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Abstract

Background The increasing emphasis on digital-age competencies in secondary education further supports the notion that students' digital literacy statistically predicts argumentative writing skills. However, it is unclear whether digital literacy directly shapes writing readiness or does so through cognitive mechanisms such as critical thinking and cognitive load, particularly among high school students in Global South countries.

Objective This study examines a moderated-mediation model of self-reported argumentative writing readiness, in which critical thinking mediates the relationship between digital literacy and students' self-reported readiness to write argumentative texts among high school students in Indonesia, while cognitive load is tested as a boundary condition that moderates the strength of the critical thinking to writing readiness relationship.

Methods This study applied a cross-sectional survey design with a purposive sample of 513 high school students from 12 districts/cities in South Sulawesi, Indonesia. Data analysis was carried out using partial least squares structural equation modeling (PLS-SEM) with bootstrapping, with a significance threshold of 0.05.

Results The results showed that digital literacy played a significant role in predicting critical thinking ($\beta = 0.736$; $p < 0.001$), and, in turn, critical thinking significantly predicted argumentative writing readiness ($\beta = 0.656$; $p < 0.001$). The indirect pathway from digital literacy to writing readiness via critical thinking was also significant ($\beta = 0.482$; $p < 0.001$). In contrast, cognitive load did not show a significant relationship with writing readiness ($\beta = –0.031$; $p = 0.579$), even though it was positively predicted by both digital literacy and critical thinking.

Conclusion: These findings suggest that critical thinking is the main mechanism that fully mediates the relationship between digital literacy and argumentative writing readiness, and interestingly, this mechanism actually strengthens, not weakens, when the cognitive load is at a higher level. weakens, when the cognitive load is at a higher level. Implicitly, digital skill training alone is not enough to improve students' writing readiness, unless accompanied by explicit critical thinking instruction. On the other hand, cognitively demanding writing tasks do not always need to be minimized, as long as students have critical thinking skills that let them turn that cognitive engagement into productive reasoning.

Keyword: Digital literacy, Critical thinking, Cognitive load, Argumentative writing readiness, PLS-SEM

1. Introduction

Argumentative writing is considered the highest literacy skill because it requires students to evaluate evidence, anticipate counterarguments, and build logical, coherent claims (Bidang [1]). In line with a global curriculum that emphasises 21st-century competence, critical thinking skills and digital literacy are positioned as the two main pillars for producing evidence-based writing [2]. However, students' actual readiness to write arguments has not been explained by the theoretical path connecting these competencies, especially outside the context of high school education.

The foundations of writing readiness are often linked to digital literacy, assuming that the ability to find, assess, and synthesize information online naturally contributes to stronger arguments [3]. Empirical evidence also strengthens this assumption. Even for prospective teachers in Indonesia, digital literacy is still understood as limited to the technical ability to use online tools, while the construct's critical-thinking dimension is consistently the weakest aspect. [4]. Similar findings emerged in EFL students in Indonesia, where digital literacy was significantly related to research competence, but not to critical thinking skills, so the author concluded that digital literacy alone is not enough to encourage the improvement of critical thinking [5]. In line with this, a recent qualitative study of high school students in Indonesia found that new digital tools support critical thinking skills when students actively evaluate the reliability of the sources they use, rather than simply the results of using digital tools themsel [6]. Overall, the evidence indicates that digital literacy serves more as a supporting resource than as the main determinant of writing readiness. The effect is only seen if digital literacy is accompanied by serious critical involvement from its users

In contrast to digital literacy, critical thinking shows a more consistent and direct empirical relationship with argumentative writing performance in a variety of contexts. A strong positive correlation between critical thinking and argumentative writing skills was found in engineering students in Morocco [7], and Indonesian students [8]. Meanwhile, a study of Grade 12 students in China found that the subdimensions of critical thinking disposition are cognitive maturity, truth-seeking, analyticality, and fairness significantly predict argumentative writing skills [9]. This pattern is also reinforced by a number of intervention studies: explicit teaching of critical thinking, either through metacognitive strategy training [10], Socratic Question Framework [11], as well as a structured critical thinking curriculum [12], proven to repeatedly improve students' argumentative writing results. However, one question left unanswered by this series of studies is the causal sequence between digital literacy and critical thinking itself: whether digital literacy serves as a predictor equivalent to critical thinking in influencing writing outcomes, or whether its influence is fully mediated by critical thinking. These differences have direct implications for how the writing curriculum should set teaching priorities.

Another complexity arises from cognitive load. According to the Cognitive Load Theory, human working memory has a limited capacity. If the demands of a task exceed this capacity, performance in the high-level thinking process, including the evaluative reasoning needed in writing arguments, can be impaired [13], [14]. Writing itself can serve as a strategy to shift cognitive load, thereby easing working memory[15]. For example, writing collaboratively has been proven to reduce cognitive burden while improving the quality of writing [16]. Even so, there is no empirical certainty about whether cognitive load directly hinders writing outcomes or acts as a conditional factor that affects the strength of relationships among other

variables. A 2026 study of college students in Indonesia found that cognitive load did not significantly moderate the relationship between metacognition and critical thinking at the dispositional level, but the study authors proposed that this effect of moderation is likely to be more easily detected in the context of performative and specific tasks, just as in the context of argumentative writing discussed here than in general dispositional measurements [17]. This proposal is supported by another mediated study on university students, which found that critical thinking significantly strengthens the relationship between generative AI use patterns and deep learning, particularly through its interaction with cognitive load (Khoo et al., 2026). These findings indicate that critical thinking and cognitive load are likely to shape learning outcomes together through conditional pathways, rather than through simple, summative direct effects. In other words, these diverse results suggest that the functional role of cognitive load, whether as an inhibitor, as a moderator, or even having no effect at all, is likely to depend on the respective task and context, and has so far not been tested specifically in the realm of argumentative writing readiness.

