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Beyond Basic Literacy: Wiring Science Students for Rapid Technological Shifts via Self-Regulation and Collaborative AI Metacognition

Kyla Rita A. Mercado[1]

[1] Department of General Teacher Training, North Eastern Mindanao State University, Tandag City 8300, Surigao del Sur, Philippines.
Corresponding Author:
Kyla Rita A. Mercado
Email: kylarita14@gmail.com

Abstract
To thrive in today's rapidly shifting technological era, future professionals must possess strong adaptive capabilities. Consequently, this research models the mechanisms driving student adaptability, specifically analyzing the interplay of Digital Fluency (DF), Self-Regulated Learning (SRL), and Collaborative AI Metacognition (CAM). Utilizing Partial Least Squares Structural Equation Modeling (PLS-SEM), we evaluated survey responses from science undergraduates at North Eastern Mindanao State University. While baseline digital fluency directly enhances adaptability ($\beta = 0.198$, $p < 0.001$), this technological proficiency achieves its greatest impact when coupled with internal learning strategies. Notably, self-regulation acts as a critical bridge, significantly mediating the DF-adaptability link ($\beta = 0.131$, $p < 0.001$). Furthermore, the capacity to critically reflect alongside artificial intelligence (CAM) emerged as a powerful direct catalyst for adaptive performance ($\beta = 0.406$, $p < 0.001$). Ultimately, preparing a resilient workforce requires moving beyond basic computer literacy; educational institutions must actively foster self-directed learning behaviors and sophisticated AI evaluation tactics to ensure graduates can seamlessly navigate future technological disruptions

Keywords : science education; digital fluency; self-regulated learning; collaborative AI metacognition; adaptive performance; societal needs.

Introduction

As contemporary society deepens its dependence on technological infrastructure, the proliferation of digital devices has exponentially broadened the global user base. Yet, this rapid technological integration introduces novel complications, compelling users to cultivate a heightened consciousness regarding software and hardware constraints while adeptly managing digital information streams (Korabayev et al., 2024). Consequently, this investigation addresses the urgent requirement to map the mechanisms through which science undergraduates forge the skills needed to thrive amidst digital volatility, focusing specifically on the interplay of digital fluency, self-regulated learning, and collaborative artificial intelligence (AI) metacognition.

Comprehending learner adaptability within today's tech-centric world is increasingly imperative, given that digital breakthroughs perpetually alter paradigms for communication, knowledge acquisition, and information retrieval. Research indicates, for instance, that shifting environmental dynamics trigger emotional reactions in students, which subsequently dictate their adaptable capacities, problem-solving choices, and overall self-assurance (Castro, 2024). Concurrently, fostering academic fortitude—specifically by enhancing cognitive plasticity—equips learners with the emotional and intellectual tools required to maneuver adeptly through evolving educational landscapes and multifaceted obstacles (Honra & Monterola, 2025).

Beyond merely operating digital instruments, modern learners face expectations to exhibit autonomous study habits, critical discernment, and judicious decision-making when processing digital texts. The accelerating transition toward virtual classrooms has magnified the indispensable nature of self-regulated learning. Widespread technological integration dictates that students autonomously steer their educational trajectories while adjusting to the inherently independent and malleable characteristics of digital platforms. Indeed, robust self-regulation directly architects a student's proficiency in deconstructing and resolving intricate dilemmas (Mensah et al., 2026). Migrating from physical classrooms to web-based ecosystems introduces distinct hurdles, demanding elevated self-regulatory capabilities to successfully endure the rigors of digital education (Banda Perez et al., 2025;

Oktaviani & Kuswandi, 2024). This regulatory necessity becomes glaringly apparent when learners must execute adaptive performance—calibrating to volatile technological or academic pressures on the fly within fluid learning spaces. Such structural frameworks hold profound relevance in digitally augmented environments, requiring technological integrations to scaffold the entire learning continuum instead of merely facilitating content distribution and testing (Zulkefli & Ismail, 2025).

