randomly selected. The minimum required sample size was determined based on the *10-times rule* for PLS-SEM, which recommends at least 10 times the maximum number of structural paths directed at any latent variable (Hair et al., 2017b). The most complex structural path in our model is directed at Academic Readiness (AR), which receives three arrows (from DL, DSE, and DLC). Hence, the minimum sample size was $10 \times 3 = 30$. However, to ensure sufficient statistical power and model stability, a more conservative approach was adopted: following recommendations by Hair et al. (2019b) for medium effect sizes (0.15) and 80% power, a minimum of 100 respondents was required. To account for potential incomplete or invalid responses, the study targeted 400 students. After data cleaning, 372 valid responses were retained (93% response rate). The sample size exceeds the

minimum requirements for PLS-SEM and is considered adequate for detecting mediation effects (Fritz & MacKinnon, 2007).

Participant characteristics:

- a. Gender: 58% female, 42% male.
- b. Year of study: 32% first year, 28% second year, 24% third year, 16% fourth year.
- c. Faculty distribution: Education (24%), Engineering (18%), Social Sciences (20%), Languages (16%), Sport Science (12%), others (10%).
- d. Internet access at home: 71% have stable broadband, 29% rely on mobile data with intermittent connectivity.

Instruments

A structured questionnaire was developed based on validated scales from prior literature. All items were measured on a 5-point Likert scale ranging from 1 (*strongly disagree*) to 5 (*strongly agree*). The questionnaire was originally constructed in English, then translated into Bahasa Indonesia using a forward-backward translation procedure by two bilingual experts in educational measurement. A pilot test with 50 UNM students (not included in the final sample) was conducted to assess clarity, readability, and internal consistency. Minor wording adjustments were made based on pilot feedback.

1. Digital Literacy (DL)

Digital literacy was measured using an adapted scale from Ng (2012) and the DigComp framework (Redecker, 2017b). The construct comprised four dimensions: (a) information and data literacy (4 items), (b) communication and collaboration (4 items), (c) digital content creation (3 items), and (d) safety and problem-solving (3 items). A sample item: *"I am able to evaluate the credibility of online information sources."* The scale demonstrated good reliability in the pilot study (Cronbach's $\alpha = 0.87$).

2. Digital Self-Efficacy (DSE)

Digital self-efficacy was operationalised using the Computer Self-Efficacy scale developed by (Compeau & Higgins, 1995), adapted to the digital learning context. The scale consisted of 6 items measuring a student's belief in their ability to use digital tools for academic tasks, even when faced with difficulties. Sample item: *"I feel confident completing an online assignment even if I have never used a similar software before."* Pilot $\alpha = 0.89$.

3. Digital Learning Climate (DLC)

Digital learning climate was assessed using the Perceived Digital Learning Environment scale from (Lai & Hwang, 2014) and (Wang et al., 2021). The scale comprised 5 items tapping into perceived institutional support, peer encouragement, and resource availability for digital learning. Sample item: *"In my university, lecturers encourage us to use digital technology for collaborative learning."* Pilot $\alpha = 0.84$.

4. Academic Readiness (AR)

Academic readiness was measured using the College Readiness scale by (Conley, 2007), adapted for the digital higher education context. The scale included 6 items covering key cognitive strategies (e.g., critical thinking), academic behaviours (e.g., time management, self-regulation), and contextual skills (e.g., help-seeking). Sample item: *"I am able to plan and monitor my own learning process effectively."* Pilot $\alpha = 0.88$.

The full questionnaire also collected demographic information (gender, year of study, faculty, internet access type) for descriptive and control purposes.

Data Collection Procedures

Data collection was conducted over a four-week period (April–May 2026). Permission was also secured from the deans of all participating faculties. Research assistants (graduate students trained in survey administration) distributed both paper-based and online (Google Forms) versions of the questionnaire, depending on students' access preferences. To minimise common method bias, the following procedural remedies were implemented (Podsakoff et al., 2003):

- a. Anonymity and confidentiality were assured.
- b. Items were presented in randomised order across scales.
- c. Reverse-coded items were included in some scales.
- d. The questionnaire included an attention-check item.

