How to Prepare Students for a Technology-Driven Society? The Case of Digital Fluency, Self-Regulated Learning, and AI Metacognition in 21st-Century Adaptive Performance

Kyla Rita A. Mercado
Department of General Teacher Training
North Eastern Mindanao State University, Philippines
kylarita14@gmail.com

Abstract

Modern soeciety requires individuals to adapt to the rapidly evolving digital landscape. Adaptability in modern society is becoming inscreasingly critical for growing workforce. This study examined how adaptive performance is being influenced by digital fluency, self-regulated learning, and collaborative AI metacognition. Data were collected through an online survey among science students from North Eastern Mindanao State University. The variables were measured using validated scales, including the 19-item multidimensional scale for adaptive performance (Charbonnier-Voirin & Roussel, 2012). PLS-SEM (Partial Least Squares Structural Equation Modeling) was employed to analyze the relationships between digital fluency, self-regulation, collaborative AI metacognition, and adaptive performance. Statistical analysis showed that digital fluency significantly influenced adaptive performance ($\beta = 0.203$, $p < 0.001$), albeit with a moderate effect size, suggesting it works well with other cognitive factors. Self-regulation was found to significantly mediate the relationship between digital fluency and adaptive performance ($\beta = 0.134$, $p < 0.001$), emphasizing the importance of self-regulatory strategies in applying digital skills effectively. Furthermore, collaborative AI metacognition had a substantial direct effect on adaptive performance ($\beta = 0.410$, $p < 0.001$), showing the importance of reflection with AI tools in building adaptability. Essentially, students are more likely to adapt effectively to technological advancements when they develop digital fluency, self-regulated learning skills, and the ability to critically evaluate AI-generated information. This study empahasized the notion that preparing students for a technology-driven society requires cultivating competencies that enable them to respond to rapid changes, navigate emerging digital environments, and distinguish reliable information from potentially misleading sources.

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

1. Introduction

The increasing reliance of modern society on technology has resulted in the widespread adoption of digital devices and the expansion of their users. However, alongside technological advancements are emerging challenges that require individuals to develop greater awareness of hardware and software limitations, as well as the ability to navigate issues related to digital information (Korabayev et al., 2024). This study responds to the need to understand how science students develop the competencies necessary to adapt within rapidly evolving digital environments, particularly through their digital fluency, self-regulated learning, and artificial intelligence (AI) metacognitive abilities.

There is a growing need to understand the adaptability of students in a modern technology-driven society, primarily because technological advancements continue to reshape the ways individuals learn, communicate, and access information. For example, students' emotional responses toward changes in their environment influence their confidence, decision-making, and adaptability (Castro, 2024). Meanwhile, building students' academic resilience, particularly strengthening cognitive flexibility, can cultivate their' cognitive and emotional competencies, enabling them to respond more effectively to complex challenges and changing learning environments (Honra & Monterola, 2025).

As technology continues to transform educational and social landscapes, students are expected not only to utilize digital tools effectively but also to demonstrate critical awareness, independent learning capacity, and the ability to make informed decisions when interacting with information they read.

As the educational landscape increasingly shifts to online learning environments, the ability for students to engage in self-regulated learning has become more critical than ever. With the rapid integration of technology in education, students are now required to not only manage their learning independently but also adapt to the flexible, often autonomous nature of digital tools and platforms. In fact, it was found that self-regulated learning helps in shaping students' capacity to analyze and address complex problems effectively (Mensah et al., 2026).

Now, the shift from traditional classroom-based learning to online environments has created new challenges for students, necessitating higher levels of self-regulation to effectively navigate the demands of digital learning (Banda Perez et al., 2025; Oktaviani & Kuswandi, 2024). This need for self-regulation is especially evident as students engage in adaptive practices, the ability to adjust to changing academic or technological demands in real-time, within these ever-evolving educational settings. This tripartite structure proves especially relevant in technology-enhanced contexts, where digital tools must support learners across all phases rather than privileging assessment and content delivery (Zulkefli & Ismail, 2025).

Furthermore, recent research in AI-augmented science pedagogy demonstrates that continuous, adaptive feedback from AI tools fosters self-regulated learning, provided that the learner possesses the metacognitive tools to evaluate AI-generated scientific hypotheses (Calzada et al., 2026; Zhai et al., 2021; Su & Yang, 2023). AI-mediated environments do not automatically encourage self-regulated learning; instead, the design choices embedded within these systems directly determine whether they function as scaffolds or barriers to learner autonomy.

