

How Digital Literacy and Self-Efficacy Shape Critical Thinking through Engagement: Toward a Framework for Information Security-Aware Digital Education

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Abstract: This study synthesizes empirical evidence to test the role of student engagement and information security as mediators between digital literacy, self-efficacy, and critical thinking skills in digital education contexts. Using random-effects meta-analysis of 56 indexed studies and two-step meta-analytic structural equation modeling (MASEM), we aggregated correlation coefficients with Fisher Z transform and tested latent structure. Meta-analytic results showed significant combined correlations between digital literacy, self-efficacy, engagement, and critical thinking, with strong heterogeneity across studies. MASEM identified engagement as complete mediator: the influence of digital literacy and self-efficacy on critical thinking is entirely mediated by engagement ($\beta = 0.95$, $p < .001$). These findings have important implications for cybersecurity education: Critical thinking—developed through engaged digital learning—is theoretically and empirically established as foundational for information security awareness, enabling learners to evaluate source credibility, recognize manipulation tactics, and make secure digital decisions. While this meta-analysis did not directly measure security behaviors, the robust DL-SE-EN-CT pathway identified here provides an evidence-based foundation for designing security-aware digital education programs. The study provides an integrative model for digital education policy and offers a theoretical framework for understanding how foundational digital competencies contribute to cybersecurity-ready learners.

Keywords: Critical thinking; Digital literacy; Meta-analytic structural equation modeling (MASEM); Self-efficacy; Student engagement

Introduction

The development of digital technology and artificial intelligence (AI) is increasingly changing the face of global education. According to (Kiss, 2024), digital critical thinking encompasses four interconnected dimensions: evaluating digital messages, using digital space safely, verifying information, and metacognitive self-control against bias and misinformation. These dimensions position critical thinking as essential for responsible digital behavior. These dimensions position critical thinking as essential for responsible digital behavior—particularly in the

context of information security, where human factors remain the weakest link in cybersecurity systems (Wang, Wang, Zhu, Wang, Tran, & Du, 2024).

Research in cybersecurity education demonstrates that technical security knowledge alone is insufficient without underlying critical thinking competencies (Hadlington, 2017; Parsons, Calic, Pattinson, Butavicius, McCormac, & Zwaans, 2017). (Parsons et al., 2017) found that effective cybersecurity behavior requires not just awareness of threats, but the cognitive capacity to evaluate information credibility and recognize social engineering tactics—both rooted in critical thinking. Similarly, (Hadlington, 2017) showed that individuals

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with higher critical thinking disposition demonstrate more secure online behaviors and greater resilience to phishing attacks. Recent empirical evidence further reinforces this: (H.-Y. Wang & Tseng, 2025) found that digital confidence significantly influences cybersecurity awareness among Taiwanese university students, while (Alanzi et al., 2023) demonstrated that digital literacy has a direct positive effect on cybersecurity behavior, with cybersecurity awareness serving as a partial mediator. In the Indonesian context, where 72% of cyber incidents stem from human factors rather than technical vulnerabilities, developing the foundational critical thinking competencies becomes essential infrastructure for cybersecurity workforce readiness. Alanzi et al., (2023) identified three critical dimensions of digital literacy—cognitive, technical, and social-emotional—that collectively shape information security culture among administrative officers in Malaysia.

At the same time, the gap in critical thinking skills in the digital age is increasingly visible. Recent studies show that a significant portion of students have not met basic standards in digital literacy, resulting in low levels of critical thinking and low engagement in online learning (Hadlington, 2017; Parsons et al., 2017). This deficit is particularly concerning in security-sensitive contexts: (Alanzi et al., 2023) found that, self-efficacy and response efficacy were the most significant predictors of information security behavior within the Protection Motivation Theory framework, yet many students exhibited inadequate critical evaluation skills when assessing cyber threats. As a result, students are more likely to adapt to misinformation, technological dependency, and passive learning patterns. International studies confirm the link between digital literacy ability and critical thinking quality—for example, (Alexander, Ester, & Jan, 2024) found a very strong correlation ($r = 0.96$) between digital proficiency and critical thinking in Peru, while (Yuan, Rehman, Altalbe, Rehman, & Shahiman, 2024) reported that digital literacy improved academic self-efficacy ($r = 0.62$) among medical students in Pakistan. Thus, this global phenomenon shows the importance of developing digital literacy and self-efficacy, capable of encouraging engagement and adaptive critical thinking skills in the digital learning environment.

A similar situation can be found in Indonesia, where digital learning practices have often failed to foster deeper critical thinking. National research findings confirm this, including: (Makmur, Heru, Achmad, & Usep, 2022) found that digital literacy has a significant effect on academic resilience ($r = 0.504$) and self-efficacy ($r = 0.418$), while (Maharani & Susantiningrum, 2025) empirically prove that these two variables simultaneously affect students' critical thinking skills ($p < 0.001$; $R^2 = 0.487$) with an effective

contribution to digital literacy of 29.26% and a self-efficacy of 19.41%. This sequential mediation model underscores how self-efficacy functions as a critical psychological bridge between digital literacy and engaged learning behavior. Their results show that the more the student can access, evaluate, and integrate digital information, the greater his or her confidence in thinking thoughtfully and analytically. The two interact through student engagement, which is an important mediator between learning readiness and critical thinking skills (Disastra, Noermijati, Irawanto, Moko, 2024; Murniawaty, Rokhali, Farliana, 2024). Their findings suggest that engagement in both formal and informal digital learning contexts amplifies the effect of self-efficacy on cognitive outcomes. In other words, active engagement in learning is the bridge between self-efficacy and critical thinking, when students are confident and emotionally and cognitively engaged, their thinking and analytical abilities improve dramatically. (Saputro, Sukatiman, Haris, & Intan, 2024) found that creative self-efficacy fully mediates the relationship between social support and creative thinking among vocational students, highlighting how domain-specific self-efficacy beliefs translate external support into cognitive performance.