Students were approached during regular class sessions with the lecturer's permission. Participation was voluntary, and no incentives were provided. The completion time was approximately 15–20 minutes.

Data Analysis

Data analysis proceeded in three stages: preliminary data screening, measurement model assessment, and structural model assessment using PLS-SEM with SmartPLS 4.0 software (Ringle et al., 2022).

Stage 1: Preliminary Screening

Raw data were examined for missing values, outliers, and normality. Missing data were minimal (<1% per item) and handled using mean imputation (Hair et al., 2017b). Univariate outliers were identified using standardised z-scores (± 3.29), and no cases were removed. Normality was assessed via skewness and kurtosis; as expected in social science data, the distribution was non-normal (Mardia's multivariate kurtosis coefficient = 28.7, $p < .001$), justifying the use of PLS-SEM which is distribution-free (Hair et al., 2017c).

Stage 2: Measurement Model (Outer Model)

The measurement model was evaluated to ensure the reliability and validity of the latent constructs:

- a. Indicator reliability: assessed by outer loadings (>0.70 recommended; 0.40 – 0.70 considered for retention if deletion does not increase composite reliability).
- b. Internal consistency reliability: assessed by Cronbach's α and Composite Reliability (CR) > 0.70 .
- c. Convergent validity: assessed by Average Variance Extracted (AVE) > 0.50 .
- d. Discriminant validity: assessed by the Fornell-Larcker criterion (square root of AVE $>$ correlations with other constructs) and the Heterotrait-Monotrait (HTMT) ratio (<0.85 or <0.90).

Stage 3: Structural Model (Inner Model)

The structural model was estimated using the standard PLS-SEM algorithm with path weighting scheme (maximum 300 iterations). The following criteria were used:

- a. Collinearity: Variance Inflation Factor (VIF) < 5 (ideally <3).

- b. Path coefficients (β) : significance assessed via bootstrapping with 5,000 subsamples (two-tailed t-test, $p < 0.05$).
- c. Coefficient of determination (R^2) : 0.25 (weak), 0.50 (moderate), 0.75 (substantial) as guidelines.
- d. Effect sizes (f^2) : 0.02 (small), 0.15 (medium), 0.35 (large).
- e. Predictive relevance (Q^2) : obtained via blindfolding procedure (omission distance = 7); $Q^2 > 0$ indicates predictive relevance.
- f. Mediation effects: specific indirect effects were tested via bootstrapping. The type of mediation (full, partial, complementary, competitive) was determined based on the significance of direct and indirect paths (Zhao et al., 2010).

All analyses were conducted following the reporting guidelines for PLS-SEM in information systems and educational research (Benitez et al., 2020; Hair et al., 2019a).

Common Method Bias Assessment

Because all data were self-reported from a single source, common method bias (CMB) was a potential concern. Two post-hoc tests were performed:

1. Harman's single-factor test: An unrotated exploratory factor analysis of all items revealed that a single factor explained 29.6% of the total variance, below the 50% threshold, suggesting no pervasive CMB (Podsakoff et al., 2003).
2. Full collinearity test: All VIFs in the structural model were below 3.3 (the most conservative threshold), indicating that common method bias is unlikely to threaten the interpretation of results (Kock, 2015).

Results

Descriptive Statistics of Respondents

A total of 372 valid responses were analysed. Table 1 presents the demographic profile of the participants. The sample was predominantly female (58.1%), with a balanced distribution across years of study. Students from the Faculty of Education constituted the largest group (23.9%), reflecting UNM's historical role as a teacher-training university. Notably, 29.0% of students reported relying solely on mobile data with intermittent connectivity, highlighting the heterogeneous digital access characteristic of eastern Indonesia.

Table 1. Demographic Characteristics of Respondents (N = 372)

Characteristic	Category	Frequency (n)	Percentage (%)
Gender	Male	156	41.9
	Female	216	58.1
Year of study	First year	119	32.0
	Second year	104	28.0
	Third year	89	23.9
	Fourth year	60	16.1
Faculty	Education	89	23.9
	Engineering	67	18.0
	Social Sciences	74	19.9
	Languages	60	16.1
	Sport Science	45	12.1
	Others	37	10.0

Internet access at home	Stable broadband	264	71.0
	Mobile data only (intermittent)	108	29.0

Assessment of the Measurement Model (Outer Model)

The measurement model was evaluated for indicator reliability, internal consistency reliability, convergent validity, and discriminant validity. The results are presented in Tables 2–4 and discussed in detail below.