There are three gaps that can be identified from this literature. First, although there is quite consistent evidence that digital literacy alone is not reliable as a predictor of critical thinking [5] As well as the results of writing more broadly, there has been no study that has formally tested critical thinking as a mediation mechanism that channels the influence of digital literacy on the readiness of argumentative writing, for example through structural modeling and effect decomposition approaches. Second, although initial theoretical and empirical findings support the conjecture that cognitive load plays a role more as a conditional factor than as a direct determinant of writing outcomes [17], None of the studies have specifically tested cognitive load as a moderator in the path from critical thinking to writing skills. Third, this combination of cognitive and digital constructs has been almost entirely studied among students and prospective teachers in previous studies [4], [5], [6]. As a result, middle school students who are developing basic argumentative skills while navigating the ever-evolving digital learning environment remain underrepresented in the existing evidence base.

This study attempts to fill these three gaps by testing a moderated mediation model in high school students: critical thinking is positioned as a mediator in the relationship between digital literacy and argumentative writing readiness, while cognitive load is positioned as a moderator that influences the strength of the pathway from critical thinking to writing readiness. Through this approach, this study is expected to make three contributions: first, empirical evidence regarding the causal sequence between digital and cognitive competencies in writing pedagogy; second, clarity regarding the conditional role of cognitive load on argumentation-related outcomes; and third, the expansion of the evidence base into the context of secondary education in Global South countries, which have been underrepresented in the literature on writing readiness in the digital age.

1.1 Research Questions and Hypotheses

Building on the gaps identified above, this study addresses four research questions:

1. Does digital literacy significantly predict critical thinking among senior high school students? (RQ1)

2. Does critical thinking significantly predict argumentative writing readiness? (RQ2)
3. Does critical thinking mediate the relationship between digital literacy and argumentative writing readiness, such that digital literacy's effect operates indirectly rather than directly? (RQ3)
4. Does cognitive load moderate the strength of the relationship between critical thinking and argumentative writing readiness? (RQ4)

Correspondingly, five hypotheses are advanced. Consistent with the indirect-only mediation testing logic recommended by [18], both the indirect pathway and its competing direct pathway are hypothesized explicitly, allowing the subsequent structural test to establish whether mediation is full or partial rather than assuming it a priori.

1. H1: Digital literacy has a significant positive effect on critical thinking.
2. H2: Critical thinking has a significant positive effect on argumentative writing readiness.
3. H3: Digital literacy has a significant positive direct effect on argumentative writing readiness.
4. H4: Critical thinking mediates the relationship between digital literacy and argumentative writing readiness.
5. H5: Cognitive load moderates the relationship between critical thinking and argumentative writing readiness, such that the strength of this relationship varies with the level of cognitive load experienced during the writing task.

H1 and H2 are grounded in the consistent empirical convergence reviewed in Section 2.1-2.2, where digital literacy's effects on academic outcomes are repeatedly transmitted through more proximal cognitive mechanisms [19], [20] and critical thinking shows a direct, mechanistic relationship with writing and literacy outcomes [7], [21]. H3 and H4 jointly test whether digital literacy's influence on readiness is direct, indirect, or both. H5 follows from Cognitive Load Theory's prediction that working-memory demands condition higher-order cognitive performance [22] and from direct empirical evidence that cognitive load's relevance to writing is task-conditional rather than uniformly direct [23], [24], combined with methodological precedent for testing such conditioning effects within a PLS-SEM moderated mediation framework [25], [26].

2. Literature Review

Digital literacy is viewed as a multidimensional construct encompassing technical, cognitive, and social competencies, rather than a single skill [27], [28]. This construct also rarely predicts advanced academic outcomes directly; both its influence on the intention to adopt technology and on the productive use of generative AI in academic contexts have been shown to work through more contextual mechanisms, rather than independently [19], [29]. This is in line with the Digital Literacy Scale for Academic Writing that has been validated in prospective teachers in Indonesia, where critical thinking is one of the shaping factors, indicating that the influence of digital literacy is likely to flow towards critical thinking, rather than running as two independent predictors in parallel [20]. Critical thinking itself, conventionally divided into skill- and disposition-based components

and now supported by validated instruments for high school students [30], [31], has been shown to predict academic performance beyond general cognitive abilities [32]. In fact, critical thinking shows one of the most consistent direct relationships with argumentative writing performance in this literature, including its mediating role that is structurally comparable to the model hypothesized in this study [21].

Cognitive Load Theory states that working memory has a limited capacity and that excessive extrinsic load can interfere with the schema-construction process that is precisely needed for complex cognitive performance [22], [33], [34]. This is supported by a six-dimensional Cognitive Load Scale that has been validated for the context of argumentative writing in English as a second language [24], as well as evidence that working memory capacity predicts argumentative writing performance but not narrative writing performance in a second language [23] both indicate that cognitive load is more accurately understood as a conditional factor rather than a uniform inhibitor. PLS-SEM-based moderation designs to test such conditional effects, e.g., gender as a moderator of the critical thinking disposition pathway, are methodologically well established [25] [26], although cognitive load itself has never been tested in comparable structural configurations. On the other hand, writing process theory distinguishes between basic cognitive readiness to construct arguments and the quality of the resulting text [35], [36]. Current process models are still incapable of explaining the dimensions of pre-writing preparation that should reflect the readiness of argumentative writing itself — in contrast to the post-hoc essay quality assessment approach that has dominated digital literacy and critical thinking research [7], [9], [37]

3. Methods

To test the moderated mediation model, this study was designed with a quantitative approach that is both cross-cutting and explanative. The model estimation was conducted using Partial Least Squares Structural Equation Modeling (PLS-SEM) in SmartPLS 4. The choice of PLS-SEM, instead of covariance-based SEM, was based on two main considerations. First, this technique is more suitable for prediction-oriented composite-based models, especially when the measurement structure involves relatively complex moderated mediation [38]. Second, a number of methodologists now also tend to recommend a composite-based approach rather than regression-based methods such as macro PROCESS, especially to test mediation and conditional process models such as those used in this study [39].