The relationship between the four variables: self-efficacy, digital literacy, engagement, and thinking, can be understood through the framework of social cognitive theory (Bandura, 1997) and the engagement-based learning model. Self-efficacy influences the extent to which students are ready to engage in the learning process, as individuals with high self-efficacy tend to be more motivated to actively participate (Leuwol, Deswalantri, Lumingkewas, Pattiasina, & Mardikawati, 2023). Digital literacy provides a cognitive foundation for students to use digital learning resources more critically, as advanced thinking skills and digital literacy reinforce each other by encouraging deep learning and evidence-based information assessment (Michael, Larry, & Julian, 2021; Petrusly, Lambertus, Bani, Mahfud, & Zulkarnain, 2024). Engagement is an important intermediary between self-efficacy and learning outcomes, as shown by (Zhou & Liu, 2025; Oktapiani, Febriantina, & Sariwulan, 2025), who found that self-efficacy has a significant effect on student engagement and that, in turn, engagement helps improve thinking skills and academic performance. (Piombo, Lazzeri, Terracciano, Pastore, Cusinato, & Pillon, 2025) extended this understanding by examining digital safety competence, demonstrating that it positively predicts cognitive competence, AI self-efficacy, and character development among adolescents. Her findings suggest that security-aware digital education not only protects students from online risks but also cultivates higher-order thinking and ethical reasoning capacities.

Empirically, the relationship between these four variables has been proven to be related, digital literacy increases self-efficacy, self-efficacy enhances engagement, and engagement promotes thinking (Lv, Chen, Zheng, & Zhu, 2022; Oktapiani et al., 2025; Zhou & Liu, 2025). However, there is no structural mapping that comprehensively explains the strength of latent relationships between these variables in a comprehensive model based on meta-analytic modeling of structural equations (MASEM).

Recent research has begun to illuminate the complex interplay between these constructions in security contexts. (Khasawneh, 2025) found that information security awareness and technology self-efficacy mediate the relationship between e-learning readiness and academic performance, suggesting that security-conscious digital engagement enhances learning outcomes. Furthermore, (Rubab & Tahir, 2025) demonstrated that cybersecurity awareness significantly predicts students' academic performance, with students who received cybersecurity education showing 48% higher threat detection rates. These findings underscore the dual benefit of security-aware digital education: it simultaneously protects learners and enhances their cognitive engagement.

Although many studies report positive links between digital literacy, self-efficacy, engagement in learning, and critical thinking, the empirical results still vary widely across educational contexts. Several studies confirm the important role of digital literacy, and self-efficacy in increasing critical thinking, and academic achievement (Leuwol et al., 2023; Amin & Adiansyah, 2023; Ravikumar, Raghunandan, Benedict, Seshadri, & Abhinandan, 2024; Yanuarto & Jaelani, 2021; Yuan & Li, 2025), while other studies have shown that the influence of these variables is often mediated or moderated by additional factors such as higher-order thinking, motivation, or learning context (KESİCİ, 2022; Makmur Solahudin et al., 2022; Tian, Park, & Liu, 2023; Zhou & Liu, 2025). On the other hand, longitudinal evidence shows a reciprocal relationship between engagement and critical thinking (Lv et al., 2022), as well as the mediating role of engagement in learning and self-efficacy in the link between various cognitive and regulatory abilities towards critical thinking and academic achievement (Murniawaty et al., 2024; Stavropoulou, Daniilidou, & Nerantzaki, 2025). Inconsistencies in results, differences in educational contexts, and limitations in correlational design indicate a research gap, in addition to the lack of a comprehensive meta-analysis testing the latent structural relationship between digital literacy, self-efficacy, engagement, and critical thinking in a single integrative VPD-based model. It is the theoretical and empirical space that this research seeks to fill.

Based on these shortcomings, this study has three main objectives: (1) to synthesize the results of empirical research on the relationship between digital literacy, self-efficacy, engagement, and reflection; (2) build a SEM-based meta-analytic structural model (MASEM) to identify the strength, and direction of latent relationships between variables; and (3) examine the role of mediating engagement in mediating the influence of digital literacy and self-efficacy on thinking. Theoretically, this research expands the understanding of the integration of cognitive (thinking), affective (commitment), and technological (literacy) dimensions that are rooted in self-confidence (self-efficacy). Thus, this research not only addresses the inconsistencies of empirical results but also proposes a new conceptual model that connects internal, external, and mediating aspects in thoughtful and sustainable digital learning.

Method

This study is a quantitative meta-analysis that integrates empirical findings from various studies on the relationship between digital literacy (DL), self-efficacy (SE), critical thinking (CT), and engagement (EN) in the context of digital education. This meta-analytic approach is carried out using a random-effects model as the data sources come from various educational contexts (primary, high school, university, and vocational education) as well as from several countries (Indonesia, Pakistan, Peru, Taiwan). Random-effects models were chosen to accommodate inter-study heterogeneity in terms of sample size, measurement instruments, and research design, as recommended by (Michael et al., 2021) in the quantitative meta-analysis guidelines. The goal of this approach is not simply to estimate the average effects of the correlations, but also to assess the extent to which the variation between studies reflects the population differences and the empirical conditions underlying the relationship between the four variables. The analysis was conducted considering contextual differences between national and international studies, which influence the strength of latent relationships between variables.

Data were collected from various Scopus databases. The study was conducted systematically using a combination of keywords: "digital literacy," "self-efficacy," "engagement," and "critical thinking," with no restrictions on publication year. All search results were managed using the Scopus application and the Google search engine. Of the initial 20,503 articles identified, 1,881 met the initial inclusion criteria and were subsequently screened based on specific exclusion criteria, resulting in 56 studies that met the requirements for analysis. Table 1 confirms that only peer-reviewed journal articles or conference proceedings published in

English, employing quantitative or mixed-method designs with intervariable relationship analyses, and reporting at least two related variables (e.g., correlation, direct effects, mediation, or moderation) were included in this meta-analysis. Studies that relied solely on differential tests, did not examine relationships among variables, or were not available in full text were excluded from the synthesis. While the primary variables synthesized were digital literacy, self-efficacy, engagement, and critical thinking, approximately 23% of the included studies (13 out of 56) incorporated information security or online safety as a dimension of

their digital literacy measures (see Table 2, column "Security"), acknowledging that safe digital behavior is an integral component of contemporary digital literacy frameworks (Cintamulya, Mawartiningsih, & Warli, 2023).