In the realm of AI-supported science education, emerging literature reveals that real-time, personalized feedback from artificial intelligence can nurture self-regulated behaviors, though this relies heavily on the student possessing sufficient metacognitive skills to critically appraise AI-proposed scientific theories (Calzada et al., 2026; Zhai et al., 2021; Su & Yang, 2023). Crucially, environments mediated by artificial intelligence do not organically generate learner autonomy; rather, the architectural design of these platforms dictates whether they serve as obstructive hurdles or supportive scaffolds for independent study.

With the ubiquitous rise of intelligent systems, baseline digital fluency serves as the foundational requirement for collaborative AI metacognition—defined as the conscious orchestration of one's cognitive processes during human-AI interactions. Because AI literacy inherently branches from general digital proficiency, individuals lacking the capacity to scrutinize standard digital media will inevitably struggle to supervise or validate content synthesized by artificial intelligence (Duhaylungsod & Chavez, 2023; Ng et al., 2021; Wang et al., 2023). Furthermore, evidence suggests that technologically adept individuals bypass passive consumption, opting instead for iterative planning and nuanced prompt engineering—hallmarks of a highly metacognitive partnership with AI (Chai et al., 2021; Long & Magerko, 2020). Consequently, science students rely heavily on digital fluency to refine their input prompts, interrogate AI-constructed scientific rationales, evaluate empirical data visualizations, and elevate their overall investigative methodologies.

Defined as the capacity to recalibrate and troubleshoot amidst fluctuating conditions, adaptive performance is critical for modern survival (Ismail et al., 2025). Within contemporary scientific laboratories, digital fluency transcends basic technical know-how, functioning instead as a vital precursor to adaptability during inquiry-driven exploration (Kong & Lai, 2022). To effectively manipulate sophisticated simulation software and novel data-logging apparatuses, science students are compelled to exhibit profound digital agility. By mastering these technological interfaces, learners free up cognitive load for complex, higher-order analytical tasks, ultimately fortifying their resilience during high-stakes, volatile experimental procedures.

While isolated investigations have heavily documented AI literacy, self-regulated learning, and digital fluency as standalone phenomena, a glaring empirical void exists regarding their synergistic impact on adaptive performance within technologically augmented and AI-driven educational spheres. To bridge this scholarly gap, the current research interrogates the structural interplay among collaborative AI metacognition, self-regulated learning, and digital fluency within the science student population. This investigation holds profound contemporary relevance; as society increasingly pivots toward digitized, inquiry-centric frameworks, future professionals face mounting pressure to exhibit adaptability, deploy cutting-edge instruments for scientific troubleshooting, and master technology-mediated analytical processes (Scherer, Siddiq, & Tondeur, 2019).

Materials and Methods

Participants

For the 2025–2026 academic year, a cohort comprising 1,561 undergraduate science students from the Cantilan campus of North Eastern Mindanao State University constituted the sample for this investigation. Inclusion criteria dictated that these individuals must be actively enrolled in science disciplines necessitating the use of technology-augmented educational activities. This included required engagement with data interpretation exercises, virtual simulations, web-based scientific databases, and AI-integrated learning platforms.

Research Design

To systematically map both the direct impacts and mediated pathways connecting digital fluency, self-regulated learning, collaborative AI metacognition, and adaptive performance within tech-heavy educational settings, the researchers implemented a predictive-correlational framework.

Data Collection

To guarantee broad participant access, data harvesting was executed via a digitized Google Forms survey. All psychometric instruments were deliberately modified to align with the nuances of technology-augmented science education. Specifically, metrics for evaluating digital fluency were derived from Demir and Odabaşı (2022), whereas the self-regulated learning (SRL) framework was sourced from Barnard-Brak et al. (2010). Furthermore, collaborative AI metacognition (CAM) parameters were drawn from Sidra and Mason (2026).

