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When teachers overestimate: Unpacking media and information literacy gaps in Vietnamese secondary schools

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Abstract

While Media and Information Literacy (MIL) is paramount in the digital transformation of education, empirical evidence on the alignment between teacher assessments and student self-perceptions of MIL remains scarce. Adopting a dual-perspective, cross-sectional design with two independent (non-dyadic) samples, this study examined the perceptual discrepancy in MIL competencies and identified the behavioural predictors of student MIL. Data were collected from 277 high school students and 126 teachers across four schools in central Vietnam. Independent samples t-tests revealed a systematic overestimation by teachers, who rated students' overall MIL significantly higher ($M = 4.07$, $SD = 0.56$) than students rated themselves ($M = 3.86$, $SD = 0.64$), $t(401) = 3.28$, $p < 0.001$, $d = 0.36$. K-means clustering of teachers' self-reported MIL yielded three profiles whose ratings of students differed substantially ($\eta^2 = 0.68$), revealing how teachers' own MIL self-concept co-shapes their assessment of students. A Random Forest model ($R^2 = 0.38$) identified purposeful Internet use for learning, IT proficiency, and learning engagement as the strongest predictors of MIL, whereas device ownership and Internet time were not predictive. The findings reposition MIL as a process-oriented competence and indicate that teacher-education programmes should pair evidence-based MIL assessment tools with subject-integrated digital learning tasks rather than relying on observable exposure cues.

Keywords: Educational data mining, Media and information literacy, Random Forest, Secondary education, Teacher–student perceptual gap.

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Contribution of this paper to the literature
This study pioneers unpacking the Media and Information Literacy (MIL) perceptual gap between teachers and secondary students in Vietnam. Combining traditional statistics with a Random Forest model, it reveals that teachers systematically overestimate students' higher-order cognitive MIL competencies, demonstrating that purposeful Internet use, not mere technology exposure, is the core determinant of MIL.

1. Introduction

Media and Information Literacy (MIL) has emerged as a cornerstone of 21st-century education, transcending basic technical fluency to encompass critical evaluation, ethical content creation, and responsible digital citizenship (Lazer et al., 2018). Despite its significance in global educational policy, a persistent digital native fallacy continues to permeate pedagogical discourse, assuming that ubiquitous exposure to technology inherently fosters sophisticated digital competencies. However, recent empirical evidence suggests a digital native paradox, where students' superficial technical fluency often masks profound deficits in critical thinking and complex information processing (McGrew, Breakstone, Ortega, Smith, & Wineburg, 2018).

The discrepancy between perceived and actual digital competence is not merely a theoretical concern but a significant barrier to effective instructional design. Drawing on Cognitive Load Theory, instructional effectiveness depends on the precise alignment between task complexity and the learner's actual prior knowledge. When teachers overestimate students' MIL, often by misinterpreting recreational digital use as academic proficiency, they risk implementing technology-integrated activities that fall outside the students' Zone of Proximal Development (Van Deursen & van Dijk, 2011). Such instructional misalignment inevitably leads to cognitive overload, hindering the meaningful integration of technology in the classroom (Ertmer & Ottenbreit-Leftwich, 2010).

Despite the critical role of teacher perception in shaping pedagogical practices, the degree of accuracy in these assessments remains empirically under-examined (Südkamp, Kaiser, & Möller, 2012). Existing literature has predominantly adopted fragmented approaches, focusing either on student self-reports or teacher beliefs in isolation (Tondeur, van Braak, Ertmer, & Ottenbreit-Leftwich, 2017). Few studies have utilized dyadic data to directly investigate the perceptual discrepancy (cognitive gap) between teachers and students within the same ecological school context. Furthermore, while digital behaviours are assumed to influence MIL, the specific behavioural drivers that robustly predict literacy levels remain elusive, leaving pedagogical decisions without an empirical anchor (Hargittai, 2010).

To address these critical gaps, the present study adopts a dual-perspective approach, integrating frequentist statistics with machine learning algorithms. We aim to: (1) quantify the magnitude of the assessment gap between teachers and students across multidimensional MIL scales, and (2) identify the behavioural determinants that best predict student MIL proficiency. By unraveling these dynamics, this research contributes to a more nuanced understanding of MIL as a complex construct and provides an empirical foundation for data-driven pedagogical recalibration in the digital era. These three questions correspond to three theoretical axes: Cognitive Load Theory and the Zone of Proximal Development (RQ1); a person-centered reading of teacher cognition (RQ2); and Self-Regulated Learning (RQ3).

RQ1: To what extent do teachers' assessments of students' MIL differ from students' self-assessments across specific competency dimensions?

RQ2: Do distinct profiles exist in teachers' MIL self-concept, and how do these profiles relate to their assessment of students?

RQ3: Which digital learning behaviours serve as the most significant predictors of students' MIL levels?

1.1. Contribution of the Study

This study makes three explicit contributions to the literature on Media and Information Literacy and teacher cognition.

First, it provides empirical evidence of a directional teacher–student perceptual gap in MIL within a Vietnamese secondary-school context, disaggregated across five MIL sub-dimensions. The pattern shows that the gap is concentrated in higher-order cognitive competencies (creation, evaluation) rather than in observable behaviours (ethics, practice), refining prior accounts that have treated the gap as a uniform phenomenon.

Second, it offers a person-centered typology of teachers' MIL conceptualization profiles. Teachers' assessment of students is co-shaped by teachers' own MIL self-concept ($\eta^2 = 0.68$), revealing an evaluator-side mechanism for the perceptual gap that goes beyond conventional rater-bias accounts.

Third, it presents a behaviour-driven Random Forest model that repositions MIL as a process-oriented competence: purposeful Internet-for-learning behaviour, IT proficiency, and learning engagement predict MIL, whereas device ownership and Internet time do not. This finding refocuses MIL pedagogy from infrastructural conditions to instructional design.