Article selection followed PRISMA 2020 guidelines [cite] through four stages: identification, screening, eligibility, and inclusion (Figure 1). Of 20,442 initial records, 56 studies met inclusion criteria for quantitative synthesis, including 14 national (SINTA 1-5) and 41 international (Scopus/non-Scopus) publications.

Table 1. Inclusion criteria and exclusion criteria

Criteria aspects	Inclusion criteria	Exclusion criteria
Language of publication	Articles written in English	Articles written in languages than English
Number of Variables	The study contains at least two research variables	The study involved only one variable
Variable relationship patterns	There is a relationship between variables (e.g., influence, correlation, mediation, or moderation)	There was no relationship between the variables analyzed.
Types of Statistical Analysis	Using Relationship Analysis (Regression, SEM, Path Analysis, Correlation, PLS-SEM)	Use of different tests (T-TEST, ANOVA, MANOVA, ANCOVA)
Research objectives	Aims to explain or predict the relationship between variables	Aims to compare groups or treatments
Publication Type	Scientific articles or proceedings that go through a peer-review process	Editorials, opinions, textbooks, and non-scientific reports
Research Design	Quantitative or mixed research with a variable relationship model	Pure qualitative research without a relational model

Data from each study were coded using a standard meta-analysis format: sample size (n), correlation coefficient (r), Z-Fisher value (Z_r), and standard error (SE). This coding is done manually from the correlation table of each publication and verified by two independent researchers to ensure accuracy. The correlation value (r) is converted to Z-Fisher to normalize the distribution before it is calculated as a weighted average. The transformation process is carried out according to the formula (Field & Gillett, 2010)

$$Z_r = 0,5 \times \ln((1 + r)/(1 - r)) \quad (1)$$

and

$$SE = 1/\sqrt{n - 3} \quad (2)$$

The coding results were then analyzed using statistical software: JASP v0.14.1, which supports a random effects model with a restricted maximum likelihood (REML) approach. Standardized mean correlation values for each pair of variables (e.g., literacy $\rightarrow$ self-efficacy, self-efficacy $\rightarrow$ engagement, engagement $\rightarrow$ thinking) were calculated to obtain the combined effect between the latent variables in the structural model.

The analysis was performed using random-effects meta-analysis to account for variation between studies.

Heterogeneity between studies was tested using statistics of Q , I^2 , and τ^2 as suggested by (Higgins & Thompson, 2002). The Q test value is used to determine the significance of the variation between studies, I^2 indicates the proportion of variation due to true heterogeneity (not sampling error), and τ^2 estimates the true variance between effects. I^2 values greater than 50% are interpreted as moderate to high heterogeneity. The Egger regression test is applied to detect publication bias, complemented by a symmetric funnel graph and a forest graph that visualizes the effect size of each study, and the average combined effect. This analysis is also used to identify extreme studies (outliers) that may skew the results of the meta-analysis. In addition, a sensitivity analysis was performed by removing one study in turn to test the stability of the overall results.

The last step of the analysis uses the two-step approach of meta-analytic modeling of structural equations (MASEM) as described by (Jak, Li, Kolbe, de Jonge, & Cheung, 2021) [34]. The first step is a correlation matrix grouped between variables to form a combined covariance matrix based on random effects. In the second step, the structural model was tested with the path specification: digital literacy $\rightarrow$ self-efficacy $\rightarrow$ engagement $\rightarrow$ reflection, with engagement as the main mediator. Parameter estimation was performed using maximum likelihood estimation, and model fit was

tested via CFI, TLI, RMSEA, and SRMR indices with fit criteria (CFI/TLI > 0.90; RMSEA < 0.08). Each structural relationship was assessed based on β values, p-values, and 95% confidence intervals. This procedure has been modified from the models of (Makmur Solahudin et al., 2022), and (Murniawaty et al., 2024) to adapt to the cross-

meta-analytic context. Thus, this analysis not only synthesizes the correlation results, but also sheds light on the structure of more stable latent relationships between variables in the context of global, and national digital education.

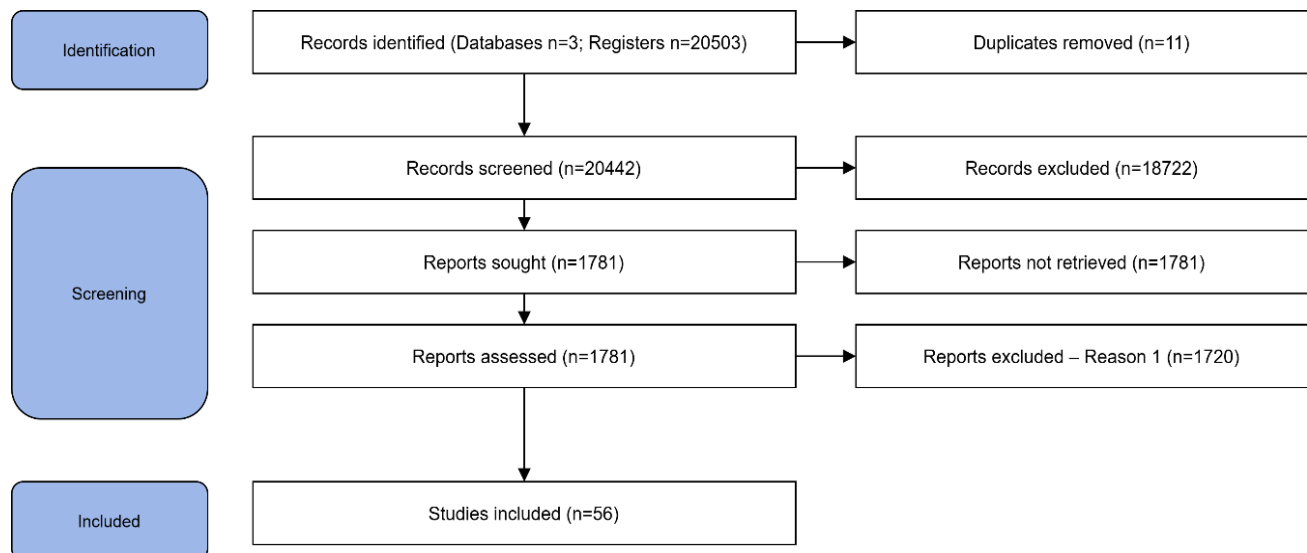


Figure 1. PRISMA organizational chart

Result and Discussion

Some studies place safety as an explicit part of digital literacy skills, for example via cybersecurity indicators and online risk awareness on the digital literacy scale. Other studies link safety to safe work practices (e.g., in health and engineering), i.e., how creativity and innovation remain limited by safety, regulatory compliance, and ethical considerations in