As AI becomes increasingly common, digital fluency acts as a prerequisite for collaborative AI metacognition, the awareness and control of thinking processes when interacting with AI tools. AI literacy is an extension of digital fluency; without the ability to evaluate digital outputs, learners cannot effectively monitor or evaluate AI-generated content (Duhaylungsod & Chavez, 2023; Ng et al., 2021; Wang et al., 2023). Studies indicate that users with higher digital competencies are more likely to engage in prompt engineering and iterative planning, reflecting a sophisticated metacognitive approach to AI collaboration rather than passive acceptance (Chai et al., 2021; Long & Magerko, 2020). Thus, digital fluency is necessary for science learners to critique AI-generated scientific explanations, improve prompts, assess data-based outputs, and improve their inquiry-based learning strategies.

Adaptive performance, sometimes adaptability, is defined as the ability to adjust to changes and solve problems in dynamic environments (Ismail et al., 2025). In the modern science laboratory, digital fluency is no longer just a technical skill but a prerequisite for adaptive performance in inquiry-based learning (Kong & Lai, 2022). Science learners must demonstrate high digital agility to navigate emerging computational tools and data-logging interfaces used in complex simulations. Mastery of these relevant tools allows science learners to focus on higher-order problem-solving, thereby enhancing their flexibility in dynamic and high-pressure experimental environments.

Although previous studies have explored digital fluency, self-regulated learning, and AI literacy as individual constructs, limited empirical evidence has examined the combined influence of these competencies in predicting students' adaptive performance within AI-supported and technology-enhanced learning environments. To address this gap in the existing literature, this study seeks to investigate the relationships among digital fluency, self-regulated learning, and collaborative AI metacognition among science learners. This inquiry is particularly relevant because the modern society continues to evolve toward digitally mediated and inquiry-based contexts, where students are expected to demonstrate adaptive capacities, engage in technology-assisted problem-solving, and effectively utilize emerging tools in addressing complex scientific challenges (Scherer, Siddiq, & Tondeur, 2019).

2. Materials and Methods

2.1. Participants

The participants of this study were 1,561 science learners enrolled during SY 2025–2026 at North Eastern Mindanao State University, Cantilan. Participants were selected from science-related programs/courses that required engagement with digital tools, AI-assisted learning platforms, online scientific resources, simulations, data interpretation tasks, or technology-enhanced science learning activities.

2.2. Research Design

The predictive-correlational design was used to examine the direct and indirect relationships among digital fluency, self-regulated learning, collaborative AI metacognition, and adaptive performance in technology-enhanced science learning contexts.

2.3. Data Collection

Data were collected through an online questionnaire distributed via Google Forms, ensuring accessibility for all participants. The scales were adapted to fit the context of technology-enhanced science learning. Specifically, the digital fluency scale was adapted from Demir & Odabaşı (2022), the self-regulated learning (SRL) scale was adapted from (Barnard-Brak et al., 2010), the collaborative AI metacognition (CAM) scale was adapted from (Sidra & Mason, 2026) and the adaptive performance (AP) scale was adapted from (Charbonnier-Voirin & Roussel, 2012). Adaptive performance was measured using five selected indicators adapted from the multidimensional Adaptive Performance Scale of Charbonnier-Voirin and Roussel (2012). Although the original instrument consists of 19 items, the present study focused only on five indicators that represent the key dimensions of adaptive performance relevant to technology-enhanced science learning: creativity, reactivity, interpersonal adaptability, learning effort, and stress management. These indicators were selected because they reflect the essential adaptive behaviors expected of 21st-century science learners when engaging with digital tools, AI-supported learning environments, and changing academic or inquiry-based tasks.

The questionnaire used different response formats based on the original structure of the adapted instruments. Digital fluency was measured using a 5-point agreement scale, while self-regulated learning was measured using a 5-point frequency scale. Collaborative AI metacognition and adaptive performance were measured using 7-point agreement scales.

2.4. Data Analysis

Data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with WarpPLS version 6.0, chosen for its capability to handle complex relationships in predictive models. The analysis included both the measurement model (to evaluate reliability and validity) and the structural model (to examine relationships between constructs). Reliability was assessed using Cronbach's alpha and composite reliability, with values above 0.70 deemed acceptable. Convergent validity was measured with Average Variance Extracted (AVE), and values above 0.50 were considered satisfactory. Discriminant validity was tested using the Fornell-Larcker criterion and the Heterotrait-Monotrait (HTMT) ratio.