2. Literature Review and Theoretical Background

2.1. The Conceptual Evolution of Media and Information Literacy in the Era of Algorithmic Complexity

Media and Information Literacy (MIL) has undergone a profound conceptual transformation, evolving from a fragmented set of technical abilities into a multidimensional construct essential for cognitive agency in an increasingly automated information landscape (Lazer et al., 2018; Vosoughi, Roy, & Aral, 2018). In the current era characterized by generative artificial intelligence and algorithmic curation, MIL has transitioned into a form of critical digital agency (Gagrčin, Naab, & Grub, 2026). Learners must not only retrieve information but also navigate sophisticated misinformation produced by large language models, necessitating a high-order capability often described as scientific online reasoning (Pimentel, 2025). This shift suggests that MIL is no longer a static achievement but a dynamic process of self-regulated inquiry that requires constant recalibration as technology evolves.

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The complexity of MIL is further highlighted by its operationalization through several interrelated dimensions, including access, critical evaluation, creative production, and ethical practice. These competencies are not inherent traits but are deeply influenced by instructional quality and the digital competence-related beliefs of educators (Runge, Lazarides, Rubach, Richter, & Scheiter, 2023). A persistent challenge in secondary education remains the discrepancy between the formal curriculum and the actual digital practices of students. As digital environments become more opaque due to algorithmic filtering, the ability of students to critically notice and evaluate information becomes the primary differentiator of literacy levels. This conceptual depth forms the basis for investigating how these competencies are perceived and assessed within the ecological context of the modern classroom.

2.2. The Digital Native Fallacy and the Mechanics of Perceptual Discrepancy

The persistent influence of the digital native myth continues to distort pedagogical discourse, creating a significant gap between perceived and actual student competencies. This fallacy assumes that ubiquitous exposure to technology inherently fosters sophisticated digital literacy, yet decades of research have refuted this assumption by showing that superficial technical fluency does not translate into academic or critical information proficiency (Bennett, Maton, & Kervin, 2008; Helsper & Eynon, 2010; Kirschner & De Bruyckere, 2017). Reports on teacher policies highlight that this overestimation is a global phenomenon where educators often conflate high levels of screen time with high levels of media literacy. This pedagogical blind spot is critical because it directly influences the types of tasks teachers design and the level of scaffolding they provide. The foundational meta-analysis on teacher-based judgments of academic achievement (Hoge & Coladarci, 1989) established that teacher judgement is generally moderately accurate but systematically biased toward overestimation, a pattern that the present MIL findings extend into the digital-competence domain.

Scherer, Tondeur, Siddiq, and Baran (2018), the cognitive mechanisms behind this overestimation can be explained through attitudinal filters, suggesting that a teacher's own positive disposition toward technology or their professional self-efficacy can lead to a projection of competence onto their students. When teachers exhibit high digital confidence, they are statistically more likely to assume their students possess similar levels of proficiency, thereby widening the perceptual gap. This discrepancy is further exacerbated by attributional patterns where teachers often attribute students' digital failures to external factors such as lack of home access or parental guidance rather than recognizing a fundamental deficit in the students' critical MIL competencies. Consequently, without empirical tools to calibrate such teacher perceptions, the assessment of MIL remains subjective and prone to significant bias. Consistent with this evaluator-side mechanism, Praetorius, Berner, Zeinz, Scheunpflug, and Dresel (2013) demonstrated that teachers' confidence in their own competence is positively associated with their judgment accuracy of student characteristics, supporting the hypothesis that teacher self-perception co-shapes the assessment of students.

2.3. Theoretical Integration: Cognitive Load Theory and the Paradox of Instructional Overload

To understand the structural impact of teacher overestimation on student learning, it is necessary to integrate Cognitive Load Theory (CLT) with the pedagogical implications of the Zone of Proximal Development (ZPD). CLT posits that human cognitive architecture has a limited working memory capacity, divided among intrinsic, extraneous, and germane loads (Sweller, van Merriënboer, & Paas, 2019). In a digital learning context, extraneous load, the mental effort spent on navigating poorly designed instructions or complex technical interfaces, can severely hinder the learning process. When a teacher overestimates a student's MIL, they tend to provide less explicit technical instruction. This lack of scaffolding increases the extraneous load, forcing students to exhaust their cognitive resources on the tool itself rather than the learning objective.

This misalignment is closely linked to the violation of the Zone of Proximal Development, which emphasizes that effective instruction must occur in the space between a learner's independent ability and their potential achievement with guidance. By assuming high levels of MIL, teachers inadvertently place tasks in the frustration zone, beyond the student's actual capacity. Recent findings suggest that non-teaching workloads and the increasing complexity of digital resources have made it harder for teachers to accurately notice student struggles (Zhu, Li, Su, Hu, & Zhao, 2025).

When instructional quality is poorly calibrated to actual digital readiness, students often experience cognitive paralysis. Furthermore, the lack of targeted academic support in digital environments can correlate with increased externalizing problem behaviours as students struggle to cope with the frustration of unmanageable cognitive demands.

2.4. Behavioural Antecedents as Proxies for MIL within Self-Regulated Learning Frameworks

Given the limitations of subjective assessment, contemporary research has sought objective behavioural proxies to predict MIL proficiency. This study identifies three primary behavioural determinants: Internet Use for Learning (IUL), IT Proficiency (ITP), and Learning Engagement (LE), grounded in the framework of Self-Regulated Learning (SRL). SRL is defined as the process by which learners systematically direct their thoughts and behaviours toward the attainment of their goals. In this context, IUL represents the strategic, goal-oriented exploitation of technology for academic inquiry rather than recreational consumption. Policy perspectives emphasize that professional learning for teachers should focus on helping students transition toward this strategic agency, as it is a robust indicator of internalized MIL competencies (Tondeur et al., 2012; Zimmerman, 2002).

Similarly, IT proficiency and learning engagement serve as critical behavioural indicators that bridge technical readiness and cognitive effort. Technical proficiency functions as prior knowledge that mitigates extraneous cognitive load; students with high ITP are more likely to engage in critical digital noticing because they are not preoccupied with functional hurdles.

Meanwhile, learning engagement captures the behavioural and emotional persistence required to navigate the challenges of digital learning. Research suggests that engagement is not a stable trait but a mediator for competency acquisition. By analyzing these behavioural patterns through advanced predictive models such as the Random Forest algorithm, researchers can uncover non-linear relationships that traditional frequentist statistics often overlook. This

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methodological shift toward data-driven calibration allows for a more granular understanding of MIL, ensuring that pedagogical interventions are grounded in the actual digital practices of 21st-century students.