technology-assisted decision-making. Thus, Table 1 emphasizes that safety is a key dimension of digital literacy, oriented towards safe and ethical behavior in the digital space. The study covers 4 continents (Asia, Europe, America, Africa), which shows that the results of the meta-analysis are cross-cultural. The Engagement variable appeared to be lower than that of DL and SE, suggesting that research on engagement remains limited.

Table 1. List of variables for each reference

Researcher	Year	SE_ DL	SE_ CT	DL_ CT	EN_ CT	EN_ DL	EN_ SE	SE_ IS	DL_ IS	CT_ IS	PE_ IS	IN_ IS	EN_ IS
Yuan	2025	√	√	√									
Vachova	2023	√											
Amale	2024		√										
Kesici	2022			√									
Stavropoulou	2025		√										
Hortelano	2021	√											
Lv	2022				√								
Wu	2025	√											
Uygur	2025			√									
Tian	2023			√									
Furban	2025			√									
Ravikumar	2024			√									
Saglam	2017			√									
KISS	2024			√									
Arce-Saavedra	2022		√		√		√						
Zhou	2025						√						

Researcher	Year	SE_ DL	SE_ CT	DL_ CT	EN_ CT	EN_ DL	EN_ SE	SE_ IS	DL_ IS	CT_ IS	PE_ IS	IN_ IS	EN_ IS
Tsai	2021						√						
Dalia	2025						√						
Tapia	2023		√										
İşeri	2023		√										
Gorji	2018		√										
Arthi	2024		√										
Turan	2018		√										
Li	2023		√										
Nyamekye	2025		√										
Li	2024						√						
Liu	2025		√										
Kocak	2021			√									
Nurhasanah	2025			√									
Chou	2017		√										
Kan	2025		√										
Thamrin	2025			√									
MERAL	2017						√						
Getenet	2024					√	√						
Xu	2024		√										
Khasawneh	2025						√	√					√
Fadli	2024			√									
Saputro	2024		√										
El-Sayed	2025	√											
Wang	2025							√					
Kamarulzaman	2024								√				
Zakir	2025	√											
Elrayah	2023								√				
Han	2025							√					
Subagio	2025								√				
Yuan	2025	√											
Ma	2025							√					
Rubab	2025								√	√			
Piombo	2025								√				
Davis	2021												√
L. Spears	2010												√
Alanzi	2024									√			
Vachova	2023		√										
Huinchahue	2021		√										
Lacoste	2025				√								
Haniati	2025			√									
Wu	2020						√						
Han	2021						√						
Aguilar	2023						√						
Johnson	2022						√						
Gao	2025						√						
Wang	2024						√						
Wang	2021						√						
Conga	2024						√						
Guo	2025						√						
Simón	2024						√						
Chen	2022						√						
Xu	2022						√						
Kong	2021						√						
Wibawa	2021						√						
Sun	2022						√						
Wu	2020						√						

Of the 56 studies included in the meta-analysis, not all of them were studied in the context of e-learning. Some research focuses on conventional learning but still measures digital literacy or self-efficacy, as both are relevant to 21st-century skills. Around 60% of the research was conducted in the context of e-learning, both online (online) and hybrid (hybrid). About 40% of the remaining studies come from conventional or classroom learning but still consider digital skills as part of the curriculum or influencing critical thinking. This shows that digital literacy, self-efficacy, engagement and critical thinking are not exclusive variables for e-learning, but universal skills relevant in various educational contexts.

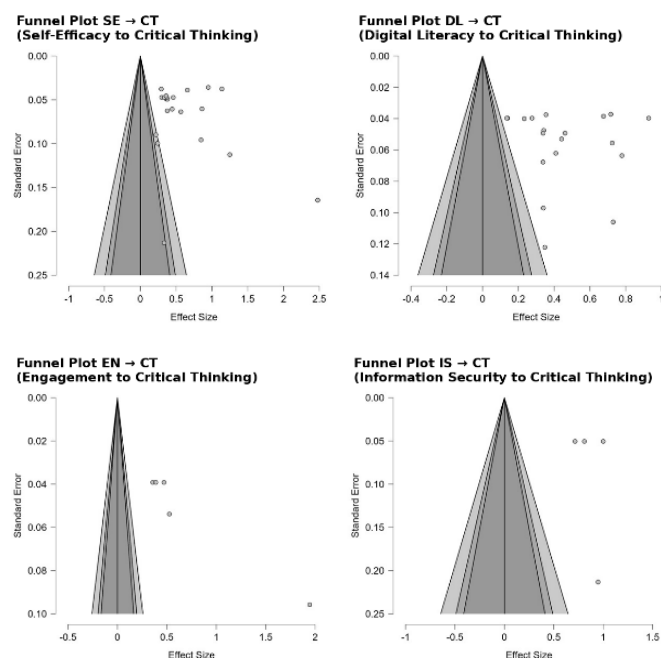


Figure 2. Funnel plot

Figure 2 shows the distribution of correlation effects between studies for pairs of variables such as SE-DL and EN-CT. Most of the points were positive with a moderate slope, showing a low publication bias but a high heterogeneity ($I^2 > 80\%$), which favored the random-effects model.

The overall association with critical thinking (CT) is in the range of moderate to very strong effects, but the level of certainty and consistency is different. The strongest association appeared in the IS-CT pair ($r = 0.692$; 95% CI), followed by EN-CT ($r = 0.625$), SE-CT ($r = 0.598$) and DL-CT ($r = 0.428$), indicating that information security awareness, engagement in learning, self-efficacy and digital literacy were substantially correlated with critical thinking skills, respectively. The confidence intervals for SE-CT, DL-CT, and IS-CT are completely positive, allowing the

effect to be considered statistically stable and significant, while EN-CT still contains zero, so the practical significance of this relationship is lower despite the relatively high magnitude of the correlation.