For the structural model, path coefficients (β) were used to assess the strength of relationships, R^2 to evaluate explanatory power, and effect sizes (f^2) to gauge relationship strength. Predictive relevance (Q^2) was assessed using the Stone-Geisser Q^2 method, with values above 0 indicating predictive validity. Mediation analysis was performed to explore the indirect effects of self-regulated learning and collaborative AI metacognition on the relationship between digital fluency and adaptive performance, using bootstrapping techniques to test the significance of these effects.

3. Results

3.1 Evaluation of the Measurement Model

The evaluation of the measurement model involves assessing the reliability and validity of the constructs. Reliability was measured using Cronbach's alpha (CA) and composite reliability (CR). As shown in Table 1, the CA values range from 0.911 to 0.959, while the CR values range from 0.931 to 0.966. These values exceed the 0.70 threshold, indicating high internal consistency (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	0.865			
DF2	0.819			
DF3	0.846	0.692	0.911	0.931
DF4	0.834			
DF5	0.800			

DF6	0.827			
Self-Regulated Learning				
SRL1	0.784			
SRL2	0.812			
SRL3	0.870			
SRL4	0.785			
SRL5	0.843	0.662	0.943	0.951
SRL6	0.798			
SRL7	0.818			
SRL8	0.836			
SRL9	0.804			
SRL10	0.784			
Collaborative AI Metacognition				
CAM1	0.860			
CAM2	0.905	0.802	0.959	0.966
CAM3	0.915			
CAM4	0.902			
CAM5	0.881			
CAM6	0.902			
Adaptive Performance				
AP1	0.845			
AP2	0.852			
AP3	0.807	0.751	0.917	0.938
AP4	0.914			
AP5	0.910			

Convergent validity was assessed through item loadings and the Average Variance Extracted (AVE). All item loadings for Digital Fluency (DF), Self-Regulated Learning (SRL), Collaborative AI Metacognition (CAM), and Adaptive Performance (AP) were above the 0.50 threshold, ranging from 0.784 to 0.915. Furthermore, the AVE for all constructs (ranging from 0.662 to 0.802) exceeded the 0.50 requirement, confirming that the measurement model possesses adequate convergent validity (Hair et al., 2021).

Table 2 Discriminant Validity (Fornell-Larker Criterion)

	DF	SRL	CAM	AP
DF	**0.832**			
SRL	0.519	**0.814**		
CAM	0.478	0.333	**0.896**	
AP	0.543	0.581	0.543	**0.867**

Discriminant validity was evaluated using two methods. First, the Fornell-Larcker Criterion (Table 2) shows that the square root of the AVE for each construct (diagonal values) is greater than the correlation coefficients between constructs (off-diagonal values). Second, the Heterotrait-Monotrait (HTMT) Ratio (Table 3) reveals that all values are below the conservative threshold of 0.85. These results collectively manifest that the measures used in the study have established discriminant validity.

Table 3 Discriminant Validity (HTMT)

	DF	SRL	CAM	AP
DF		0.559	0.511	0.592
SRL			0.349	0.623

CAM	0.579
AP	

3.2 Evaluation of Structural Model

The structural model was evaluated by examining collinearity, path coefficients (β), the coefficient of determination (R^2), effect sizes (f^2), and predictive relevance (Q^2).

To check for lateral and vertical collinearity VIFs were assessed. As shown in Table 5, all VIF values (ranging form 1.525 to 1.992) are well below the 3.3 threshold, indicating that the model is free from common method bias (Kock, 2017)

Predictive relevance was measured using the Stone-Geisser test or Q^2 for SLR (0.347), CAM (0.265) and AP (0.598) are all greater than zero, signifying the model's predictive validity (Geisser, 1974).

Regarding the explanatory power of the model, the study utilized the thresholds proposed by (Chin, 1998). The R^2 for adoptive performance (0.600) is approaching substantial, suggesting that the exogenous variables explain a significant portion of its variance. The R^2 for self-regulated learning (0.341) is considered moderate, while collaborative AI Metacognition (0.263) is classified as weak to moderate.