Taken together, the foregoing literature converges on a three-part theoretical framework that organizes the present analysis. Cognitive Load Theory and the Zone of Proximal Development theorize the instructional consequences of teacher overestimation: when teachers infer high MIL from observable exposure cues, the tasks they design fall outside students' actual capacity and overload working memory. The literature on teacher judgment accuracy provides a complementary, evaluator-side mechanism: teachers' own MIL self-concept functions as an evaluative lens that biases their perception of students. Self-Regulated Learning, finally, supplies the behavioural axis: purposeful, goal-oriented digital activities serve as observable proxies of the latent MIL construct. The three axes map directly onto the research questions of this study, where RQ1 tests the magnitude and locus of the perceptual gap, RQ2 examines the typology of teachers' MIL self-conceptualization, and RQ3 identifies the behavioural antecedents that empirically predict student MIL.

3. Research Method

3.1. Research Design

This study employs a quantitative research design with a cross-sectional approach, structured into three distinct analytical phases to explore MIL within the educational context (Setia, 2016). The design integrates: (i) a comparative analysis to quantify the perception gap between teachers and students; (ii) a typological investigation into teachers' latent profiles regarding MIL; and (iii) predictive modeling of students' MIL levels. By combining traditional inferential statistics with machine learning algorithms, this design provides a robust framework for analyzing both linear differences and complex, non-linear relationships in digital learning behaviours (Breiman, 2001).

3.2. Participants

The research involved a total of 403 participants, comprising 277 high school students and 126 teachers recruited via a convenience sampling strategy. The student cohort was predominantly female (63.2%) and primarily aged between 16 and 18 years (71.8%), with the majority residing in urban areas (66.8%). The teacher sample was also largely female (88.1%), representing a professionally experienced group: 37.3% had between 11 and 20 years of teaching tenure, and 22.2% had exceeded 20 years. Regarding academic qualifications, 77.8% of the teachers held a bachelor's degree, while 22.2% had attained a master's degree. The data were collected from four public secondary schools located in Da Nang City and Quang Nam Province, central Vietnam, between October 2024 and January 2025.

The participating institutions span urban (n = 2), suburban (n = 1), and rural (n = 1) catchments to capture variation in digital infrastructure access, school size, and socio-economic intake. School-level identifiers are anonymized in this report under the IRB-approved consent procedure; aggregate institutional information is available from the corresponding author upon reasonable request and within the limits of participant consent. Because the sample was recruited through institutional contacts, it is non-probabilistic; we therefore do not claim distributional generalizability beyond the participating schools but rather frame our findings as a theoretical replication of the perceptual-gap mechanism.

Data collection was designed to capture dual perspectives on Media and Information Literacy (MIL). Students provided self-reports on their competencies, whereas teachers assessed students' MIL proficiency through pedagogical observations. Notably, as data were aggregated at the institutional level without direct teacher-student dyadic pairing, the participants were treated as two independent groups. This person-centered approach aims to delineate the collective cognitive discrepancy between educators and learners within a shared digital transformation landscape. Individual-level dyadic matching between teachers and students was not feasible in the current data collection because students completed self-assessments anonymously and could not be linked to specific teachers without compromising the student-level confidentiality protected by our IRB protocol. Consequently, the perceptual misalignment reported in the present study should be interpreted as an aggregate, group-level indicator rather than as a per-pair measure of teacher judgment accuracy. Ethical clearance for the study, including informed consent from teacher participants and informed consent from the legal guardians of student participants under 18 (with assent obtained from students), was granted by the Research Ethics Committee of the University of Science and Education, the University of Da Nang.

3.3. Measure

3.3.1. Media and Information Literacy (MIL) Scale

The MIL competencies were operationalized using a parallel-instrument design adapted from the UNESCO MIL framework to ensure comparability between student self-perceptions and teacher pedagogical observations. The student version of the scale comprises 62 items organized into six theoretical dimensions: (a) Access & Awareness (12 items), (b) Practice (14 items), (c) Evaluation (12 items), (d) Creation (8 items), (e) Ethics (8 items), and (f) Communication (8 items).

The teacher's pedagogical assessment version was streamlined into 28 items across the same six dimensions to facilitate efficient classroom-based observation. For analytic reporting in the present article, the combined Access & Awareness composite (12 items) is reported as a single sub-dimension labelled Awareness, presented in aggregate rather than disaggregated into its constituent items; the Communication subscale is retained in the overall MIL composite but not reported at the sub-dimensional level, as differentiation among its items did not reach a level we consider robust for separate sub-dimensional inference in the present sample. The full Communication results will be developed in a forthcoming paper that focuses on production-side competencies.

The internal consistency for both scales was exceptionally high. For the student self-assessment, Cronbach's α coefficients for the subscales ranged from 0.909 to 0.964, with a total scale reliability of $\alpha = 0.974$. For the teacher-reported assessment, subscale alphas ranged from 0.752 to 0.961, with an overall reliability of $\alpha = 0.976$. These values significantly exceed the 0.70 threshold recommended for educational research (Cronbach, 1951).

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Construct validity was established through inter-factor correlation analysis. All subscales demonstrated strong, positive correlations with the total MIL score (r ranging from 0.52 to 0.88 for students; 0.70 to 0.94 for teachers, all $p < 0.001$). Content validity was ensured through adaptation of the UNESCO framework and expert review.

3.3.2. Predictive Behavioural Variables

To examine the nuances of digital engagement, three behavioural constructs were integrated as primary features for the Random Forest classification model. All variables were measured on a 5-point Likert scale (1 = *Never/Strongly Disagree* to 5 = *Very Frequently/Strongly Agree*).

1. Internet Use for Learning (IUL; 4 items): Measures the goal-oriented frequency of academic digital activities, including information seeking, peer collaboration, and LMS engagement ($\alpha = 0.85$). This construct reflects strategic technology exploitation rather than recreational usage.
2. IT Proficiency (ITP; 5 items): A self-reported measure of technical self-efficacy, assessing mastery over software applications, hardware troubleshooting, and platform navigation ($\alpha = 0.89$). It identifies the technical readiness essential for high-level MIL.
3. Learning Engagement (LE; 4 items): Evaluates the behavioural and cognitive effort in digital environments, including participation in online discussions, persistence through technical challenges, and proactive feedback-seeking ($\alpha = 0.82$).