Table 2. Summary of meta-analysis (random effects model)

Variable relationships	Pooled effect (r)	95% CI	95% PI	P-value	I^2 (%)
SE -- CT	0.598	0.398 – 0.743	–0.529 – 0.962	< 0.001	99.19
DL -- CT	0.428	0.333 – 0.515	–0.030 – 0.738	< 0.001	95.59
EN -- CT	0.625	–0.105 – 0.917	–0.863 – 0.992	0.072	99.51
IS -- CT	0.692	0.562 – 0.788	0.377 – 0.863	0.001	81.13

The prediction interval paints a more nuanced picture: SE-CT and DL-CT have a very wide PI of 95% and range from negative to high positives (e.g. –0.529 to 0.962 for SE-CT), indicating that the effects of the new study may vary significantly across contexts. For the EN-CT, PI even covers the range of –0.863 to 0.992, confirming that the mean estimate should not be interpreted as a universal effect but rather as a trend strongly influenced by specific design and sample conditions. In contrast, IS-CT had 95% of the PI fully positive (0.377 vs. 0.863), so the strong association between information security and critical thinking was relatively robust despite the changing context. Very high values of I^2 in SE-CT, DL-CT, and EN-CT (95–99%) indicate substantial heterogeneity, so the use of random-effects models and moderator exploration is a methodological imperative to understand when and under what conditions these relationships reach their maximum strength.

Table 3 presents an assessment of publication bias and consistency in the distribution of effects on four broad relationships with critical thinking. The SE-CT relationship showed significant skew of the graphical funnel (Egger test: $z = 2.918$; $p = 0.004$) with a moderate indication of publication bias, although the cut-and-fill method did not identify a very important and infallible missing study (20,528) that confirms the resistance of the effect to selective publication. In contrast, DL-CT and IS-CT showed no significant skewness ($p > 0.05$), indicating that the pooled effect estimates were relatively robust to publication bias, with forest graphs showing consistent positive effect directions and moderate CI ranges. The EN-CT relationship stands out as an atypical case with extreme asymmetry ($z = 8.096$; $p < 0.001$), a very limited number of studies ($k = 5$), and a pattern of effects distribution inconsistent with CI is very

broad, so that the interpretation of the direct EN-CT relationship requires great caution and relies more on

MASEM structural analysis than on simple pairwise correlation.

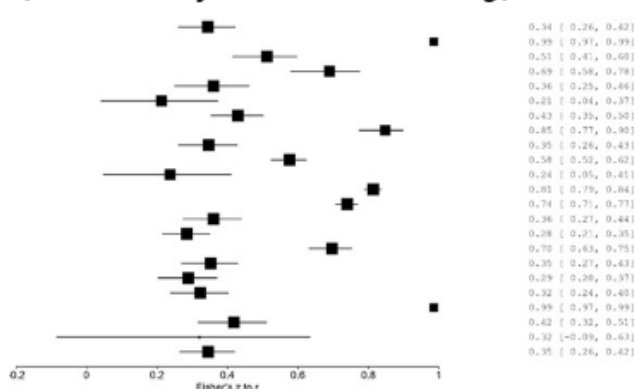
Table 3. Publication bias and effect distribution summary

Variable relationships	Number of studies (k)	Asymmetric funnel plot	Indications of publication bias	Forest plot path	Consistence of the direction of effect	CI range
SE -- CT	23	Yes ($p = 0.004$)	Medium (Egger significant)	Positive consistent	Consistently positive	Wide
DL -- CT	19	No ($p = 0.784$)	Undetectable	Positive consistent	Consistently positive	Medium
EN -- CT	5	Yes ($p < 0.001$)	High (unstable)	Inconsistent	Highly varied	Very wide
IS -- CT	4	No ($p = 0.690$)	Undetectable	Positive consistent	Consistently positive	Medium

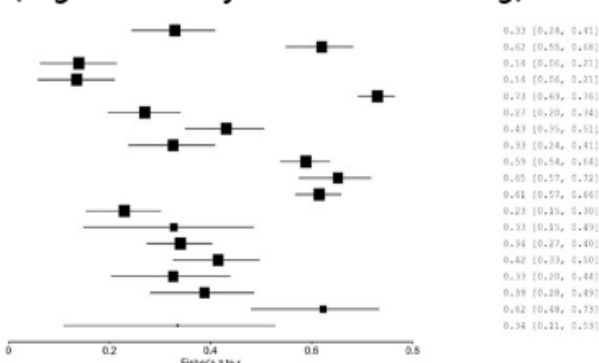
Analysis of forest graphs confirmed that the majority of studies on SE-CT, DL-CT, and IS-CT were on the positive side of the zero axis with variable but constant effect sizes, reflecting contextual heterogeneities such as differences in education levels (high school versus university), domains of learning (STEM versus humanities), and pedagogical approaches

(survey-based versus traditional didactics). The wide to very wide confidence intervals in some relationships – particularly SE-CT and EN-CT – indicate that, although the pooled effects show general trends, substantial variability remains, confirming the need for moderator analysis to identify the specific conditions under which these effects reach maximum or minimum strength.