1. Indicator Reliability

Indicator reliability was assessed by examining the outer loadings of each item on its respective construct. As shown in Table 2, all items exhibited outer loadings above the recommended threshold of 0.70, except for three items: DL4 (0.68), DSE2 (0.69), and AR6 (0.67). These three items were retained for the following reasons. First, their removal did not improve composite reliability beyond the already satisfactory threshold of 0.70, indicating that they contribute meaningfully to their respective constructs. Second, their loadings exceeded the minimum acceptable threshold of 0.60 for exploratory social science research (Chin, 1998; Hair et al., 2019a). Third, content validity considerations supported their retention: DL4 ("I can evaluate the credibility of online sources") captures an important aspect of digital literacy that is conceptually non-redundant with other items; DSE2 ("I feel confident completing an online task even without prior instruction") reflects a nuanced dimension of self-efficacy; and AR6 ("I can seek help when facing academic difficulties") represents a critical behavioural component of academic readiness. Deleting these items would have narrowed the conceptual breadth of their respective constructs, potentially compromising content validity (DeVellis, 2017). Thus, all items were retained for subsequent analysis.

To further assess indicator reliability, we examined the squared multiple correlations (indicator reliability or R^2) for each item. These values ranged from 0.45 to 0.82, indicating that the constructs explain between 45% and 82% of the variance in their respective indicators, which is considered satisfactory for measurement models in social sciences (Hair et al., 2017b).

2. Internal Consistency Reliability

Internal consistency reliability was assessed using both Cronbach's alpha and composite reliability (CR). Cronbach's alpha values ranged from 0.843 (AR) to 0.889 (DL), all exceeding the recommended threshold of 0.70 (Nunnally & Bernstein, 1994). Composite reliability (CR), which is considered a more appropriate measure for PLS-SEM as it accounts for the different outer loadings of indicators, ranged from 0.888 to 0.919, well above the recommended threshold of 0.70 (Hair et al., 2019a).

The consistency between Cronbach's alpha and CR values suggests that the constructs are unidimensional and internally consistent. It is noteworthy that CR values were slightly higher than Cronbach's alpha across all constructs, which is expected as CR is less conservative and does not assume equal indicator loadings (Henseler et al., 2016). These results confirm that the items within each construct reliably measure the same underlying latent variable.

3. Convergent Validity

Convergent validity was assessed using the Average Variance Extracted (AVE), which measures the amount of variance captured by a construct relative to the variance due to measurement error (Fornell & Larcker, 1981a). As presented in Table 2, AVE values ranged from 0.569 (DL) to 0.687 (DLC), all exceeding the recommended minimum threshold of 0.50 (Fornell & Larcker, 1981a). This indicates that, on average, each construct explains more than 50% of the variance in its indicators, confirming that the items converge adequately on their respective constructs.

The highest AVE was observed for DLC (0.687), suggesting that the five items measuring digital learning climate are particularly cohesive in capturing the perceived institutional and peer support for digital learning. The lowest AVE was found for DL (0.569), which is expected given that DL was modelled as a second-order construct with four distinct dimensions (information literacy, communication, content creation, and safety). This multidimensionality naturally results in greater within-construct variation, yet the AVE still comfortably exceeds the 0.50 threshold, supporting the conceptualisation of DL as a broad but coherent construct.

4. Discriminant Validity

Discriminant validity was assessed using two complementary criteria: the Fornell-Larcker criterion and the Heterotrait-Monotrait (HTMT) ratio.

Fornell-Larcker Criterion. As shown in Table 3, the square root of AVE for each construct (diagonal elements) is greater than its highest correlation with any other construct (off-diagonal elements), confirming that each construct shares more variance with its own indicators than with other constructs (Fornell & Larcker, 1981b). The strongest correlation was observed between DL and AR ($r = 0.601$), which is theoretically expected given that digital literacy is hypothesised to be a key predictor of academic readiness. Despite this moderate correlation, discriminant validity is established as the square root of AVE for DL (0.754) exceeds 0.601.