These predictors provide a structured analytic framework for differentiating MIL proficiency levels by capturing the transition from passive technology exposure to active pedagogical exploitation.

3.4. Data Analysis

Data were analyzed through a multi-stage approach using SPSS v.26 and Python's Scikit-learn library. First, descriptive statistics and independent samples t-tests were conducted to examine the perceptual discrepancy between teacher and student cohorts. Cohen's d was calculated to determine the magnitude of these differences, following standard effect size benchmarks (Cohen, 1992).

Second, to identify distinct pedagogical viewpoints, a K-means cluster analysis was performed. This person-centered technique allowed for the classification of teachers into homogeneous profiles based on their MIL assessment patterns (Hartigan & Wong, 1979). The three-cluster solution was selected based on substantive interpretability and the elbow inflection in the within-cluster sum of squares; alternative solutions with $K = 2$ and $K=4$ yielded less differentiated profiles and were therefore not retained.

Finally, a Random Forest (RF) algorithm was employed to model the predictive relationships between behavioural variables and student MIL proficiency. RF was selected for its robustness in capturing non-linear interactions and complex data structures. Model performance was substantiated by the coefficient of determination (R^2), while variable importance indices were extracted to rank the relative contribution of each predictor. The Random Forest implementation used scikit-learn 1.3 in Python 3.10.

The 277-student dataset was partitioned into a stratified 80/20 train–test hold-out on student MIL terciles. Hyperparameters were tuned through 5-fold cross-validation on the training set, with grid search over n_estimators ∈ {100, 300, 500, 1000}, max_depth ∈ {None, 5, 10, 20}, min_samples_leaf ∈ {1, 2, 5}, and max_features ∈ {sqrt, log2, 0.5}. The selected configuration was n_estimators = 500, max_depth = 10, min_samples_leaf = 2, max_features = sqrt. Out-of-bag error and held-out test R^2 were both monitored to detect overfitting, and the small gap between training and held-out performance, together with the stable OOB performance, indicates that overfitting was effectively mitigated. To stabilize the variable importance ranking, the model was refit with 25 random seeds; rank stability across seeds was confirmed with Spearman $\rho \geq 0.92$ between any two seeds. For a regression target, the variable importance index reported in Table 3 corresponds to permutation importance (Mean Decrease in Impurity), rescaled to sum to one across predictors.

4. Results

4.1. The Perception Gap Between Teachers' Assessments and Students' Self-Assessments of MIL (RQ1)

To examine whether a perceptual misalignment exists between teachers' assessments and students' self-assessments of Media and Information Literacy (MIL), an independent-samples comparison was conducted at both the overall MIL level and across five MIL sub-dimensions (Cohen, 1992).

4.1.1. Overall Difference in MIL Assessments

Results indicated a statistically significant difference between the two groups. Teachers rated students' overall MIL substantially higher ($M = 4.07$, $SD = 0.59$) than students rated themselves ($M = 3.86$, $SD = 0.64$), $t(401) = 3.28$, $p < 0.001$, $d = 0.36$. This pattern reflects a systematic tendency for teachers to assign higher levels of MIL competence to students than students attribute to themselves. Importantly, this difference is not trivial in magnitude, suggesting a divergence in perception rather than a measurement artifact.

4.1.2. Differences Across MIL Sub-Dimensions

To locate where this perceptual gap is most pronounced, the analysis was disaggregated across five core MIL dimensions: Awareness, Evaluation, Creation, Ethics, and Practice (Figure 1).

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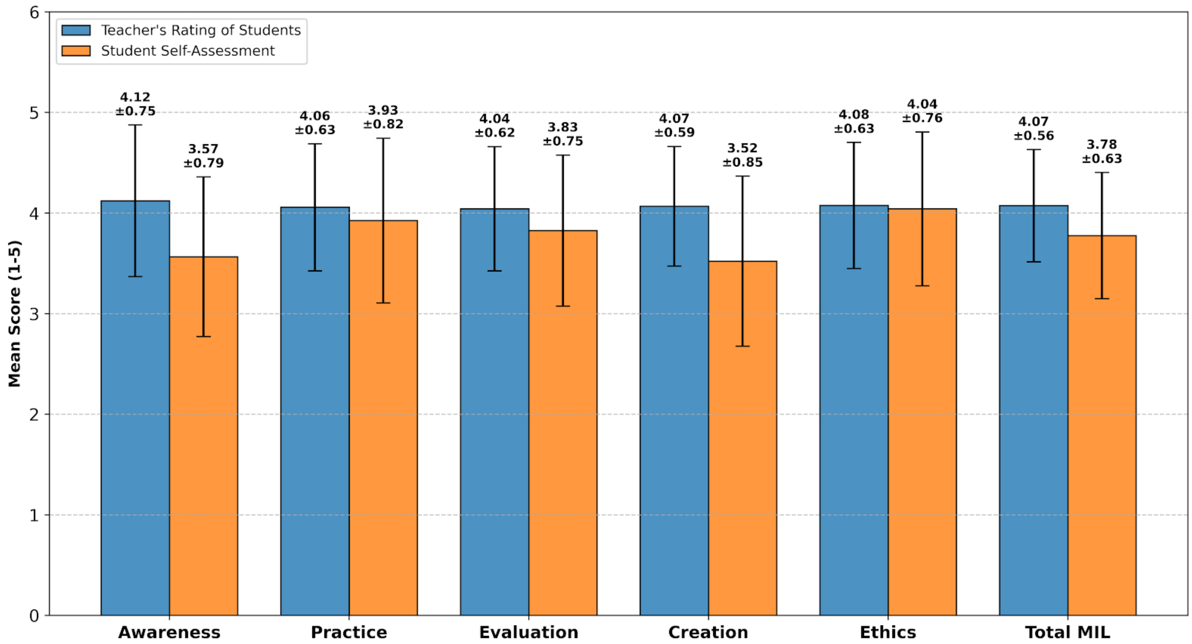

Figure 1. Mean Media and Information Literacy (MIL) ratings across five sub-dimensions, comparing teachers' assessment of students (n = 126) and students' self-assessment (n = 277).