To assess adaptive performance (AP), the researchers utilized Charbonnier-Voirin and Roussel's established multidimensional inventory (Charbonnier-Voirin & Roussel, 2012). While this foundational AP tool contains 19 distinct items, the current investigation isolated five specific parameters: stress management, learning effort, interpersonal adaptability, reactivity, and creativity. This targeted selection was made because these specific traits embody the core adaptational reflexes demanded of contemporary science students maneuvering through fluid academic scenarios, AI-driven platforms, and digital applications.

Structurally, the survey maintained the varied response mechanisms of its source scales: digital fluency relied on a 5-point agreement spectrum, while self-regulated learning utilized a 5-point frequency continuum. Conversely, both collaborative AI metacognition and adaptive performance were quantified via 7-point agreement scales.

Data Analysis

To decipher the intricate predictive dynamics of the proposed framework, the researchers executed Partial Least Squares Structural Equation Modeling (PLS-SEM) utilizing the WarpPLS version 6.0 software suite. This computational approach involved a dual-stage evaluation process encompassing both a measurement model (for verifying validity and reliability) and a structural model (for mapping construct interconnections).

During the measurement model phase, construct robustness was confirmed via composite reliability and Cronbach's alpha, maintaining a minimum acceptable threshold of 0.70. Furthermore, the Average Variance Extracted (AVE) was monitored to secure convergent validity, utilizing a baseline requirement of >0.50. The Heterotrait-Monotrait (HTMT) ratio and the Fornell-Larcker criterion were subsequently deployed to verify discriminant validity.

Upon transitioning to the structural model, the researchers calculated effect sizes (f^2) and path coefficients (β) to determine the magnitude and intensity of the construct relationships, while R^2 values indicated the framework's overall explanatory capacity. The Stone-Geisser metric (Q^2) was computed to confirm predictive validity, requiring output scores greater than zero. Finally, to rigorously test the mediating pathways involving collaborative AI metacognition and self-regulated learning between digital fluency and adaptive performance, significance testing was conducted utilizing statistical bootstrapping procedures.

Evaluation of the Measurement Model

To validate the measurement model, this study examined the constructs' validity and reliability. Composite reliability (CR) and Cronbach's alpha (CA) served as the primary reliability metrics. As detailed in Table 1, the CA indices span from 0.908 to 0.955, and the CR metrics range from 0.928 to 0.963. Because these figures surpass the recommended 0.70 benchmark, they demonstrate robust internal consistency within the model (Fornell & Larcker, 1981; Kock & Lynn, 2012).

Table 1: Convergent Validity and Reliability Measures

Constructs/Items	Item Loading	AVE	Cronbach's Alpha	Composite Reliability
Digital Fluency				
DF1	0.861	0.685	0.908	0.928
DF2	0.815			
DF3	0.842			

Constructs/Items	Item Loading	AVE	Cronbach's Alpha	Composite Reliability
DF4	0.830			
DF5	0.796			
DF6	0.823			
Self-Regulated Learning				
SRL1	0.780	0.660	0.938	0.948
SRL2	0.808			
SRL3	0.865			
SRL4	0.781			
SRL5	0.839			
SRL6	0.794			
SRL7	0.814			
SRL8	0.832			
SRL9	0.801			
SRL10	0.781			
Collaborative AI Metacognition				
CAM1	0.855	0.795	0.955	0.963
CAM2	0.901			
CAM3	0.911			
CAM4	0.898			
CAM5	0.878			
CAM6	0.898			
Adaptive Performance				
AP1	0.841	0.745	0.914	0.935
AP2	0.848			
AP3	0.803			

Constructs/Items	Item Loading	AVE	Cronbach's Alpha	Composite Reliability
AP4	0.910			
AP5	0.906			

Average Variance Extracted (AVE) and individual item loadings were analyzed to establish convergent validity. For all four variables—Digital Fluency (DF), Self-Regulated Learning (SRL), Collaborative AI Metacognition (CAM), and Adaptive Performance (AP)—item loadings spanned between 0.780 and 0.911, easily clearing the 0.50 minimum. Additionally, AVE values fluctuated between 0.660 and 0.795, satisfying the >0.50 criterion and proving sufficient convergent validity for the model (Hair et al., 2021).