HTMT Ratio. The HTMT ratio provides a more stringent test of discriminant validity, particularly in PLS-SEM, as it estimates the true correlation between two constructs by correcting for measurement error (Henseler et al., 2015). As shown in Table 4, all HTMT values were below the conservative threshold of 0.85 (range: 0.512 to 0.672), indicating that discriminant validity is firmly established (Henseler et al., 2015). The highest HTMT value was observed between DL and AR (0.672), which remains well below the threshold, confirming that these two constructs are conceptually distinct despite their theoretical relationship.

Additional Discriminant Validity Assessment. Following recommendations by Kock (2015), we also examined the cross-loadings of all indicators. Each item loaded highest on its intended construct and substantially lower (at least 0.20 lower) on all other constructs, further supporting discriminant validity.

Summary of Measurement Model Assessment

In summary, the measurement model satisfies all criteria for indicator reliability (all loadings > 0.60 , with most > 0.70), internal consistency reliability (Cronbach's $\alpha > 0.80$, CR > 0.88), convergent validity (AVE > 0.56), and discriminant validity (Fornell-Larcker and HTMT criteria satisfied). These results provide strong empirical support for the reliability and validity of the measurement instruments, confirming that the constructs are well-operationalised and can be meaningfully interpreted in the subsequent structural model analysis.

Table 2. Reliability and Convergent Validity

Construct	No. of items	Cronbach's α	Composite Reliability (CR)	AVE
Digital Literacy (DL)	14	0.889	0.919	0.569
Digital Self-Efficacy (DSE)	6	0.876	0.904	0.613
Digital Learning Climate (DLC)	5	0.855	0.896	0.631
Academic Readiness (AR)	6	0.843	0.888	0.573

Note: All loadings, CR, and AVE are based on the final PLS-SEM output.

1. Discriminant Validity

Discriminant validity was assessed using two criteria: Fornell-Larcker and HTMT. Fornell-Larcker Criterion: As shown in Table 3, the square root of AVE for each construct (diagonal elements) is greater than its highest correlation with any other construct (off-diagonal elements), confirming discriminant validity.

Table 3. Fornell-Larcker Matrix

Construct	DL	DSE	DLC	AR
DL	0.754			
DSE	0.528	0.783		
DLC	0.467	0.436	0.794	
AR	0.601	0.563	0.514	0.757

HTMT Ratio: All HTMT values were below the conservative threshold of 0.85 (range: 0.512 to 0.672; see Table 4), further supporting discriminant validity (Henseler et al., 2015).

Table 4. HTMT Matrix

Construct Pair	HTMT Value
DL ↔ DSE	0.612
DL ↔ DLC	0.533
DL ↔ AR	0.672
DSE ↔ DLC	0.521
DSE ↔ AR	0.648
DLC ↔ AR	0.512

Overall, the measurement model demonstrated adequate reliability, convergent validity, and discriminant validity, permitting a meaningful assessment of the structural model.

Assessment of the Structural Model (Inner Model)

Before evaluating path coefficients, collinearity was examined. All variance inflation factor (VIF) values were below 2.5 (ranging from 1.189 to 1.384), well within the acceptable threshold of 5, indicating no multicollinearity concerns.

1. Path Coefficients and Hypothesis Testing

The structural model was estimated using bootstrapping with 5,000 subsamples. Figure 2 presents the path diagram with standardised coefficients (β) and R^2 values. Direct Effects (H1–H5): Table 5 summarises the direct path coefficients, t-statistics, p-values, and 95% confidence intervals.