Note: Error bars represent 95% confidence intervals. Asterisks denote significant teacher–student differences (** p < 0.01, *** p < 0.001). The Creation sub-dimension exhibits the largest gap (Δ = 0.55, p < 0.001); Ethics and Practice show no statistically significant gap.

Table 1. Teacher–student descriptive statistics across MIL sub-dimensions.

Sub-dimension	Teachers M (SD)	Students M (SD)	Δ (T − S)	p
Creation	4.07 (0.59)	3.52 (0.71)	+0.55	< 0.001
Evaluation	4.04 (0.61)	3.83 (0.69)	+0.21	< 0.01
Ethics	4.08 (0.55)	4.04 (0.62)	+0.04	0.67
Practice	4.06 (0.58)	4.00 (0.66)	+0.06	0.45
Awareness	4.12 (0.75)	3.57 (0.79)	+0.55	< 0.01

Note: Teacher ratings are based on n = 126 teachers; student self-assessments are based on n = 277 students. p-values are from independent samples t-tests with df = 401. The Awareness sub-dimension is reported in aggregate only because it was not separately disaggregated in the present analysis. Means and SDs for the Practice sub-dimension are reproduced from the analytic file used for Figure 1.

Table 1 presents the descriptive statistics and independent samples t-test results across specific MIL sub-dimensions, highlighting areas where the teacher-student perception gap diverges or converges. A significant institutional overestimation is concentrated within higher-order cognitive domains of Creation and Evaluation.

The largest discrepancy was observed in the Creation dimension. Teachers perceived students as competent in producing digital content (M = 4.07), whereas students reported only moderate confidence (M = 3.52), resulting in the widest gap (Δ = 0.55, p < 0.001). Teachers may equate digital device operation with content creation ability.

A similar, though smaller, misalignment was found in the Evaluation dimension. Teachers rated students' ability to verify and critically assess information more favorably (M = 4.04) than students did (M = 3.83), p < 0.01. This suggests potential overestimation of students' critical information literacy, central to MIL.

In contrast, near convergence was observed in the Ethics and Practice dimensions. For Ethics, no statistically significant difference was found between teachers' and students' assessments (M = 4.08 vs. M = 4.04, p = 0.67), suggesting shared perceptions regarding appropriate online behaviour. Similarly, in the Practice dimension, the gap was minimal (Δ = 0.06, p = 0.45), indicating teachers are relatively accurate in judging students' basic technical operations.

4.1.3. Pattern of Perceptual Misalignment

Taken together, these results reveal a consistent pattern: teachers' assessments align closely with students' self-assessments in areas where competencies are observable (technical practice, ethical behaviour) but diverge substantially in areas where competencies are cognitive and internal (content creation and critical evaluation) (Südkamp et al., 2012; Sweller et al., 2019). This pattern suggests that teachers may rely primarily on surface behavioural cues when judging students' MIL, while students base their self-assessment on the cognitive difficulty they experience during information processing and content production tasks. From a pedagogical standpoint, this perceptual misalignment is consequential. If teachers assume that students are already proficient in higher-order MIL competencies such as creation and evaluation, they may be less likely to explicitly teach or scaffold these skills in classroom practice.

4.2. Teacher MIL Self-Concept Profiles and their Association with Assessment of Students (RQ2)

4.2.1. Profile Structure: Three Distinct Clusters of Teacher MIL Conceptualization

We examined whether teachers form distinct profiles in how they conceptualize MIL and whether these profiles are associated with systematic differences in how they rate students' MIL. To address this, we conducted an exploratory cluster analysis using K-means on teachers' self-reported MIL subscales: Awareness, Practice, Evaluation, Creation, and Ethics (Jain, 2010; Kanungo et al., 2002). Prior to clustering, variables were standardized to ensure comparability across dimensions. The three-cluster solution provided the most interpretable profile structure for the dataset (N = 126 teachers who provided student ratings; see more in Table 2).

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Table 2. Comparison of teacher profiles on personal MIL and assessment of student competencies (N = 126).

Profile Name	N (%)	Teacher's Own MIL Mean (SD)	Student MIL Assessment Mean (SD)	Perception Gap (Mdiff)*
1. Empowered Advocates	33 (26.2%)	4.63 (0.25)	4.70 (0.24)	+0.84
2. Developing professionals	84 (66.7%)	3.90 (0.22)	3.96 (0.24)	+0.10
3. Skeptical beginners	9 (7.1%)	2.85 (0.74)	2.89 (0.85)	−0.97
Overall mean	126 (100%)	4.07 (0.56)	4.07 (0.56)	+0.21

Note: Teacher profiles were derived using K-means clustering on standardized teacher self-reported MIL subscales (awareness, practice, evaluation, creation, ethics). One-way ANOVA indicated significant differences across profiles in teachers' ratings of students' MIL, $F(2, 123) = 131.80$, $p < 0.001$, $\eta^2 = 0.68$. Tukey HSD post-hoc tests indicated all pairwise differences were significant ($p < 0.001$). The perception gap is a descriptive index computed relative to students' self-assessment mean reported in RQ1 (3.86); positive values indicate higher teacher ratings.

The clustering results identified three substantively distinct teacher profiles, differing in both their self-reported MIL and their ratings of students' MIL (see Table 2): (1) Empowered Advocates ($n = 33$, 26.2%): Teachers reporting uniformly high MIL across all five domains ($M = 4.63$, $SD = 0.25$); (2) Developing Professionals ($n = 84$, 66.7%): Teachers reporting moderately high MIL across domains ($M = 3.90$, $SD = 0.22$); (3) Skeptical Beginners ($n = 9$, 7.1%): Teachers reporting comparatively lower and more heterogeneous MIL ($M = 2.85$, $SD = 0.74$). This pattern indicates that teachers are not a homogeneous group in their MIL conceptualization; rather, they exhibit differentiated profiles in perceived competence across core MIL dimensions.