The population of this study was high school students in South Sulawesi, Indonesia. Using purposive sampling, in which both schools and students are deliberately selected by the researcher rather than through probability-based random sampling, 518 responses were obtained in the early stages of data collection. After excluding the five respondents who did not include regional (district/city) information, the final sample size was n = 513. This number exceeded the commonly recommended minimum for PLS-SEM based on the 10-times rule and was also comparable to the sample size reported in similar PLS-SEM studies on digital literacy and critical thinking constructs, e.g., n=150 and n=258 in [40], [41]

It should be noted that, since purposive sampling is a non-probability sampling technique, statistical generalisations of this study's findings to the population of high school students in Indonesia as a whole should be made with caution. These limitations are explicitly discussed in the Research Limitations section. In addition,

the final sample is grouped by region (Wilayah_Group) into two clusters: urban clusters (Makassar, Gowa, and Maros; n = 229, 44.6%) and rural clusters (other districts/cities; n = 284, 55.4%). This grouping opens opportunities for multi-group analysis in future studies, although in this study the main hypothesis test is still conducted on the combined sample

All constructs in this study were measured reflexively using Likert-scale items (1 = strongly disagree to 5 = strongly agree), with items in the Cognitive Load construct reverse-scored so that higher values consistently reflect higher levels of the construct. The research instruments were developed through a combined approach. Most of the item redactions were compiled by the researcher themselves based on the theoretical dimensions of each construct: Digital Literacy refers to a tripartite framework [42], Critical Thinking refers to an attitude-skill model [30], while Cognitive Load refers to the intrinsic-extrinsic-germane typology of Sweller [33], [34]. In addition, the formulation of the item also refers to a number of scales that have recently been validated in the literature, including the Digital Literacy Scale for Academic Writing (Nabhan & Habók, 2025) and the Critical Thinking Attitude Scale for high school student [31].

The final instrument used in the analysis consisted of 21 items spread across four constructs and is reported in Table 1.

Table 1: Construct item

Construct	**Items Retained**	**Notes**
Digital Literacy (DL)	6 (DL1-DL6)	All items retained; loadings 0.63-0.85
Critical Thinking (CT)	6 (CT1-CT6)	All items retained; loadings 0.66-0.79
Cognitive Load (CL)	4 (CL1, CL2, CL3, CL6)	CL4 and CL5 dropped in earlier psychometric refinement
Argumentative Writing Readiness (AWR)	5 (AWR1, AWR2, AWR4, AWR6, AWR7)	AWR3 and AWR5 excluded at data-consolidation stage

Argumentative writing readiness was operationalized as students' self-reported perception of their preparedness to construct argumentative texts, encompassing their perceived ability to formulate claims, evaluate evidence, and anticipate counterarguments, rather than as an evaluator-scored assessment of actual writing performance or essay quality.This distinction is consistent with the study's conceptual framing of readiness as a pre-writing cognitive state, as opposed to the post hoc essay quality assessment approach that has dominated prior digital literacy and critical thinking research [7], [9], [37].

Data collection was carried out through a self-administered online questionnaire distributed via Google Forms over a period of two months, namely December 2025 to January 2026. Participant recruitment relied more on school-based referral channels than direct contact from researchers: questionnaire links were distributed through class WhatsApp groups and teacher community WhatsApp groups, which

were then forwarded to students on the recommendation of their respective subject teachers or homeroom teachers. Through the distribution strategy, 518 complete responses were collected. After the data cleansing process, in which 5 responses lacking regional (district/city) information were excluded, 513 responses were retained for the final analysis. Given that the recruitment process is highly dependent on teacher referrals and does not involve the withdrawal of random samples or being completely controlled by the researcher, the samples in this study should be understood as purposive and convenience-based, in line with the sampling techniques described earlier.

Data analysis was carried out using a two-stage PLS-SEM procedure, as described by Sarstedt et al. [38]. In the first stage, namely the evaluation of the measurement model (outer model), the reliability of the indicators, the reliability of internal consistency (Cronbach's alpha and composite reliability with a value of ≥ 0.70), convergent validity (AVE ≥ 0.50), and discriminant validity were assessed through the Fornell-Larcker criteria and the HTMT value below 0.90. In the second stage, namely the evaluation of the structural model (inner model), the determination coefficient (R^2), effect size (f^2), the significance of the path through the bootstrapping procedure with 5,000 resamples ($T > 1.96$; $p < 0.05$), and the fit of the model measured through the SRMR value (< 0.08) were assessed. The moderated mediation hypothesis (H4 and H5) was tested using a two-stage approach to the effects of interaction in composite-based SEM, as recommended by Henseler and Chin [43] and Hayes [44]. The effect of mediation was evaluated using specific indirect effects with bootstrap confidence intervals, which were then interpreted according to the typology of full mediation, partial mediation, or direct effects, following Zhao et al. [18] no longer referring to the cause-and-effect approach of Baron and Kenny, which is now considered to be no longer relevant.

Throughout the research process, ethical principles are applied consistently. Each participant is first given an adequate explanation of the purpose of the research, the procedures to be followed, and their rights as a participant. Integrated consent in the google form (informed consent) is obtained from all respondents before the data collection process begins. The participants are also assured that their answers will be kept confidential and anonymous, and that their participation is completely voluntary. In addition, they are informed that they have the right to withdraw from the research at any time without causing adverse consequences. All data collected is stored securely and is only used for academic and research purposes.

5. Result

5.1 Data Screaning and Respondent Profile

In the initial stage, the questionnaire collected 518 responses. However, in the data preparation process, five responses had to be issued because the respondents did not adequately complete the geographic information so that they could not be classified into the regional categories that had been established in the analysis dataset. It should be emphasized that this data expenditure was solely based on the completeness of the demographic information, not due to changes in the respondent's construct score, a practice that is in line with the guidelines for handling missing data in survey studies, where listwise deletion of the proportion of data lost is relatively small and unsystematic as long as it does not distort the substantive scores of the research variables [45], [46]. Thus, the final sample retained for analysis using PLS-SEM totalled 513 complete cases, and all results

reported in the next section, including measurement models, structural models, bootstrapping, and out-of-sample predictions, were based on this analytical sample.