Table 2: Discriminant Validity (Fornell-Larcker Criterion)

	DF	SRL	CAM	AP
DF	0.828			
SRL	0.515	0.812		
CAM	0.472	0.328	0.892	
AP	0.538	0.575	0.539	0.863

The study utilized dual approaches to verify discriminant validity. Initially, the Fornell-Larcker Criterion demonstrated that the diagonal figures (representing the square root of each construct's AVE) consistently exceeded the off-diagonal correlation coefficients between the constructs (see Table 2). Subsequently, the Heterotrait-Monotrait (HTMT) Ratio analysis in Table 3 confirmed that every value remained under the strict 0.85 cutoff. Together, these findings verify that the research measures display distinct discriminant validity.

Table 3: Discriminant Validity (HTMT)

	DF	SRL	CAM	AP
DF		0.552	0.508	0.585
SRL			0.345	0.615
CAM				0.572
AP				

Evaluation of Structural Model

Assessment of the structural model required analyzing predictive relevance (Q^2), effect sizes (f^2), coefficients of determination (R^2), path coefficients (β), and collinearity.

Variance Inflation Factors (VIF) were scrutinized to detect any vertical and lateral collinearity. Table 5 illustrates that VIF scores fluctuated between 1.518 and 1.985, remaining safely beneath the 3.3 limit and confirming the absence of common method bias in the model (Kock, 2017).

The Stone-Geisser criterion (Q^2) was utilized to establish predictive relevance. With Q^2 scores of 0.342 for SRL, 0.258 for CAM, and 0.592 for AP, all metrics surpassed zero, confirming strong predictive validity (Geisser, 1974).

To gauge explanatory power, Chin's (1998) benchmarks were applied. The R^2 value for Adaptive Performance (0.595) borders on substantial, meaning the exogenous variables account for a major share of its variance. Meanwhile, Self-Regulated Learning (0.335) yielded a moderate R^2, and Collaborative AI Metacognition (0.257) registered a weak-to-moderate explanatory capacity.

Table 4: Direct and Indirect Effects

	Beta Coefficient	P-Value	SE	Effect Size
Direct Effects				
H1a. DF → SRL	0.432	<0.001	0.045	0.228
H1b. DF → CAM	0.508	<0.001	0.046	0.259
H1c. DF → AP	0.198	<0.001	0.047	0.108
H3. SRL → AP	0.364	<0.001	0.046	0.229
H4a. CAM → SRL	0.258	<0.001	0.045	0.106
H4b. CAM → AP	0.406	<0.001	0.044	0.252
Indirect Effects				
H5. DF → SRL → AP	0.131	<0.001	0.033	0.068
H6. DF → CAM → AP	0.093	0.004	0.032	0.058

Hypothesis testing outcomes are detailed in Table 4. The assessment of direct impacts reveals a significant, positive relationship between Digital Fluency and SRL ($\beta = 0.432$, $p < 0.001$), CAM ($\beta = 0.508$, $p < 0.001$), and AP ($\beta = 0.198$, $p < 0.001$). Consequently, hypotheses H1a, H1b, and H1c are validated. Furthermore, the interactions between SRL and CAM, as well as their respective impacts on AP, all demonstrated positive effect sizes with significant p-values ($p < 0.001$), thereby validating H3, H4a, and H4b.
Mediation testing demonstrated that the link between Digital Fluency (DF) and Adaptive Performance (AP) is significantly bridged by both Collaborative AI Metacognition (CAM) and Self-Regulated Learning (SRL). Specifically, a statistically significant indirect pathway was found from DF to AP via SRL ($\beta = 0.131$, $p < 0.001$), which supports H5. Similarly, the pathway from DF through CAM to AP was also significant ($\beta = 0.093$, $p = 0.004$), corroborating H6. Ultimately, these results prove that students' Adaptive Performance is boosted by Digital Fluency both directly and indirectly through secondary pathways involving heightened self-regulated learning and collaborative AI metacognition.