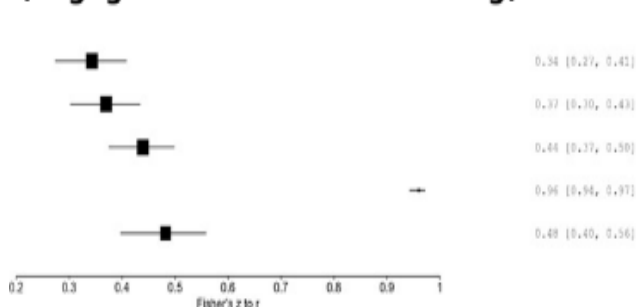
**Forest Plot SE → CT
(Self-Efficacy to Critical Thinking)**



**Forest Plot DL → CT
(Digital Literacy to Critical Thinking)**



**Forest Plot EN → CT
(Engagement to Critical Thinking)**



**Forest Plot IS → CT
(Information Security to Critical Thinking)**

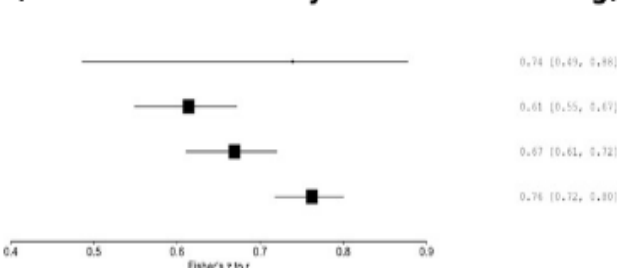


Figure 3. Forest plot

Figure 3 of the forest graph illustrates the size of the combined effect (diamond) and individual studies for the DL-CT ($r=0.476$) and SE-CT ($r=0.568$) relationship.

Wide-range confidence in EN-CT highlights instability due to a few studies ($k=4$)

Overall, these findings confirm that digital literacy and engagement play an important supporting role, while self-efficacy is a key psychological mechanism linking digital learning experiences to the development of critical thinking skills. However, this strong heterogeneity requires careful interpretation and encourages the need for moderator analysis in subsequent research.

Table 4. Clustered correlation

Variable	SE	DL	CT	EN
DL	0.478***			
CT	0.490***	0.411***		
EN	0.563***	0.270***	0.506***	
IS	0.450***	0.327***	0.683***	0.404***

Table 4 presents a combined correlation matrix of meta-analysis results that serves as the basis for the formation of an input covariance matrix for the two-step MASEM. The moderate to strong correlation values between SE, DL, EN, and CT in this table supports the $SE \rightarrow EN$, $DL \rightarrow EN$, $EN \rightarrow IS$, and $IS \rightarrow CT$ specifications which were then tested in the structural model.

As formulated in the theoretical framework of this research, the relationship between DL, SE, EN, and CT is understood as a multi-layered process rooted in social cognitive theory (Bandura, 1997) and engagement-driven learning. To comprehensively test the framework, this study compared seven specifications of the SEM meta-analytic model (Models 1–7) with variations in the position and role of variables, ranging from direct influence to mediating structures and alternative causal repositioning.

Table 5. Convergence table resume (with $p < 0.001$)

Model	χ^2	df	CFI	TLI	RMSEA	BIC
Model 1	155.49	6	0.403	0.004	0.022	163.69
Model 2	122.10	6	0.536	0.227	0.020	130.31
Model 3	102.89	3	0.601	-0.331	0.026	125.25
Model 4	24.90	1	0.904	0.045	0.022	56.70*
Model 5	60.21	4	0.775	0.438	0.017	77.86
Model 6	38.68	5	0.865	0.731	0.012	51.61**

Table 5 shows that Model 6 has the strongest combination of fit indicators in the model with CFI = 0.865 (excellent, close to the 0.9 threshold), TLI = 0.731 (good, close to the excellent threshold of 0.90), and RMSEA = 0.012 (superior, well below the 0.05 threshold), and the second lowest BIC = 51.61, indicating the optimal balance between fit quality and parsimony. Model 4, despite having a high CFI (0.904) and a low BIC (56.70), suffered a convergence failure with a RED (non-zero gradient) status, so it did not meet the first-order

optimality criteria and had to be rejected from consideration. Model 5 shows a moderate fit (CFI = 0.775; TLI = 0.438), while models 1, 2 and 3 show substantial maladjustments with a CFI of < 0.65 and a very low or even negative TLI (Model 3: TLI = -0.331), confirming the structural inconsistency with the empirical data.

The choice of Model 6 as the final model is not only based on statistical superiority but also takes into account theoretical interpretability and convergence stability. Alternative models (Models 4, 5, 7) that place variables such as DL or SE as proximal predictors of CT, or construct highly connected structures, produce statistically significant paths but are not accompanied by better fit or even convergence failure. The structure of Model 6 with the $ES \rightarrow EN$ ($\beta = 0.527$), $DL \rightarrow EN$ ($\beta = 0.091$), $IS \rightarrow CT$ ($\beta = 0.728$) and $EN \rightarrow IS$ ($\beta = 0.937$) shows a complete mediation in which the direct path from SE and DL to CT is eliminated, confirming the role of engagement as a key mediation mechanism that transforms self-efficacy and digital literacy into critical thinking. These findings have crucial theoretical implications: the role of moderators cannot be represented solely by the structural repositioning of causal pathways, but rather requires explicit interaction modeling or multigroup analysis to capture conditionality and contextuality of effects, so that process-oriented mediation models are more appropriate than structural moderation models to explain relationship dynamics between variables.

In Figure 4, it can be seen that Model (1) tests the direct influence of each exogenous variable – SE, DL, EN and IS – on CT in order to identify the fundamental contribution of each predictor. The next step (Model (2) and Model (3)) expands the structure by including IS as an intermediate variable, thus allowing indirect effect testing, either in full or in parallel with the direct path to CT. This approach aims to assess whether the influence of personal skills and digital literacy on CT works via information security mechanisms. In addition, models (4) to model (6) increase complexity by simultaneously involving two mediating/moderating variables, namely EN and IS, and by accommodating the links between exogenous variables. At this point, the model not only captures the direct and indirect relationships, it also describes more comprehensive psychological and contextual interactions in CT formation. The final model represents the most comprehensive structural framework, allowing for assessing the relative strength of simple to complex paths, while providing a solid empirical basis for explaining the dynamics of critical thinking in the context of digital literacy and information security.