In terms of regional distribution, the study respondents came from 12 cities and districts in South Sulawesi, although the distribution was uneven. Most of the respondents came from six regions, namely Makassar, Pinrang, Jeneponto, Bulukumba, Maros, and Gowa, which together dominated the composition of the sample. The other respondents were spread across Pangkep, Barru, Luwu, Selayar Islands, Wajo, and Bantaeng. This distribution shows that the research sample does cover the geographical diversity of the South Sulawesi region, although it cannot be interpreted as a proportionate representation of the overall population of high school students in the province, a limitation that is prevalent in non-probability samples, since the findings of both purposive and convenience samples can only be generalized to the (sub)populations where the samples were taken, not to the population as a whole [47], [48], especially considering that empirically based samples tend to be less representative of the general population in their area [49].

Table 2. Data Screening and Demographic Profile of the Initial Respondent Poo

Screening Stage/region	Frequency	Percentage
Initial responses	**518**	**100.00**
Excluded because geographical information was unavailable	5	0.97
Final analytical sample	**513**	**99.03**
Geographical distribution of the analytical sample		
Makassar	106	20.66
Pinrang	89	17.35
Jeneponto	73	14.23
Bulukumba	70	13.65
Maros	69	13.45
Gowa	54	10.53
Pangkep	14	2.73
Barru	13	2.53
Luwu	11	2.14
Selayar Islands	8	1.56
Wajo	5	0.97
Bantaeng	1	0.19
Total analytical sample	**513**	**100.00**

The data screening procedure managed to retain 99.03% of the total responses initially collected, indicating a very minimal sample loss rate, a proportion that is well below the average of data loss in survey studies in general, which, according to some methodological studies, is around 12% of the total sample [50]. Thus, the final dataset retained almost all of the initial respondents, while ensuring that each case analysed had a complete geographical classification. However, the concentration of respondents centred on six cities or districts suggests that the findings of this study should be generalised to the student population in South Sulawesi carefully, given that this kind of non-probability sample can basically only

be generalised to the (sub)population where the sample was taken, not to the population as a whole.

5.2 Measurement Model Assessment

Before testing the hypothesised structural relationships, reflective measurement models are evaluated to ensure that each indicator measures its respective construct with adequate reliability and validity [51], [52]. This evaluation includes four main aspects: indicator reliability through outer loadings; internal consistency through Cronbach's alpha (CA) and composite reliability (CR); convergent validity through average variance extracted (AVE); and collinearity between indicators through variance inflation factor (VIF) [53], [54]. Referring to the well-established PLS-SEM guidelines, an outer loadings value of around 0.708 or higher is considered ideal, while indicators with loadings between 0.40 and 0.70 are not necessarily deleted, but rather evaluated first based on their theoretical relevance and their impact on the reliability of the construct and convergent validity [51]. Values of CA and CR above 0.70 are considered adequate, while an AVE of at least 0.50 indicates that a construct is capable of explaining at least half of the variance of its indicators [51], [55]. A VIF value below 3.00 is interpreted as not indicating problematic collinearity between indicators [56]. The results of the evaluation of this measurement model are presented in Table 3.

Table 3. Reflective Measurement-Model Assessmentle

Variable	Code	Loading Factor	CA	CR	AVE	VIF
Digital Literacy	DL1	0,736	0.802	0.859	0.505	1.523
	DL2	0,,631				1.336
	DL3	0,709				1.447
	DL4	0,798				1.773
	DL5	0,707				1.476
	DL6	0,669				1.380
Critical Thinking	CT1	0,745	0.826	0.873	0.536	1.651
	CT2	0,721				1.564
	CT3	0,792				1.829
	CT4	0,664				1.407
	CT5	0,725				1.521
	CT6	0,739				1.568
Cognitive Load	CL1	0,852	0.717	0.816	0.529	1.388
	CL2	0,661				1.347
	CL3	0,670				1.391
	CL6	0,709				1.311
Arumentative Writing Readiness	AWR1	0,647	0.781	0.850	0.533	1.332
	AWR2	0,775				1.553
	AWR4	0,759				1.553
	AWR6	0,741				1.562
	AWR7	0,722				1.433

Before testing the hypothetical structural relationships, the reflective measurement model is first evaluated to ensure that each indicator measures its respective construct with adequate reliability and validity. This evaluation includes four aspects: the reliability of the indicators through outer loadings, internal consistency through Cronbach's alpha (CA) and composite reliability (CR), convergent validity through the average variance extracted (AVE), and the

corlinearity between indicators through the variance inflation factor (VIF) which is a commonly recommended stage in the evaluation procedure of the PLS-SEM reflective measurement model [53], [54], [57].

Referring to the well-established PLS-SEM guidelines, an outer loadings value of around 0.708 or higher is considered ideal, while indicators with loadings between 0.40 and 0.70 are not necessarily removed, but rather evaluated based on their theoretical relevance and impact on construct reliability and convergent validity [51]. A CA and CR value above 0.70 is considered adequate, while an AVE of at least 0.50 indicates that a construct explains at least half the variance of its indicators [55]; These threshold values are also consistent with the finding that PLS-SEM tends to produce higher AVE and CR values than the CB-SEM approach, so it is important to interpret it in the context of the method [56]. A VIF below 3.00 is interpreted as indicating no problematic collinearity between indicators. Therefore, Section 4.3 examines whether digital literacy, critical thinking, cognitive load, and argumentative writing readiness can be empirically distinguished from one another using the Fornell–Larcker criteria and the heterotrait-monotrait ratio (HTMT).

4.3 Discriminant Validity

Table 4. Fornell- Larcker Criterion and Heterotrait-Monotrait Ratios

Variable	DL	CT	CL	AWR
DL	**0.710**	0.899	0.542	0.618
CT	0.736	**0.732**	0.611	0.790
CL	0.451	0.515	**0.727**	0.355
AWR	0.494	0.640	0.307	**0.730**

Table 4 presents the results of the discriminant validity test through the Fornell–Larcker criteria (diagonal value: square root of AVE; value below diagonal: correlation between constructs) and HTMT (value above diagonal). The Fornell–Larcker criteria are met for most constructs: the square root of AVE for critical thinking (0.732), cognitive load (0.727), and argumentative writing readiness (0.730) each outweighs their correlation with other constructs, indicating that all three explain greater variance in their own indicators than in other constructs. Exceptions occurred in the digital literacy and critical thinking pairs, where the correlation of the two (0.736) slightly exceeded the square root of AVE (0.710 and 0.732), respectively, so this criterion was not fully met, indicating a considerable conceptual and empirical proximity between the ability to evaluate digital information and the critical reasoning process, although the difference was still relatively small. The HTMT results reinforce this picture: five of the six construct pairs were in the range of 0.355–0.790, well below the conservative threshold of 0.85 and the liberal threshold of 0.90, while the digital-literate–critical thinking pair recorded an HTMT of 0.899, below 0.90 but above 0.85, making it borderline. This suggests that the two constructs capture closely related cognitive activities, although conceptually they remain distinct: digital literacy is concerned with locating, verifying, and using evidence from digital information, while critical thinking is concerned with evaluating reasons, identifying weaknesses in arguments, and drawing conclusions.