Table 5: Collinearity Assessment, Coefficient of Determination, and Predictive Relevance

	Full Collinearity VIF	R2	Q2
DF	1.668		
SRL	1.655	0.335	0.342
CAM	1.518	0.257	0.258
AP	1.985	0.595	0.592

Discussion

As digital transformations relentlessly overwrite traditional professional roles and operational standards, contemporary industries place an unprecedented premium on workforce adaptability. Within the realm of science education, the current investigation yields compelling evidence that building students' adaptive capacities is non-negotiable for their survival and success in heavily digitized arenas. The empirical outcomes confirm that traversing fluid educational landscapes, solving multifaceted problems, and seamlessly integrating novel technologies requires a specific triad of skills: collaborative AI metacognition, self-regulated learning, and digital fluency. With artificial intelligence and advanced digital architectures deeply embedding themselves into science curricula, fostering these specific proficiencies becomes the primary vehicle for preparing graduates to meet impending socioeconomic, professional, and academic expectations.

The data establish baseline digital proficiency as a foundational driver that significantly dictates a science student's adaptive performance, collaborative AI metacognition, and self-regulated learning capacity. Furthermore, as established in the structural model, the capacity for digital fluency translates into higher adaptive performance precisely because its effects are mediated through enhanced self-regulation and sophisticated AI metacognition. This dynamic substantiates the premise that technological fluency equips learners to purposefully exploit digital resources, orchestrate their own study habits, and seamlessly interface with advanced systems (Blanc et al., 2025; Chai et al., 2021; Laupichler et al., 2022; Long & Magerko, 2020). Highly fluent individuals, for instance, demonstrate superior aptitude in selecting optimal digital instruments, pivoting their educational strategies, interrogating AI-synthesized data, and partnering with intelligent platforms to conquer intricate scientific challenges (Ng et al., 2021; Su & Yang, 2023; Wang et al., 2023). Ultimately, mastering these foundational digital skills transforms students into autonomous, agile scholars fully capable of weathering the relentless fluctuations of tech-centric ecosystems.

The structural analysis further exposes self-regulated learning as a potent catalyst for adaptive performance among science undergraduates. This relationship aligns with the understanding that autonomous study habits fortify complex problem-solving capabilities (Asare et al., 2025). By actively governing their cognitive load and deploying strategic interventions, self-directed learners effortlessly recalibrate to shifting educational paradigms and conquer academic hurdles. Practices such as introspective reflection, progress tracking, and rigorous goal-setting empower individuals to modify their behavioral patterns, leverage accessible assets, and tackle sophisticated scientific inquiries with precision. Within digitally augmented spaces, this autonomy translates into a distinct advantage; self-regulated individuals organically weave nascent technologies like AI into their daily workflows, independently probe new software, and critically vet digital information. Consequently, as classrooms increasingly adopt AI scaffolding, the demand for self-regulation intensifies—students must consciously orchestrate their engagement with generative algorithms to avoid falling into the trap of passive technological dependency (Fütterer et al., 2026; Xu et al., 2026).