4.2.2. Profiles and Student MIL Ratings: Strong Between-Profile Differences

Next, we tested whether these profiles differed in how teachers rated students' MIL. A one-way ANOVA showed a large and statistically significant profile effect on teachers' ratings of students' MIL ($F(2, 123) = 131.80$, $p < 0.001$, $\eta^2 = 0.68$). The effect size ($\eta^2 = 0.68$) indicates that a substantial proportion of variance in teachers' ratings of students' MIL is associated with teachers' profile membership (Lakens, 2013), suggesting that teachers' own MIL conceptualization strongly aligns with how they evaluate students' MIL. Post-hoc comparisons using Tukey HSD confirmed all pairwise differences were statistically significant ($p < 0.001$). Specifically, Empowered Advocates rated students higher than Developing Professionals, and both groups rated students higher than Skeptical Beginners.

4.2.3. Profile Patterns in "Perception Gap" Relative to Students' Self-Assessments

To interpret between-profile differences in terms of alignment with students' self-assessments, we computed a descriptive perception gap index using the student self-assessment mean reported in RQ1 (3.86) as the reference point (Perception Gap = teachers' rating of student MIL − 3.86), where positive values indicate that teachers rated students higher than students rated themselves, and negative values indicate the opposite. This index revealed three distinct patterns: Empowered Advocates exhibited the largest positive gap ($M = 4.70$; gap ≈ +0.84), indicating a tendency to rate students' MIL considerably higher than students' self-perceptions; Developing Professionals showed near alignment with students' self-assessments ($M = 3.96$; gap ≈ +0.10), suggesting closer calibration at the group level; whereas Skeptical Beginners rated students substantially lower than students rated themselves ($M = 2.89$; gap ≈ −0.97), reflecting a pattern of underestimation relative to students' self-perceptions. For clarity, the perception-gap index is computed as Δ = M_teacher rating of students − M_student grand mean (3.86). Because students' anonymous self-assessments cannot be matched to individual teachers, this index is a descriptive group-level indicator of evaluative misalignment rather than an individual-level measure of teacher judgment accuracy; positive values indicate that, on average, teachers in a profile rate students above the student grand mean, and negative values indicate the opposite.

Overall, the findings provide evidence that teachers cluster into distinct MIL conceptualization profiles and that these profiles are strongly associated with how teachers rate students' MIL. Specifically, teachers with higher self-reported MIL tend to assign higher student MIL ratings, whereas teachers with the lowest self-reported MIL profile assign markedly lower student MIL ratings.

We note, however, that the strong association between teachers' self-rated MIL and their rating of students ($\eta^2 = 0.68$) may partly reflect a halo effect inherent in self-perception data, in which teachers with positive self-concepts assimilate students' competencies upward, and teachers with more self-critical orientations do the converse. This halo dynamic does not invalidate the typology, but it qualifies the causal reading: teachers' MIL self-conceptualization is best understood as a co-shaping lens for assessment rather than as an independent predictor of student MIL.

4.3. Behavioural Predictors of Students' MIL (RQ3)

To identify which factors are empirically associated with students' Media and Information Literacy (MIL), a Random Forest (RF) model was implemented using students' digital learning behaviours and technology-related characteristics as predictors. The model achieved a coefficient of determination of $R^2 = .38$, indicating that 38% of the variance in students' MIL can be explained by the included variables. Table 3 presents the relative importance of predictors based on the Mean Decrease Gini index.

Table 3. Relative importance of predictors of students' MIL (Random Forest model).

Rank	Predictor	Importance (permutation, normalised to sum to 1)
1	Internet use for learning	0.42
2	IT proficiency	0.31
3	Learning engagement	0.18
4	Internet time	0.05
5	Device ownership	0.04

Note: Higher values indicate greater contribution of the variable to the predictive model.

The pattern of results reveals a clear contrast between purposeful learning behaviours and general technology access.

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First, internet use for learning emerged as the strongest predictor. This indicates that MIL is not fostered through passive exposure to digital environments but through engagement in goal-directed learning tasks online. Students who use the internet specifically to complete learning activities tend to demonstrate higher MIL. This finding provides an empirical explanation for the overestimation observed in RQ1: teachers may conflate frequent online presence with the ability to perform cognitively demanding digital tasks.

Second, device ownership and overall time spent online showed the lowest predictive power. Contrary to common concerns in school contexts, and contrary to the assumptions observed among the most confident teacher profiles in RQ2, access to devices and frequency of internet use alone do not meaningfully predict students' MIL. This suggests a pedagogical blind spot: attention is often placed on infrastructural conditions (necessary conditions), whereas students' actual MIL appears to be shaped by how they engage in learning processes online (sufficient conditions).

Third, IT proficiency ranked as the second most important predictor, indicating that technical operational skills remain an essential foundation for higher-level MIL competencies such as evaluation and creation. However, these skills are impactful primarily when coupled with purposeful academic use.

Taken together, the findings from RQ3 serve as a behavioural complement to the perceptual patterns identified in RQ1 and RQ2. While teachers' assessments appear influenced by visible technological fluency and access conditions, the empirical model indicates that students' MIL is consistently associated with the depth and purposefulness of their digital learning engagement.

5. Discussion

The objective of this study was to contrast teachers' pedagogical assumptions with empirical evidence regarding students' Media and Information Literacy (MIL) competencies, thereby decoding (a) the cognitive gap between these two assessment subjects, (b) the different cognitive lenses or profiles of teachers, and (c) which digital behavioural factors actually predict students' MIL. Overall, the findings reveal a consistent structure: teachers' ratings are driven by visible cues and belief systems, while students' MIL is better explained by purposeful academic uses of digital environments, a form of empirical evidence versus pedagogical assumptions with direct implications for teacher education and digital instructional design (Lucas, Bem-Haja, Siddiq, Moreira, & Redecker, 2021; Urhahne & Wijnia, 2021).