Overall, discriminant validity was well supported in five of the six construct pairs, while the evidence for the digital–critical thinking pair was relatively weaker, as the Fornell–Larcker criteria were not fully met and the HTMT value was close to the 0.90 threshold. Thus, the measurement model generally has acceptable

discriminant validity, although it is not yet entirely established for the construct pair. The final conclusion regarding this pair relies on bootstrap-based HTMT inference, where discriminant validity can still be maintained as long as the upper limit of its 95% bootstrap confidence interval is below 1.00, an inferential approach that is specifically recommended as a more reliable criterion than Fornell–Larcker as well as cross-loading checks in detecting the absence of discriminant validity [58]. This conclusion is also consistent with Monte Carlo simulations, which show that HTMT criteria with a threshold of 0.85 provide the best balance between detection sensitivity and positive error rate compared with other conventional methods [59], [60]. In other words, discriminant validity is supported for most construct pairs in this model, although the difference between digital literacy and critical thinking remains at a borderline position and requires further confirmation through bootstrap-based HTMT inference, a procedure that has been widely applied and validated in various contemporary PLS-SEM studies [61], [62]

5.4 Structural Model and Hypothesis Testing

Following confirmation of the measurement model, the structural model was assessed for explanatory power and additional model-fit diagnostics. Explanatory power was evaluated using the coefficient of determination (R^2) and adjusted R^2, whereas SRMR, d_{ULS}, d_G, chi-square, and NFI were examined as supplementary indicators of model fit. The results are presented in Table 4.

Table 5. Explanatory Power and Model-Fit Diagnostics

Panel/statistic	**Construct or model**	**Value**	**Adjusted value**	**Interpretation**
Panel A: Explanatory power				
R^2	Critical Thinking	.541	.540	Moderate explanatory power
R^2	Cognitive Load	.277	.274	Weak-to-moderate explanatory power
R^2	Argumentative Writing Readiness	.410	.407	Moderate explanatory power
Panel B: Model-fit diagnostics		**Saturated model**	**Estimated model**	
SRMR	Overall model	.074	.075	Acceptable; estimated SRMR < .080
d_{ULS}	Overall model	1.279	1.282	Reported descriptively
d_G	Overall model	.284	.284	Reported descriptively
Chi-square	Overall model	827.171	827.233	Reported descriptively

NFI	Overall model	.794	.794	Supplementary fiinformation

Among the three endogenous constructs, critical thinking showed the highest clarity in this model: digital literacy explained 54.1% of the variance ($R^2 = 0.541$), with a very small difference to R^2 adjusted (0.540) indicating that the results of this explanation were not exaggerated by the complexity of the model [52]. Meanwhile, digital literacy and critical thinking together explained only 27.7% of the variance in cognitive load, suggesting that both predictors captured some of the cognitive demands felt by students, although the remaining portion indicated the possibility of other factors outside the model such as task complexity, prior writing knowledge, instructional support, working memory capacity, or familiarity with argumentative writing that also affected cognitive load. The readiness of argumentative writing was explained by 41.0% by critical thinking and cognitive load together, which was classified as a clearly medium and substantively meaningful force; however, since the value of R^2 alone could not indicate which predictor contributed more, the difference in contribution was further traced through the path coefficient and effect size f^2, which confirmed that critical thinking contributed much more than cognitive load [63].

In terms of model suitability, the SRMR values in the saturated and estimated models were 0.074 and 0.075, respectively, with the estimated model values remaining below the general guideline of 0.080 indicating that the difference between the model's implied correlation structure and the empirical correlation structure is within an acceptable range, while the small difference between the two SRMR values suggests that the implementation of the proposed structural relationship leaves no meaningful residual. The d_ULS, d_G, chi-square, and NFI values remained descriptively reported for transparency, but were not treated as stand-alone model acceptance criteria: the d_ULS and d_G values in particular could only be concluded for match after comparison with the HI95/HI99 reference values of the complete bootstrapping results, while the NFI value of 0.794 could not be interpreted based solely on the CB-SEM convention, given that this analysis was more explanation-oriented and predictive [51], [64]. Overall, these R^2 results and additional match statistics suggest that the model has adequate explanatory performance, particularly for critical thinking and argumentative writing readiness with no indication of substantial residual error based on SRMR, thus providing a sufficient basis to proceed to the assessment of specific structural pathways and indirect effects through bootstrap procedures.

5.5. Predictive Assessment

The predictive performance of the model outside the sample was evaluated using the PLSpredict procedure, as recommended by Shmueli et al. [65], as a holdout-sample-based approach to assess the predictive ability of the PLS-SEM model beyond its explanatory strength. At the construct level, positive Q^2predict values were obtained for critical thinking (0.535), cognitive load (0.194), and argumentative writing readiness (0.237), as well as across all 15 indicators (ranging from 0.034 for CL3 to 0.329 for CT6) indicating that the model exceeded the naïve mean benchmark for each endogenous construct and its indicators, in line with the criteria set by Hair et al. [51]. However, the magnitude of predictive relevance varied between constructs: critical thinking showed the highest and most consistent values (0.204–0.329 at the indicator level), followed by lower but still

positive argumentative writing readiness, while cognitive burden showed the weakest and most varied predictive relevance, especially on the CL2, CL3, and CL6 indicators.