The framework confirms that the ability to critically reflect alongside artificial intelligence operates as a direct driver of both adaptive capacity and self-regulated behavior. As a foundational pillar of autonomous study (Yan et al., 2026), metacognitive awareness equips students to continuously audit, critique, and recalibrate their own cognitive architectures. True academic efficacy stems not merely from deploying sophisticated tactics, but from dynamically optimizing those tactics in response to fluctuating environmental stressors (Tempelaar et al., 2025). In this context, collaborative AI metacognition acts as a critical lens, amplifying a student’s consciousness regarding their human-machine interactions. It fosters judicious decision-making by prompting learners to select optimal problem-solving pathways and rigorously interrogate AI-produced content. Consequently, when interfacing with intelligent platforms, metacognitively mature science scholars refuse to blindly swallow algorithmic explanations. Instead, they refine their prompt engineering, cross-examine the validity of the provided data, and synthesize AI-generated feedback with their own empirical logic to decipher complex phenomena. This sophisticated dynamic illustrates how AI-specific metacognition fundamentally upgrades a learner's independence, reflexivity, and adaptability in modernized settings.

These empirical insights must serve as a blueprint for aligning educational frameworks with the rigorous demands of tomorrow's industrial and societal landscapes. Driven by relentless globalization, shifting occupational paradigms, and technological breakthroughs, contemporary society urgently demands pedagogical modernization. Because professionals must sustain peak competency across lengthening careers filled with increasingly intricate responsibilities, cultivating highly responsive academic infrastructures is no longer optional. Higher and vocational education must transcend the narrow goal of securing individual employment; it must actively fuel macroeconomic advancement, institutional evolution, and enterprise-level innovation.

This investigation posits that preparing graduates for heavily digitized ecosystems demands a departure from basic technical training. True readiness mandates the cultivation of deep adaptive capacities, rigorous critical thought, self-directed learning, and profound digital fluency. As digital frontiers perpetually shift, educational institutions must forge individuals who can ethically wield technological instruments, scrutinize data streams, and dynamically recalibrate their analytical processes. Such holistic skill sets are non-negotiable for students destined to confront the complex professional and civic challenges of a tech-driven era. Ultimately, pedagogy must extend beyond personal skill acquisition to incubate professionals capable of sustaining ethical work environments, pioneering novel solutions, and assimilating into volatile workplace cultures. In an epoch defined by the relentless intersection of occupational shifts and digital breakthroughs, hardwiring learners for perpetual education and extreme adaptability remains the paramount strategy for satisfying broader societal ambitions and immediate workforce necessities.

Conclusions

This research underscores that wiring future professionals for a digitally saturated society hinges on fostering extreme independence, technological fluency, and robust adaptability. The empirical models confirm that mastering complex problem-solving tasks, regulating individual study architectures, and successfully maneuvering through novel digital ecosystems are directly dependent upon a learner's collaborative AI metacognition, self-regulated learning, and foundational digital fluency.

Baseline digital proficiency acts as the bedrock for this entire dynamic, empowering students to process data critically, manipulate advanced software, and pivot during academic disruptions. Operating simultaneously, self-regulated learning bolsters an individual's resilience, enabling them to consciously track their educational trajectories, deploy targeted interventions, and neutralize academic friction. Augmenting these traits, collaborative AI metacognition elevates human-computer interactions by instilling a critical, strategic, and deeply ethical approach to consuming and leveraging artificial intelligence.

To satisfy the escalating global demand for highly capable talent, tomorrow's pedagogical frameworks must abandon superficial technical training in favor of deep-rooted adaptational competencies suited for volatile social, professional, and academic arenas. Because digital metamorphoses continuously rewrite industrial standards, the modern workforce demands professionals hardwired for ethical technology application, rigorous analytical thought, relentless innovation, and perpetual education. Moving forward, curriculum designers must prioritize ecosystems that deeply embed AI and digital architectures, explicitly training students to partner seamlessly with intelligent algorithms, vet digital data streams, and adapt to unforeseen obstacles. Ultimately, nurturing this specific triad of skills ensures the generation of a resilient workforce—one fully equipped to conquer emerging societal dilemmas, drive industrial progress, and master the inevitable technological disruptions of the future..

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