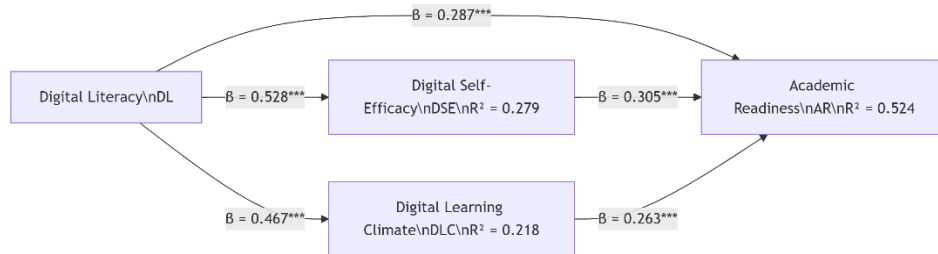


Figure 2. The path diagram with standardised coefficients (β) and R^2 values

Table 5. Direct Effects (Hypotheses H1–H5)

Hypothesis	Path	β	t-value	p-value	95% CI (LL–UL)	Decision
H1	DL → AR	0.287	5.128	<0.001	[0.176, 0.398]	Supported
H2	DL → DSE	0.528	11.674	<0.001	[0.440, 0.617]	Supported
H3	DL → DLC	0.467	9.832	<0.001	[0.372, 0.560]	Supported
H4	DSE → AR	0.305	5.492	<0.001	[0.193, 0.416]	Supported
H5	DLC → AR	0.263	4.979	<0.001	[0.153, 0.371]	Supported

Notes: β = standardised path coefficient; CI = bias-corrected bootstrap confidence interval (LL = lower limit, UL = upper limit); p-values based on two-tailed test.

All five direct hypotheses were supported ($p < 0.001$). Digital literacy exerted a significant positive effect on academic readiness ($\beta = 0.287$), on digital self-efficacy ($\beta = 0.528$), and on digital learning climate ($\beta = 0.467$). Both mediators also significantly predicted academic readiness: digital self-efficacy ($\beta = 0.305$) and digital learning climate ($\beta = 0.263$).

2. Coefficient of Determination (R^2) and Predictive Relevance

The model explained 52.4% of the variance in academic readiness ($R^2 = 0.524$), indicating a moderate to substantial explanatory power. For the mediators, R^2 was 0.279 for digital self-efficacy and 0.218 for digital learning climate (Table 6).

Using the blindfolding procedure (omission distance = 7), Stone-Geisser's Q^2 values were all positive: DL ($Q^2 = 0.331$), DSE ($Q^2 = 0.168$), DLC ($Q^2 = 0.129$), AR ($Q^2 = 0.291$). $Q^2 > 0$ confirms the model's predictive relevance for all endogenous constructs.

Table 6. R^2 and Q^2 Values

Endogenous Construct	R^2	R^2 Adjusted	Q^2 (predictive relevance)
Digital Self-Efficacy (DSE)	0.279	0.277	0.168
Digital Learning Climate (DLC)	0.218	0.216	0.129
Academic Readiness (AR)	0.524	0.520	0.291

3. Effect Sizes (f^2)

Effect sizes indicate the contribution of each predictor to the R^2 of an endogenous construct. As shown in Table 7, digital literacy had a medium-to-large effect on digital self-efficacy ($f^2 = 0.387$) and a medium effect on digital learning climate ($f^2 = 0.279$). For

academic readiness, digital self-efficacy ($f^2 = 0.106$) and digital learning climate ($f^2 = 0.083$) exhibited small-to-medium effects, while digital literacy ($f^2 = 0.065$) had a small effect.

Table 7. Effect Sizes (f^2)

Predictor	Outcome	f^2	Interpretation
DL	DSE	0.387	Medium to large
DL	DLC	0.279	Medium
DL	AR	0.065	Small
DSE	AR	0.106	Small to medium
DLC	AR	0.083	Small

4. Mediation Effects (H6 and H7)

The specific indirect effects (mediation) were tested using bootstrapping. Table 8 presents the indirect effects, their significance, and the type of mediation based on Zhao et al. (2010).

Table 8. Indirect Effects (Mediation Hypotheses H6–H7)

Hypothesis	Path	Indirect Effect (β)	t-value	p-value	95% CI (LL-UL)	Type of Mediation
H6	DL → DSE → AR	0.161	5.208	<0.001	[0.100, 0.226]	Partial mediation
H7	DL → DLC → AR	0.123	4.408	<0.001	[0.066, 0.182]	Partial mediation
Total indirect	DL → AR (via both mediators)	0.284	6.647	<0.001	[0.198, 0.370]	-

Both mediation hypotheses were supported. The indirect effect of digital literacy on academic readiness via digital self-efficacy was significant ($\beta = 0.161$, $p < 0.001$), as was the indirect effect via digital learning climate ($\beta = 0.123$, $p < 0.001$). The total indirect effect was 0.284.