When compared to the linear model (LM) benchmark using RMSE, PLS-SEM outperformed on eight of the 15 indicators, was equivalent on one indicator, and underperformed on six others, with generally small differences (0.002–0.012), except for CT4, which was even larger (0.025). Similar patterns emerge constructively after construct: PLS-SEM performance was low-to-medium for critical thinking, medium for cognitive load (though inconsistent between RMSE and MAE), and weakest for argumentative writing readiness, which was not even superior to LM on MAE. Overall, these findings confirm that the model has predictive relevance beyond the sample but does not consistently outperform the simple linear model in low-to-moderate-predictive-strength patterns, which, as emphasised by Shmueli et al. [65] and supported by the methodological review of Sharma et al. [66], remind that the apparent power of variance in the sample does not necessarily guarantee the predictive superiority outside the sample a conceptual difference that is important in interpreting the practical usefulness of the PLS-SEM model. The model showed positive predictive relevance outside the sample, although its predictive advantage over linear benchmarks was low to moderate, and varied among the endogenous constructs tested.

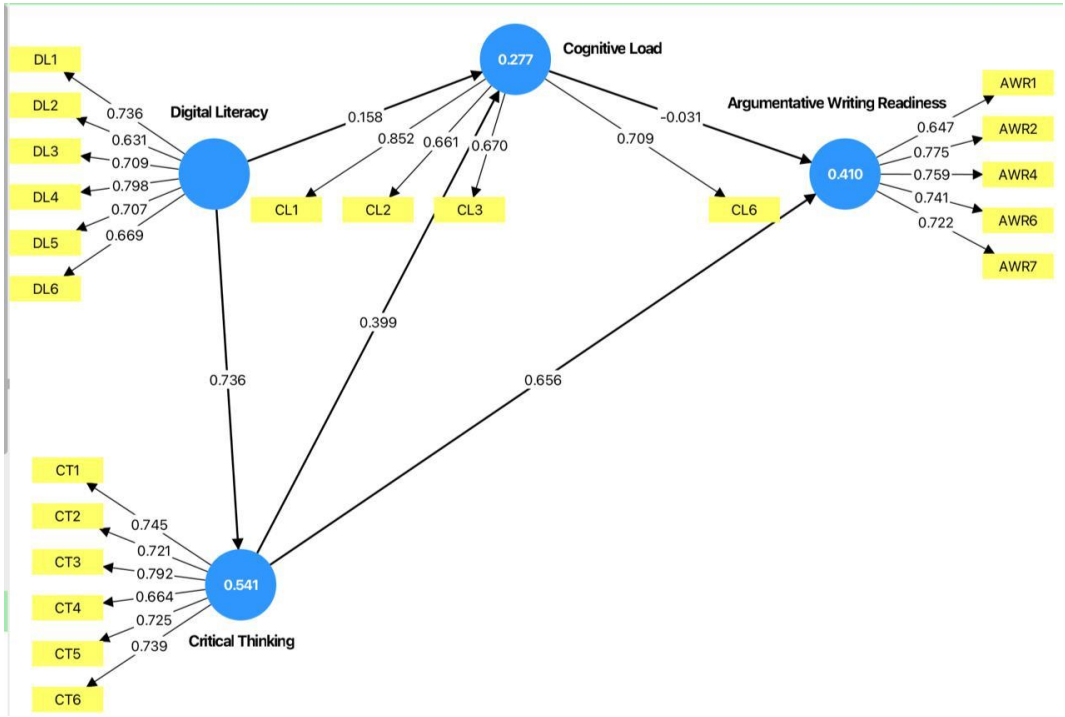
Table 6. PLSpredict results

Target Indikator	Q^2_{predict}	PLS-SEM RMS	LM RMSE	ΔRMSE	PLS-SEM MAE	LM MAE	RMSE comparison
CT1	0.310	0.736	0.736	0.000	0.510	0.507	Equal
CT2	0.279	0.755	0.757	−0.002	0.553	0.557	PLS-SEM better
CT3	0.315	0.711	0.717	−0.006	0.531	0.533	PLS-SEM better
CT4	0.204	0.805	0.780	0.025	0.627	0.593	LM better
CT5	0.272	0.737	0.743	−0.006	0.506	0.513	PLS-SEM better
CT6	0.329	0.742	0.741	0.001	0.528	0.524	LM marginally better
CL1	0.210	0.794	0.793	0.001	0.552	0.549	LM marginally better
CL2	0.052	1.023	1.026	−.003	0.790	0.787	PLS-SEM better by RMSE
CL3	0.034	1.000	1.003	−.003	0.800	0.800	PLS-SEM better by RMSE
CL6	0.075	.993	1.005	−.012	0.691	0.697	PLS-SEM better
AWR1	0.108	0.828	0.830	−0.002	0.634	0.631	PLS-SEM better by RMSE
AWR2	0.170	0.774	0.766	0.008	0.621	0.599	LM better

AWR4	0.122	0.781	0.786	−0.005	0.605	0.605	PLS-SEM better by RMSE
AWR6	0.164	0.766	0.764	0.002	0.586	0.580	LM marginally better
AWR7	0.056	0.884	0.872	0.012	0.693	0.682	LM better

Figure 1 summarises the results of estimating the measurement and overall structural models. The indicator content ranged from 0.631 to 0.852, while at the structural level, a strong positive relationship was observed between digital literacy and critical thinking (β = 0.736), and between critical thinking and argumentative writing readiness (β = 0.656). Digital literacy (β = 0.158) and critical thinking (β = 0.399) also showed positive relationships with cognitive load, whereas the path from cognitive load to argumentative writing readiness was very small and negative (β = –0.031). This model explained 54.1% of the variance in critical thinking, 27.7% of the variance in cognitive load, and 41.0% of the variance in argumentative writing readiness. This pattern of results provides an early indication that critical thinking is not a cognitive burden but the main pathway linking digital literacy to argumentative writing readiness. The statistical significance of each of these relationships was further tested through a bootstrapping procedure.