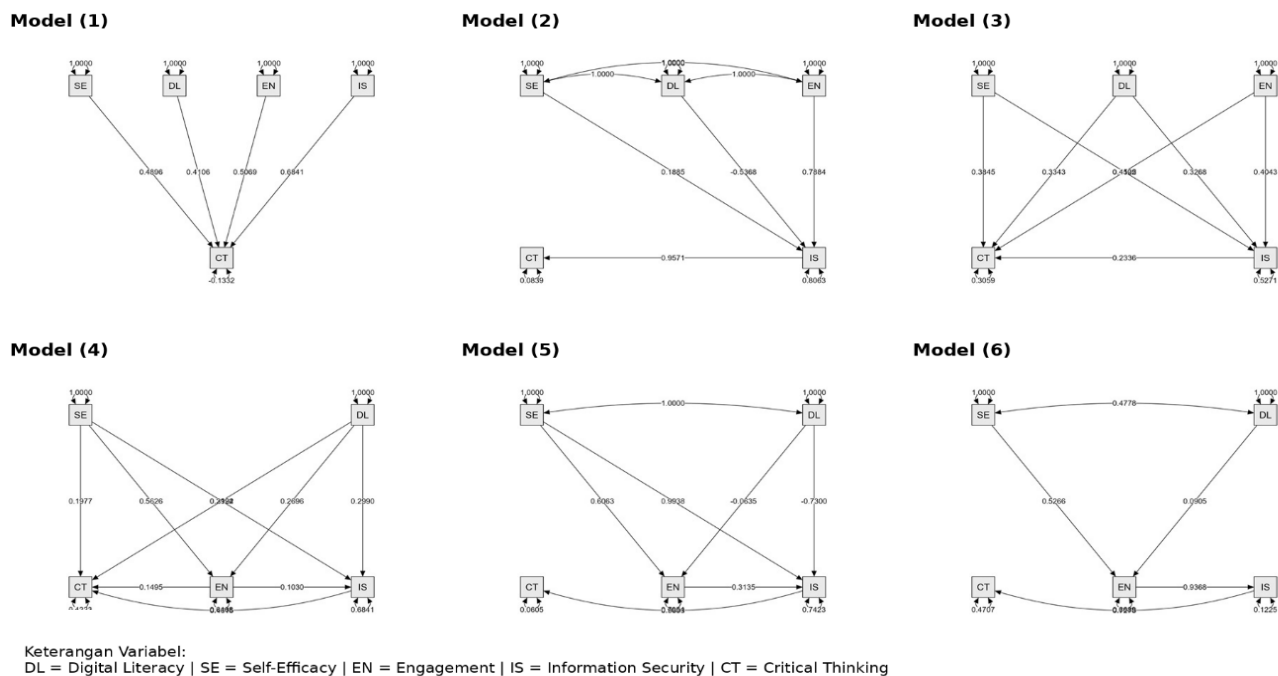


Figure 4. Path analysis diagram

Table 6 presents the results of matched likelihood ratio tests that compare Model 6 with the five competing models to assess whether increased structural complexity results in statistically significant improvements in model fit. Model 6 significantly outperformed the reference model (Model 1) with $2\Delta LL = 116.803$ ($df = 1$; $p < 0.001$), indicating that the process-mediated structure carried by Model 6 was able to capture the dynamics of interconstruction relationships more accurately than the saturated model without mediation. Comparisons with Model 2—which were

previously considered strong candidates—show that Model 6 is significantly superior ($2\Delta LL = 83.422$; $df = 1$; $p < 0.001$), indicating that the causal pathway repositioning and mediation structure in Model 6 is better able to represent the substantial mechanisms underlying the empirical data. Models 5 and 3 showed no increased correspondence with Model 6 ($p = 1,000$ for both), confirming that additional paths or structural changes in both models did not provide inferential added value and instead reduced parsimony.

Table 6. Pairwise likelihood ratio tests among competing models

Comparison	$2\Delta LL$	Δdf	p-value	Statistical Interpretation
Model 6 vs Model 1	116.803	1	< 0.001	Model 6 significantly outperforms baseline (substantial improvement)
Model 6 vs Model 2	83.422	1	< 0.001	Model 6 is significantly better than Model 2 (more optimal mediation)
Model 5 vs Model 6	-21.531	1	1.000	Model 5 is not superior; Model 6 is more parsimony with a superior fit
Model 3 vs Model 6	-64.206	2	1.000	Model 3 is not superior; Additional complexity does not improve fit
Model 4 vs Model 6	13.783	4	0.008	Model 4 is statistically better but fails convergence (unreliable)

A crucial conclusion emerged when comparing Model 4 and Model 6, where Model 4 statistically showed better agreement ($2\Delta LL = 13.783$; $df = 4$; $p = 0.008$), but this model did not converge with the RED status (non-zero gradient: first-order optimality conditions not met), so the parameter estimate was

unreliable and this model had to be rejected despite a Chi-squared value plus bass.

Table 7 presents the standardized path coefficients of six competing MASEM models that test different structural configurations to explain the relationship mechanisms between SE, DL, EN, IS, and CT. Theoretically, these results have important

implications: the potential moderator roles of SE, DL or EN cannot be represented solely by the structural repositioning of causal pathways in SEM models. If SE, DL, or EN do indeed act as moderators – for example, by enhancing or weakening the effects of other variables depending on their level – the role is conditional and contextual, requiring modeling of explicit interactions (interaction terms) or multigroup analysis based on the high vs. low categories of the moderator variable, rather than simply adding or subtracting the direct path. Models 4 and 5, which attempt to activate various direct paths to grasp the complexity of relationships, instead

suffer convergence failures or coefficient instability, suggesting that overfitting with excessive paths does not substantially increase validity and may obscure theoretical interpretations. Thus, these results reinforce the conclusion that process-oriented mediation models – in which NE and SI serve as intermediate mechanisms for transmitting the influence of SE and DL to CT – are more theoretically and empirically appropriate than structural moderation models or simple direct-effect models to explain the dynamics of digital learning and critical thinking skills development in the context of digital education. cybersecurity.