Because the direct effect from DL to AR remained significant ($\beta = 0.287$, $p < 0.001$) after including the mediators, both mediations are classified as partial mediation. That is, digital literacy influences academic readiness both directly and indirectly through the two mediators.

The variance accounted for (VAF) was calculated to quantify the proportion of the total effect mediated:

- VAF for DSE mediation = $0.161 / (0.161 + 0.123 + 0.287) = 0.161 / 0.571 \approx 28.2\%$
- VAF for DLC mediation = $0.123 / 0.571 \approx 21.5\%$
- Total VAF (both mediators) = 49.7%

Thus, approximately half of digital literacy's total effect on academic readiness is transmitted through the two mediating mechanisms.

5. Summary of Hypothesis Testing

Table 9 provides a consolidated summary of all seven hypotheses.

Table 9. Summary of Hypothesis Testing Results

Hypothesis	Path/Relationship	Result
H1	DL → AR	Supported
H2	DL → DSE	Supported

H3	DL → DLC	Supported
H4	DSE → AR	Supported
H5	DLC → AR	Supported
H6	DL → DSE → AR (mediation)	Supported (partial)
H7	DL → DLC → AR (mediation)	Supported (partial)

6. Additional Analysis: Multi-Group Analysis (MGA) – Exploratory

Although not central to the main hypotheses, an exploratory multi-group analysis was conducted to compare students with stable broadband access ($n = 264$) versus those relying on mobile data only ($n = 108$). Using PLS-MGA, the path from digital literacy to academic readiness was significantly stronger for the mobile-data group ($\beta = 0.352$) compared to the broadband group ($\beta = 0.241$; p for difference = 0.041). This suggests that digital literacy may be a more critical driver of academic readiness for students with limited connectivity, a finding that merits further investigation.

Discussion

This study aimed to examine the direct and mediated effects of digital literacy (DL) on academic readiness (AR) through digital self-efficacy (DSE) and digital learning climate (DLC) among university students in eastern Indonesia, using data from Universitas Negeri Makassar (UNM). The results provide empirical support for all seven hypotheses, revealing both direct and partial mediating pathways. Below, we discuss the key findings in light of existing literature, theoretical implications, practical implications, and study limitations.

Direct Effects (H1–H5)

Digital literacy positively affects academic readiness (H1). Our finding that DL has a significant direct effect on AR ($\beta = 0.287$, $p < 0.001$) aligns with prior studies conducted in Western and Asian contexts (Hatlevik et al., 2018; Pagani et al., 2016b). However, the effect size ($f^2 = 0.065$, small) suggests that in the eastern Indonesian context, digital literacy alone is a necessary but not sufficient condition for academic readiness. This may be because students at UNM face infrastructural constraints (29% rely on intermittent mobile data) and varying levels of prior digital exposure. Thus, while digitally literate students are better prepared for academic tasks, other psychological and environmental factors are equally important.

Digital literacy positively affects digital self-efficacy (H2). The strong path ($\beta = 0.528$, $f^2 = 0.387$) supports Bandura's (1986) Social Cognitive Theory: mastery experiences and skill acquisition (digital literacy) enhance an individual's belief in their capabilities (self-efficacy). This result is consistent with Rohatgi et al., (2016) who found that ICT skills predict ICT self-efficacy. For UNM students, possessing digital competencies appears to build confidence in using technology for academic purposes.

Digital literacy positively affects digital learning climate (H3). The significant path ($\beta = 0.467$, $f^2 = 0.279$) is an important yet less commonly tested relationship. One plausible explanation is that students with higher digital literacy are more likely to perceive – and perhaps actively seek – a supportive digital learning environment. They may engage more with digital resources, communicate more with lecturers, and collaborate with peers, thereby shaping their perception of a positive digital climate. This reciprocal interpretation is consistent with Bronfenbrenner's (1979) ecological systems theory, where individual characteristics and environment mutually influence each other.