Figure 1. PLS -SEM ALgirthm Result for the Proposes Structural Model



These empirical findings support the explanation of argumentative writing readiness through a thermomoderation mediation model. Digital literacy has been shown to have a strong and significant effect on critical thinking, which in turn

significantly predicts writing readiness; meanwhile, the direct pathway from digital literacy to writing readiness is insignificant, indicating full mediation through critical thinking. Cognitive load itself does not have a significant direct influence on writing readiness, but it significantly moderates the relationship between critical thinking and writing readiness, such that the strength of the relationship increases as cognitive load increases. This pattern suggests that cognitive load acts as a boundary condition, not as a stand-alone pathway or as a detrimental burden. Cognitive load does not directly drive writing readiness, but rather determines how strong critical thinking can be translated into readiness.

5. Discussion

5.1 Critical Thinking as a Connecting Path between Digital Literacy, Cognitive Load, and Argumentative Writing Readiness

The positive relationship between digital literacy and critical thinking in this study confirms that digital competence is not just a matter of operational skills. In an information-laden environment, students are required to sort out relevant sources, compare conflicting claims, recognize dubious information, and assess whether the available evidence is sufficient to support an argument—a process that requires evaluative assessment and reflective reasoning, rather than simply the mechanical operation of technology. This interpretation is in line with the findings of Lim et al. [67] shows that access to digital technology alone does not guarantee the development of meaningful digital competencies; its benefits are only realized when technology is integrated into instructional design, teacher engagement, and cognitively demanding learning tasks. The findings of this study expand on that argument by suggesting that critical thinking is most likely a cognitive process that bridges digital literacy with its academic value in other words, digital literacy is more precisely understood as an epistemic competence: digitally literate students are not only capable of finding information efficiently, but also better able to question the authenticity of sources, identify supporting evidence, distinguish fact from opinion, and compare alternative explanations, a crucial skill in argumentative writing because the credibility of a position depends on the quality of the evidence and the reasoning that supports it.

Correspondingly, critical thinking emerged as the cognitive construct that has the most influence on argumentative writing readiness—a finding that makes conceptual sense given that argumentative writing requires the writer to formulate defensible claims, select relevant evidence, consider alternative positions, establish logical connections, and anticipate possible rebuttals. Students who can evaluate information and examine assumptions tend to feel better prepared for the complex reasoning required in argumentative writing. Empirical support comes from Tsai [68], who shows that high school students' information-seeking strategies relate to the quality of claims, bases, assurances, and rebuttals in their argumentative essays. an important difference lies not in whether students seek information, but in how they utilize the search process to develop an argument. Lee and Lee [69] also assert that the development of argumentative writing requires a growth in alignment between the structural and rhetorical aspects of argumentation, while Kleemola et al. [70] treat critical thinking and written communication as closely interrelated academic competencies, especially during the student's transition to a more demanding educational context, a relevance that according to the study has been apparent since the high school level, when students are required to move from simply reproducing information to building and

maintaining independent positions. Thus, argumentative writing readiness should not be understood solely as confidence in the mechanics of language, but also reflects the availability of cognitive resources to determine what is worth arguing, why a claim can be defended, and how to connect evidence to conclusion, so critical thinking essentially serves as an intellectual architecture that allows students to turn information into argumentation.

The finding that cognitive load significantly moderates, rather than mediates, the relationship between critical-thinking and writing readiness refines our understanding of cognitive demand in this model. Cognitive load had no direct or mediated pathway to writing readiness, echoing Skulmowski and Xu's [71] which caution that elevated cognitive load in digital learning is not inherently detrimental but it conditioned the extent to which critical thinking translated into writing readiness. Notably, the moderation was reinforcing rather than buffering: students under higher cognitive load showed a *stronger* dependence of writing readiness on critical thinking, not a weaker one. This pattern is consistent with the possibility that the cognitive load measured here reflects germane, task-relevant effort [33],[34] rather than extraneous burden: for students experiencing greater cognitive demand during the writing task, well-developed critical-thinking skills become the decisive resource that determines whether that demand is converted into productive reasoning or into unproductive strain. Critical thinking, in other words, does not operate identically across all learners its practical value intensifies precisely when the writing task is more cognitively demanding.

A significant indirect pathway through critical thinking suggests that digital literacy is related to argumentative writing readiness primarily when accompanied by evaluative reasoning, rather than because the use of technology solely increases writing readiness. These findings reinforce the resource-based explanation: digital literacy provides access to information, while critical thinking determines how it is interpreted and integrated into arguments. Without this critical transformation, digital access may only expand information exposure, rather than support argumentative reasoning itself. Conversely, the insignificance of the indirect pathway through cognitive load confirms that cognitive load is not a mediator of the relationship between digital competence and writing readiness; it accompanies the learning process rather than serving as the primary bridge between them. Critical thinking, rather than cognitive load, is thus a more educationally meaningful pathway in this model. Since the structural model does not include a direct pathway from digital literacy to writing readiness, these findings should be interpreted as a significant, specific indirect relationship rather than as evidence of full or partial mediation. Further research needs to test alternative models that include such direct pathways before drawing stronger conclusions.

5.2 Predictive Meaning, Theoretical Implications, and Pedagogical Implications of the Model

If confirmed by PLSpredict's final analysis, the model's inconsistent performance compared to linear benchmarks would suggest that its predictive relevance outside the sample is useful but limited, especially for argumentative writing readiness—results that may also be influenced by writing motivation, metacognitive strategies, language competence, previous achievements, and genre knowledge [72], [73], [74]. Thus, the model is more appropriately used to explain the relative role of

critical thinking and cognitive load, rather than to generate precise individual predictions [75]. Theoretically, these findings make three contributions: digital literacy is placed as a multidimensional competency whose educational value only emerges when digital engagement enables high-level evaluation, rather than just technical access [76]; critical thinking is identified as the main mechanism linking digital competence with readiness to write argumentative in an information-laden environment [77]; and cognitive load is understood as a construct that can reflect productive reasoning efforts or process difficulties that can actually be avoided, so its interpretation needs to be tailored to its instructional sources and objectives [78]

Pedagogically, these findings suggest that schools should not equate digital literacy teaching with mere device operation or information search, but rather provide students with structured opportunities to assess the credibility of sources, verify information, and identify biases that should be integrated directly into argumentative writing teaching through activities such as lateral reading, claim-proof-reason mapping, and counter-argument analysis, in line with Tsai [68] finding that teaching information retrieval strategies supports argument development. Teachers also need to manage cognitive demands that can be avoided by breaking down complex writing tasks into more manageable stages (topic exploration, source evaluation, drafting, revision) with focused examples and feedback, while collaborative digital environments as shown by Ollesch et al. [79] on the benefits of cognitive and behavioral awareness tools, and Peng et al. [80] on the influence of group information types on online writing engagement need to be intentionally designed to support reasoning, feedback, and evaluation of evidence, rather than simply grouping students online.