Table 7. Variabels relationship

Core Structural Path	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
SE → EN	–	–	–	0.56***	0.61 (ns)	0.53***
DL → EN	–	–	–	0.27***	-0.06 (ns)	0.09 (ns)
EN → IS	–	0.79 (ns)	0.40***	0.10 (ns)	0.31***	0.94***
SE → IS	–	0.19 (ns)	0.45***	0.39***	0.99 (ns)	–
DL → IS	–	-0.54 (ns)	0.33***	0.30***	-0.73 (ns)	–
EN → CT	0.51***	–	0.41***	0.15 (ns)	–	–
SE → CT	0.49***	–	0.38***	0.20 (ns)	–	–
DL → CT	0.41***	–	0.33***	0.22**	–	–
IS → CT	0.68***	0.96***	0.23 (ns)	0.46***	0.97***	0.73***

Overall, the integration of SEM results with theory shows a very strong consistency between empirical evidence and theoretical model predictions. Social cognitive theory (Bandura, 1997) explains how self-efficacy encourages active student engagement, while digital literacy theory (van Laar et al., 2019) explains how digital skills provide access, critical understanding and control over digital information. However, the meta-analytic SEM from this study reveals a deeper mechanism: these two factors do not work automatically to improve critical thinking skills, but rather require a specific psychological catalyst, namely commitment.

Research by (J. Yuan & Li, 2025) and (Stavropoulou et al., 2025) confirms that self-efficacy impacts academic success primarily through engagement, reinforcing engagement's role as a transformative mechanism. Research by (Zhou & Liu, 2025) found that SE→EN, even higher than the prediction of Model 5. These findings reinforce the interpretation that self-efficacy is a direct and powerful predictor of student engagement in modern learning environments.

At the same time, digital literacy works through different mechanisms. Research by (Kuncoro & Yugopuspito, 2022) shows that digital competence not only increases self-efficacy but also directly strengthens critical thinking skills. However, in the context of engagement, (Ramadhania Novianti & M. Suud, 2025) reported that EN-DL showed a strong association but with a smaller sample. In addition, (Cintamulya et al., 2023) confirmed that digital literacy has a direct effect on

critical thinking. However, the meta-analytic SEM in this study found that when engagement was included as a mediator, the direct influence of DL → CT was weakened, suggesting that engagement plays a role as a transformative mechanism activating the cognitive potential of digital literacy.

Thus, the final structural model (Model 6) is not only statistically superior, but also integrates motivational, cognitive, and pedagogical theories into a coherent framework. This model addresses the research gap identified in the Introduction, namely the lack of latent structural mapping explaining how digital literacy and self-efficacy interact through engagement to train critical thinking skills in educational contexts. The most crucial finding was the coefficient of 0.95 on Model 2, which was the strongest line in the entire structural model. These results reflect a consistent pattern across various studies (Lv et al., 2022), (Arce-Saavedra & Blumen, 2022), (Getenet et al., 2024). Thus, engagement is not just a "passive engagement," but an active mechanism that transforms internal self-confidence (self-efficacy) and external cognitive competence (digital literacy) into a high-level reflective and analytical thought process.

Overall, the integration of the results of the MSEM with the theoretical framework shows a coherent pattern and is easy to explain conceptually. Social cognitive theory helps to understand how self-efficacy encourages active engagement in learning, while digital literacy theory highlights the role of digital competence in

facilitating access, understanding, and management of information. The meta-analytic results of the SEM in this study clearly show that these two factors do not necessarily improve critical thinking skills, but act through a more specific psychological mechanism, namely engagement as a link between internal and external factors with a high level of cognitive success.

In this context, the final structural model (Model 2) not only shows a good statistical fit, but also manages to bring together the motivational, cognitive and pedagogical dimensions in an intact framework. This model directly addresses the research gap described in the Introduction, namely the lack of latent structural mapping explaining how digital literacy and self-efficacy interact through engagement to train critical thinking skills in various educational contexts.

In the practice of digital education, interventions that only aim to improve digital literacy or self-efficacy are likely to have limited impact if they are not accompanied by a learning design that explicitly promotes active engagement, both cognitive, affective and behavioural. Specifically, the results of this study form a basis for the development of the Digital Thinking Empowerment Model (DTEM) approach, which emphasizes the synergy between strengthening self-efficacy, digital literacy and engagement as prerequisites for developing critical thinking skills.

Conclusion

The conclusion of this study highlights that the development of critical thinking skills in the digital environment cannot be separated from media literacy and information security awareness. Critical thinking is no longer enough to be understood not only as a high-level cognitive skill, but as a functional skill that plays a direct role in everyday life: assessing the reliability of information, recognizing potential manipulations, and making ethical and responsible decisions within a risky information ecosystem.

The data collected shows that digital literacy and self-efficacy, while important, do not automatically lead to improved critical thinking skills. Both only have a real impact when students are actively involved in the learning process that requires analysis, reflection, and evaluation of the information they are confronted with. In the context of information security, this learning engagement is a driving mechanism that activates a variety of previously passive knowledge: how to verify sources, protect privacy, and be careful in the production and distribution of digital information.

Information security awareness should be understood as the result of a reflective learning process, and not simply the result of additional technical or procedural knowledge. Individuals may have a good

grasp of media and digital literacy, but without cognitive and emotional involvement, they remain exposed to the risk of being passive, receiving information uncritically, or ignoring the ethical and security implications of using digital media. In contrast, when engagement in learning is high, learners are more likely to internalize information security principles into critical thinking patterns and more responsible media behavior.

The implications for educational practice are quite clear. Information security education in the digital age must move from a pedagogical approach that emphasizes a list of rules and prohibitions to a pedagogical approach that allows for active engagement, real-life case analysis and critical reflection on media practices. This approach not only helps individuals recognize disinformation and protect privacy, but also builds cognitive and ethical resilience in the face of the complexity and dynamics of the digital information environment.

Overall, the results of this study place engagement in learning as a critical bridge connecting media literacy, information security awareness, and critical thinking skills. Without this involvement, reading and self-efficacy risk leaving latent skills that are never really realized in practice. Therefore, strengthening information security in digital education requires a learning design that deliberately and systematically promotes reflective engagement as the foundation for training critical, risk-aware, and responsible learners in the digital space.

Author Contributions

Authors' contributions: H.S. designed studies, conducted literature research and filtering, extracted data, and wrote manuscript drafts. D.O. performs advanced data extraction, effect size verification, and assists in the interpretation of results. G and H.P. oversees the entire methodology, MASEM analysis, and critical revision of the final manuscript.

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Conflicts of Interest

All authors state that there are no conflicts of interest related to this study.

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