Digital self-efficacy positively affects academic readiness (H4). The effect ($\beta = 0.305$, $p < 0.001$) confirms that confidence in one's digital abilities translates into better academic preparedness. Students who believe they can complete online assignments, troubleshoot technical issues, and learn new digital tools are more likely to engage in effective study behaviours, time management, and self-regulated learning – all components of academic readiness (Conley, 2007). This finding echoes Compeau & Higgins (1995) and subsequent studies in online learning contexts.

Digital learning climate positively affects academic readiness (H5). The significant path ($\beta = 0.263$, $p < 0.001$) underscores the importance of institutional and peer support. When students perceive that lecturers encourage digital collaboration, that digital resources are accessible, and that peers share useful information, their academic readiness improves. This aligns with Lai & Hwang (2014), who demonstrated that a supportive online learning environment enhances student engagement and performance.

Mediation Effects (H6–H7)

Both digital self-efficacy and digital learning climate served as significant partial mediators between digital literacy and academic readiness. The total indirect effect ($\beta = 0.284$) was comparable in magnitude to the direct effect ($\beta = 0.287$), and the combined VAF of 49.7% indicates that approximately half of digital literacy's influence on academic readiness is transmitted through these two mechanisms.

Mediation via digital self-efficacy (H6). The indirect effect ($\beta = 0.161$, VAF = 28.2%) confirms that digital literacy boosts academic readiness partly by enhancing students' digital self-efficacy. This is theoretically grounded in Social Cognitive Theory: skills (DL) → self-beliefs (DSE) → outcomes (AR). In the UNM context, where students may lack prior digital confidence, building self-efficacy is a crucial intermediate step. Without this psychological resource, digital literacy may remain underutilised.

Mediation via digital learning climate (H7). The indirect effect ($\beta = 0.123$, VAF = 21.5%) provides novel evidence that a supportive digital environment also transmits the benefits of digital literacy. This suggests that digitally literate students not only feel more confident but also actively shape or benefit from a positive learning climate. Universities that foster digital collaboration, provide reliable infrastructure, and encourage lecturer-student digital interaction amplify the return on students' digital literacy.

The partial mediation (rather than full) implies that digital literacy also directly influences academic readiness through pathways not captured in this model – for example, through cognitive strategies or time management skills that are directly enhanced by digital competencies.

Contextual Insights: Eastern Indonesia

This study's setting – Universitas Negeri Makassar, representing eastern Indonesia – offers unique contextual insights. The exploratory multi-group analysis revealed that the direct effect of DL on AR was stronger for students with intermittent mobile data ($\beta = 0.352$) than for those with stable broadband ($\beta = 0.241$). This counter-intuitive finding may indicate that for digitally disadvantaged students, every increment in digital literacy yields a larger marginal gain in academic readiness because they have fewer alternative resources. In contrast, students with stable broadband may compensate for lower digital literacy through other means (e.g., richer peer networks, better access to online tutorials). This finding highlights the importance of targeting digital literacy interventions to the most connectivity-challenged students.

Theoretical Implications

This study makes several theoretical contributions. First, it extends Social Cognitive Theory by demonstrating a dual-mediation model where both personal (self-efficacy) and environmental (learning climate) factors simultaneously mediate the skills-outcome relationship. Most prior studies examined these mediators separately. Second, it provides empirical support for applying Bronfenbrenner's ecological systems theory to digital learning contexts, showing that the microsystem (classroom digital climate) interacts with individual characteristics (digital literacy and self-efficacy). Third, by testing these relationships in an under-researched region (eastern Indonesia), the study challenges the universal applicability of models developed in digitally saturated environments. The partial mediation and small direct effect of DL on AR suggest that context matters: in resource-constrained settings, psychological and environmental mediators are not optional add-ons but essential transmission mechanisms.