5.1. Cognitive Gap and the Collapse of the "Digital Natives" Myth (RQ1)

The results of RQ1 indicate that teachers rate students' MIL competencies significantly higher than the students' own self-assessments (Porat, Blau, & Barak, 2018). This aligns with the classic argument regarding the digital native fallacy: being born into a digital environment and possessing fluent technological manipulation skills do not equate to the ability to evaluate sources, reason, and verify information, the core components of MIL (Scheerder, van Deursen, & van Dijk, 2017). The magnitude of the gap observed here ($d = 0.36$) falls within the moderate range reported in the meta-analytic literature on teacher judgement accuracy (Hoge & Coladarci, 1989; Südkamp et al., 2012), suggesting that the Vietnamese secondary-school context exhibits a perceptual misalignment broadly consistent with patterns documented in other educational systems.

Brodsky et al. (2021) and McGrew (2024) mechanistically, although the present design cannot test cognitive processes directly, overestimation may stem from teachers' tendency to rely on surface indicators: familiarity with devices, frequency of online activity, or confidence in technological interaction. Meanwhile, deep-level MIL competencies (e.g., source verification, corroboration, evidence evaluation) are cognitive processes that are difficult to observe directly in the classroom, especially in the absence of tasks designed to make these competencies visible. This reasoning also explains why intervention programs for online reasoning or civic online reasoning often require students to practice with real online content and source evaluation strategies (such as lateral reading), because relying solely on a technological impression makes it very easy to misjudge competency.

The pedagogical consequence of overestimation is concerning: when teachers believe that "students already know it," MIL is easily demoted to secondary content or mentioned only at the level of general ethical recommendations. This contradicts international recommendations that emphasize MIL as a holistic competency encompassing access, evaluation, creation of content, and responsible participation.

An equally informative pattern is the absence of a perceptual gap in the Ethics and Practice sub-dimensions, where teachers' assessments converge with students' self-assessments. A plausible explanation is that these dimensions manifest primarily through directly observable behaviour: Ethics surfaces in conduct that teachers can monitor (compliance with platform norms, refraining from problematic posting), and Practice surfaces in routine technical operations performed in front of the teacher. By contrast, Creation and Evaluation are cognitive processes that are not easily observable in real time, leaving teachers to infer competence from surface cues. The differential pattern of significant versus null gaps therefore offers indirect support for an observability-based account of judgment accuracy: where competence is observable, teacher and student perceptions converge; where it is internal, perceptions diverge.

5.2. "Lenses of Bias" (RQ2): When Pedagogical Beliefs Turn into Assessment Metrics

Metzger, Flanagin, Markov, Grossman, and Bulger (2015) show the results of RQ2 that teachers are not a homogeneous group; they form different profiles in how they understand and define MIL, which in turn influences how they assess students. Specifically, the fact that one group of teachers leans toward viewing MIL as ethics-legal is consistent with a tentative interpretation we label compliance versus competence: teachers are prone to rate students high (or low) based on whether students are well-behaved/non-violating rather than based on their ability to perform cognitive tasks (searching, filtering, corroborating, evaluating, and synthesizing information). This framework aligns with research on teacher beliefs in digital instruction: competence-related beliefs and pedagogical beliefs regarding the role of technology shape how teachers implement activities and self-report instructional quality.

In other words, the gap in RQ1 is not merely a data source difference between teacher-rating and self-rating but also reflects a difference in the evaluative frames of reference. If teachers measure MIL using a standards/compliance yardstick, they may perceive (and assess) what is visible: attitudes, rules, and right/wrong behaviours. If students

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assess themselves using a task effectiveness yardstick, they will rely on their experiences of difficulty or ease when finding sources, verifying, and creating digital products (List & Alexander, 2018). This misalignment of reference systems creates a pedagogical blind spot: teachers believe they are measuring competency, but in reality, they are measuring a component of attitudes or norms. This observation also matches recent policy suggestions emphasizing that effective digital teaching competency is not about digitizing old teaching but rather about pedagogical redesign to clarify goals, tasks, assessment criteria, and learning evidence.

5.3. The Nature of MIL Competency (RQ3): "Process Over Infrastructure" And the Role of Self-Regulated Learning

Maksl, Craft, Ashley, and Miller (2017) and Pennycook and Rand (2019), the Random Forest results in RQ3 provide a complementary, behaviour-side perspective: students' MIL is primarily predicted by Internet for learning and IT proficiency, while device ownership and internet time are almost insignificant. This has two important theoretical implications. First, MIL is a process and action-oriented competency: it is not about having devices or using the network a lot that makes one good at MIL, but rather what students use the Internet for, according to what strategies, and with which academic tasks. This argument aligns with online reasoning models that emphasize specific digital learning tasks and source verification strategies rather than just increasing technological exposure.

Second, the variable Internet for learning can be understood as a manifestation of self-regulated learning (SRL): clear goals, strategy selection, progress monitoring, and self-assessment of information/material quality. SRL has long been considered the foundation for learners to study effectively in environments rich in choices and information noise, precisely the context of MIL.

Therefore, the RQ3 results reinforce a central line of reasoning: instead of focusing on infrastructure as the primary solution, it is necessary to shift toward a process-oriented pedagogy that helps students practice academic operations on the Internet: searching, comparing sources, authenticating, citing, synthesizing, and creating products.

5.4. Implications: Aligning Teacher Education and Task-Based MIL Instructional Design

From the three RQs, two central recommendations for teacher education and professional development can be drawn. First, teachers should shift from teaching tool usage to evidence-based assessment. Recent international recommendations emphasize that developing digital teaching competency is not just technical but involves pedagogical and assessment competency in digital environments (task design, assessment criteria, learning data). Therefore, professional development programs should provide tools and observation frameworks so that teachers can recognize deep-level MIL (evaluation, reasoning, verification) instead of inferring from surface signs (Siddiq & Scherer, 2019).

Second, MIL should be taught through digital learning tasks within subject areas, not just through online ethics lessons. Since the Internet for learning is the strongest predictor, the implication is clear: MIL is most effective when integrated into the academic tasks of subjects such as Philology, History, and Natural Sciences, including tracing the source of an argument, corroborating multiple sources, analyzing reliability, and creating multimedia products with citations. This approach aligns with online reasoning intervention designs tested in schools (McGrew, 2024).