6. Conclusion

This study set out to clarify how digital literacy, critical thinking, and cognitive load jointly shape senior high school students' readiness to write argumentative text, a question the literature had left unresolved by treating these constructs largely in isolation. The structural results converge on a resource-reasoning account: digital literacy functions as a distal, enabling resource whose association with writing readiness is realised almost entirely through critical thinking, while cognitive load, although elevated by both digital engagement and critical reasoning, does not itself emerge as a determinant of readiness within the sequential specification tested here. Critical thinking, rather than digital competence or cognitive burden, is therefore the proximal cognitive engine that converts digital-era access into the evaluative reasoning that argumentative writing demands.

These findings make three contributions. Theoretically, they refine how digital literacy should be positioned in models of writing readiness, not as a direct cognitive competency but as a resource that must be converted into critical reasoning before it carries explanatory weight, while leaving open, rather than foreclosing, the question of whether cognitive load operates as a conditional moderator once tested through a formal interaction term. Methodologically, the study demonstrates the value of decomposing direct and specific indirect pathways using PLS-SEM in a domain that prior research has largely examined with bivariate or correlational designs. In practice, the results indicate that digital skills training alone is unlikely to improve students' argumentative writing readiness unless it is paired with explicit critical-thinking instruction, an implication directly relevant to secondary-level literacy curricula in South Sulawesi and comparable Indonesian and Global South settings. Confirming the moderating role of cognitive load,

extending this design longitudinally, and testing the model across urban and rural subgroups remain the most immediate priorities for future research building on these findings.

6.1 Implications

In practice, these findings suggest that writing curricula that aim to harness students' digital fluency will not yield much if digital tools training is treated as a stand-alone program. Because the benefits of digital literacy on writing readiness are only realized through critical thinking, learning resources should be directed to explicitly reinforce these skills for example, through resource evaluation tasks, structured argument analysis exercises, and guided reasoning activities and integrated directly into digital-based learning activities, rather than just standalone digital skills training. Theoretically, this study also strengthens the view that digital literacy is more appropriately positioned as a distal supporting resource, rather than as a cognitive competency that directly determines writing outcomes. This implication also opens space for future research on argumentative writing to more carefully distinguish between the role of cognitive load as a direct predictor and as a conditional moderator.

6.2 Limitations

A number of limitations need to be considered in interpreting these findings. First, because recruitment is purposive and relies on teacher referrals across districts/cities that are geographically unevenly distributed, the generalization of results to the population of high school students in Indonesia more broadly needs to be done carefully, as explained in the Results section. Second, the cross-sectional design does not allow for the withdrawal of strong causal claims, even if the mediation framework has been applied; in addition, all constructs are measured through self-reports, thus opening the possibility that general method bias influences the observed relationships. Third, the borderline distinction between digital literacy and critical thinking, as noted at the evaluation stage of the measurement model, indicates that these two constructs should be understood as closely related but conceptually distinct capacities, rather than as two completely independent constructs. Last but not least, the structural results reported here illustrate only the contribution of cognitive load through direct and sequential pathways. Formal interaction tests are actually required to test cognitive load as a moderator of the relationship between critical thinking and writing readiness as formulated in H5 and described in the Methods section not yet reflected in the reported structural outputs, so claims regarding the effect of moderation still need to be further confirmed before they can be considered definitive.

6.3 Future Research

Further research should prioritize direct estimation of the terms of cognitive load interactions in the critical thinking–writing readiness pathway to explicitly test the moderation hypothesis, rather than relying on sequential specification as in this study. Longitudinal or quasi-experimental designs would be helpful in establishing the cause-and-effect sequence of the digital literacy pathway to critical thinking, while addressing the ambiguity of the direction of causality that cannot be resolved

through cross-sectional designs. In addition, more disaggregated measurement of cognitive load by separating the intrinsic, extrinsic, and germane components would allow for more precise testing of which, if any, types of load actually affect the relationship between critical thinking and writing readiness. Finally, cross-group analysis of the urban and rural areas represented in this sample after formally testing the measurement invariance will help clarify whether the resource-reasoning pathways identified in this study are consistently applicable in the midst of unequal digital infrastructure conditions, as is common at the secondary education level in Global South countries [81].

Declaration

Ethics approval and Consent to Participate

Ethics approval. The study received ethical approval from the Ethics Committee of the Institute for Research and Community Service (LP2M), State University of Makassar, Indonesia (Ethics Approval Number 3821/DST/UN36.12/TU/2026). All methods were carried out in accordance with relevant guidelines and regulations, and the study followed the ethical principles of the Declaration of Helsinki. Participation was voluntary, respondents' answers were kept confidential, and data were managed in accordance with the research ethics guidelines of State University of Makassar.

Informed consent. The researchers obtained informed consent from all individual participants included in the study. The opening page of the Google Forms questionnaire explains the research objectives and procedures. Students could access the questions only after indicating their willingness to participate, and they were free to decline if they did not wish to take part.

Consent for publication

Not applicable. This study does not report any individually identifiable information. The findings are presented only in anonymized and aggregated form**.**

Competing interests

The authors declare no competing interests.

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Author contributions

Hasnarianti: Conceptualization; Methodology; Formal analysis; Data curation; Investigation; Writing – original draft; Writing – review & editing; Project administration. Mantasiah: Supervision; Validation; Writing – review & editing. Azis: Supervision; Validation; Writing – review & editing. Sakaria: Supervision; Validation; Writing – review & editing. All authors read and approved the final version of the manuscript.

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Data availability
The de-identified dataset supporting the findings of this study is available from the corresponding author upon reasonable request, subject to ethical and data protection requirements.

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