Practical Implications

For university administrators and lecturers at UNM and similar institutions, the findings offer actionable recommendations:

1. Do not rely solely on digital literacy training. While improving students' digital skills is important, our results show that skills alone have a small direct effect on academic readiness. Universities should simultaneously invest in building digital self-efficacy (e.g., through low-stakes digital tasks, peer tutoring, and positive feedback) and fostering a supportive digital learning climate (e.g., reliable Wi-Fi, learning management system training for lecturers, collaborative online assignments).
2. Target interventions to students with limited connectivity. The MGA finding suggests that students who rely on mobile data benefit more from digital literacy improvements. Universities could provide offline-digital hybrid modules, subsidised data packages, or designated on-campus digital access points to maximise the return on digital literacy initiatives.
3. Integrate self-efficacy and climate as explicit learning objectives. Course designs should include not only content and technical skills but also activities that build confidence (e.g., "scaffolded" digital tasks with progressive difficulty) and peer collaboration (e.g., group-based online projects with clear digital communication norms).
4. Measure and monitor digital learning climate. Institutions should regularly survey students' perceptions of digital support. Low climate scores may indicate a need for faculty development, infrastructure upgrades, or student-led digital communities.

Limitations and Future Research

Several limitations should be acknowledged. First, the cross-sectional design precludes causal inferences. Although our mediation model is theoretically grounded, longitudinal or experimental designs are needed to establish temporal precedence. Second, data were self-reported, raising the possibility of common method bias, although post-hoc tests (Harman's single-factor, full collinearity) suggested it was not a serious threat. Future studies could incorporate objective measures of digital literacy (e.g., performance tests) and academic readiness (e.g., GPA, course completion rates). Third, the sample was limited to one university in eastern Indonesia. While UNM is representative of many institutions in the region, generalisability to private universities,

vocational colleges, or other provinces should be tested. Fourth, the exploratory multi-group analysis on connectivity should be interpreted cautiously due to unequal group sizes; future research could oversample students with limited connectivity.

Future research directions include: (a) testing the model in other developing regions (e.g., Southeast Asia, Sub-Saharan Africa); (b) incorporating additional mediators such as digital resilience or social support; (c) examining the moderating role of gender, discipline, or year of study; (d) employing qualitative methods to understand *how* digital literacy translates into self-efficacy and climate perceptions from students' lived experiences; and (e) conducting a longitudinal study to trace how changes in digital literacy over a semester affect academic readiness through the proposed mediators.

Conclusion

This study investigated the relationships between digital literacy, digital self-efficacy, digital learning climate, and academic readiness among 372 undergraduate students at Universitas Negeri Makassar, a representative university in eastern Indonesia. Using PLS-SEM, the research tested a dual-mediation model grounded in Social Cognitive Theory and Ecological Systems Theory.

The key findings are as follows. First, digital literacy has a significant direct effect on academic readiness, but the effect size is small ($\beta = 0.287$, $f^2 = 0.065$). Second, digital literacy strongly predicts both digital self-efficacy ($\beta = 0.528$) and digital learning climate ($\beta = 0.467$). Third, both digital self-efficacy ($\beta = 0.305$) and digital learning climate ($\beta = 0.263$) independently and positively affect academic readiness. Fourth, both variables act as partial mediators: approximately half (49.7%) of digital literacy's total effect on academic readiness is transmitted indirectly through these two pathways. Fifth, the model explains 52.4% of the variance in academic readiness, indicating good explanatory power.

These results lead to three main conclusions. *Conclusion 1:* In the context of eastern Indonesia, digital literacy is a meaningful but incomplete driver of academic readiness; psychological (self-efficacy) and environmental (learning climate) factors are essential mediators. *Conclusion 2:* Universities should adopt a holistic strategy that simultaneously enhances students' digital skills, builds their digital confidence, and fosters a supportive digital learning environment. *Conclusion 3:* The partial mediation underscores that digital literacy also directly benefits academic readiness through mechanisms not captured here, warranting further investigation.

Practically, this study provides evidence-based guidance for lecturers, curriculum designers, and policymakers at UNM and similar institutions: invest not only in infrastructure and training but also in the social-cognitive processes that translate skills into readiness. Theoretically, the study advances digital literacy research by integrating personal and environmental mediators within a single empirical model tested in an under-researched geographical context.

Future research should employ longitudinal designs, objective measures, and cross-regional comparisons to validate and extend these findings. Despite its limitations, this study contributes a robust empirical foundation for understanding how digital literacy can be leveraged to enhance academic readiness in resource-constrained, digitally emerging higher education settings.

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