Two illustrative examples make these recommendations concrete. For evidence-based assessment, teacher-education programmes can adopt a three-tier classroom observation rubric that distinguishes surface competence (operating digital tools), intermediate competence (locating, comparing, and verifying online information), and deep competence (creating and critically synthesising multimedia products with proper attribution). The rubric requires teachers to collect specific behavioural evidence at each tier rather than infer competence from general fluency. For subject-integrated MIL instruction, a Literature lesson can be redesigned around a lateral-reading task in which students trace the source of an argument across three online platforms, document the chain of authority, and produce a short evidence-based note; an equivalent task in History can ask students to corroborate a primary-source claim against two independent secondary sources before writing a brief synthesis. Both examples shift MIL instruction from a separate digital-citizenship lesson into a subject-driven cognitive exercise, which the present findings indicate is the locus of meaningful MIL development.

5.5. Limitations and Directions for Future Research

Although the study provided empirical evidence of differences in MIL assessments between teachers and students and identified behavioural factors predicting students' MIL, several limitations should be considered when interpreting the results. First, the research data were collected using a cross-sectional design, which allowed consideration of relationships at a single point in time but did not enable inference about changes in MIL over time. The use of cross-sectional data also means that the relationships identified, including the predictive model's explanatory power ($R^2 = 0.38$), should be understood as statistical associations rather than causal relationships.

Secondly, the measurement of MIL competence in this study is primarily based on students' self-reported data and teachers' overall assessments. This approach may be influenced by individual cognitive biases, such as the tendency to underestimate or overestimate one's own abilities, as well as differences in assessment criteria among teachers (Urhahne & Wijnia, 2021). While using the same scale for both groups ensures comparability, the results still need to be interpreted cautiously, especially since MIL competence is a complex construct that is difficult to fully reflect in cognitive scales alone.

Thirdly, the study did not use objective performance-based measures to assess students' MIL competence. Therefore, a direct comparison between self-assessment, teacher assessment, and competence demonstrated through specific learning tasks is not possible. Including scenario-based assessment tests or tasks in future studies could help clarify the cognitive gap identified in this study.

Furthermore, although the Random Forest model shows that numerical learning behaviour factors explain a significant portion of MIL's variance, a large portion of the variance remains unexplained. This suggests the possibility of other factors not considered in the study, such as cognitive traits, learning motivation, family background, or the learning environment at the grade and school levels. Future studies could expand the analytical model by incorporating these variables and applying multilevel models to account for the influence of the educational context.

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Three additional limitations should be explicitly acknowledged. First, the sample was recruited via convenience sampling and is therefore not statistically representative of the broader population of Vietnamese secondary-school teachers and students; notably, the female-dominated teacher subsample (88.1%) is particularly significant. Second, without dyadic teacher–student pairing, the perception-gap index reported here is a group-level descriptive statistic rather than an individual-level measure of teacher judgment accuracy. The cluster-level association between teacher self-rated MIL and teacher ratings of students (η^2 = .68) may partly reflect a halo effect inherent in self-perception data. Third, IT Proficiency and the Practice sub-dimension of MIL share conceptual surface area; although the items differ in framing, future studies should formally test for content overlap before interpreting the predictive contribution of IT Proficiency.

Given these limitations, several directions for further research are suggested. First, longitudinal studies could be conducted to track the development of MIL competence over time, thereby clarifying the role of digital learning behaviours in its formation and consolidation (Zhao, Li, Ma, Xu, & Zhang, 2025). Second, combining quantitative data with qualitative methods, such as interviews or classroom observations, could help deepen understanding of the mechanisms forming the cognitive gap between teachers and students. Finally, further studies could examine the impact of specific pedagogical interventions aimed at correcting teachers' perceptions of students' MIL competence, as well as evaluate the effectiveness of data-driven digital teaching strategies in enhancing MIL competence in secondary school students.

6. Conclusion

This study approached the issue of Media and Information Literacy (MIL) from an integrated perspective combining pedagogical assessment and data analysis, thereby clarifying three core aspects: (i) the existence of a cognitive gap between teachers and students, (ii) differences in teachers' "cognitive lenses" when assessing MIL literacy, and (iii) behavioural factors predicting students' MIL literacy. The results showed that teachers tend to overestimate students' MIL literacy compared to the students' self-assessments, especially in higher-order competencies such as information assessment and content creation. Simultaneously, the study also indicated that teachers are not a homogeneous group but possess diverse cognitive profiles, which significantly influence how they assess students.

Notably, the Random Forest model provided empirical evidence that MIL competence is not determined by the level of technology access or internet usage time, but rather by how learners use technology for learning, combined with IT competence and learning engagement levels. This finding clarifies the nature of MIL as a process- and action-oriented competence, rather than merely the result of technological exposure.

Theoretically, the research contributes to repositioning the concept of MIL in the context of digital transformation, emphasizing the role of purposeful learning behaviour and self-regulation in the digital environment. Integrating traditional statistical methods with machine learning also opens new approaches in educational research, enabling exploration of nonlinear and complex relationships in learning behaviour.

Practically, the research offers several important implications for teacher training and instructional design. First, there is a need to shift from perception-based to evidence-based assessment, enabling teachers to identify students' MIL competencies accurately. Second, teacher training programs should focus on developing the ability to design digital learning tasks (task-based learning), rather than solely on tool-use skills. Third, integrating MIL into subjects through activities such as searching, evaluating, comparing, and creating information will sustainably enhance digital competence.

Three priorities emerge for future research. The first and most consequential is to replicate the present findings using a dyadic design in which teachers' assessments can be matched to the specific students they teach, paired with a performance-based MIL measure (e.g., a scenario-based lateral-reading task) that triangulates self-report data with observable behaviour. This addresses the two principal validity constraints of the present study and is a precondition for any individual-level claim about teacher judgment accuracy.

The second priority is to test causal pathways through longitudinal or quasi-experimental designs. Tracking the same teachers and students across an academic year would clarify whether the perception gap narrows with targeted professional development and whether Internet-for-learning behaviour predicts MIL gains rather than merely correlating with MIL levels. The third priority is to extend the model to include unmodeled determinants that the present study could not capture, learning motivation, metacognitive strategies, family digital capital, and school-level instructional climate, using multilevel analysis to partition variance attributable to the student, the classroom, and the school.

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