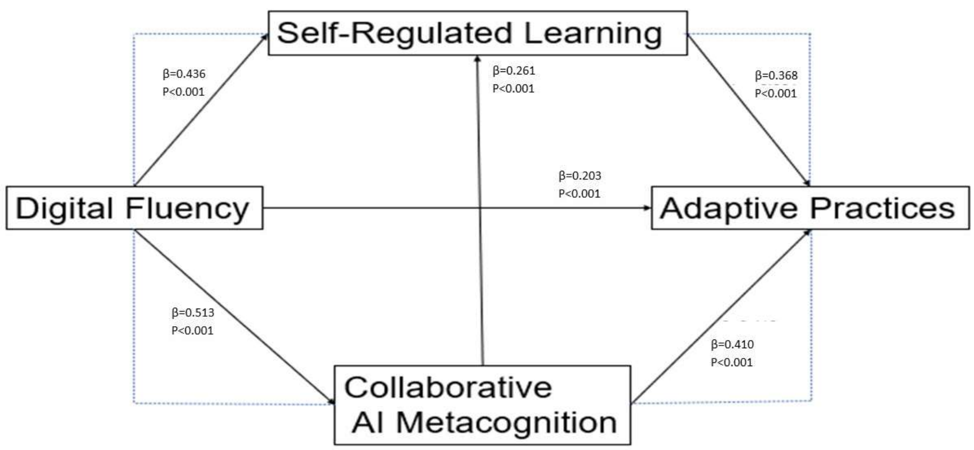

Figure 1 Digital Fluency- Adaptive Practices Model With Parameter Estimates

Table 4 Direct and Indirect Effects

	Beta Coefficient	P-Value	SE	Effect Size
Direct Effects				
H1a. DF→ SRL	0.436	<0.001	0.048	0.231
H1b. DF→CAM	0.513	<0.001	0.047	0.263
H1c. DF→AP	0.203	<0.001	0.049	0.111
H3. SRL→AP	0.368	<0.001	0.048	0.233
H4a. CAM→SRL	0.261	<0.001	0.049	0.109
H4b. CAM→AP	0.410	<0.001	0.048	0.256
Indirect Effects				
H5. DF →SRL → AP	0.134	<0.001	0.035	0.071

H6. DF→CAM→AP	0.096	0.003	0.035	0.060

Table 4 represents the results of the hypothesis testing. The direct effects analysis shows that digital fluency significantly and positively influences SRL (β= 0.436, p<0.001), CAM (β= 0.513, p<0.001), and AP (β= 0.203, p<0.001), supporting H1a, H1b, and H1c. The effect size of SRL and CAM to wards each other and towards AP are all positive and the p-value of <0.001 indicates significance, thus, H3, H4a and H4b are supported.

The mediation analysis revealed that both Self-Regulated Learning (SRL) and Collaborative AI Metacognition (CAM) significantly mediated the relationship between Digital Fluency (DF) and Adaptive Performance (AP). The indirect effect of DF on AP through SRL was statistically significant (β = 0.134, p < .001), supporting H7. Likewise, the indirect effect of DF on AP through CAM was significant (β = 0.096, p = .003), supporting H8. These findings indicate that Digital Fluency enhances Adaptive Performance not only directly but also indirectly through improvements in students' self-regulated learning and collaborative AI metacognition.

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

	Full Collinearity VIF	R^2	Q^2
DF	1.674		
SRL	1.662	0.341	0.347
CAM	1.525	0.263	0.265
AP	1.992	0.600	0.598

4. Discussion

Modern society increasingly emphasizes the importance of adaptability in workplaces, particularly within the context of technological advancement, as rapid digital transformation continues to redefine professional roles, processes, and expectations. This study provided notable results in science learning and emphasized the significance of developing students' adaptive capacities to effectively respond to the demands of technology-driven environments.

The findings revealed that competencies such as digital fluency, self-regulated learning, and AI metacognition are necessary in enhancing students' abilities to engage with emerging technologies, perform complex problem-solving tasks, and adjust to continuously evolving learning contexts. As science education becomes increasingly integrated with digital technologies and AI, cultivating these competencies is crucial in equipping learners with the skills necessary to address future academic, professional, and societal demands.

Digital Fluency. It was observed that science students' digital fluency significantly influences their self-regulated learning, collaborative AI metacognition, and adaptive performance. In addition, digital fluency had a mediating effect on the relationship between self-regulated learning and collaborative AI metacognition in predicting students' adaptive performance. This confirms that digital fluency enables students to effectively interact with technology, manage their learning processes, and utilize necessary resources in meaningful ways (Blanc et al., 2025; Chai et al., 2021; Laupichler et al., 2022; Long & Magerko, 2020). For example, students with stronger digital fluency are more capable of identifying appropriate digital tools, evaluating AI-generated information, adjusting learning strategies, and collaborating with AI systems to address complex scientific tasks (Ng et al., 2021; Su & Yang, 2023; Wang et al., 2023) . Consequently, digital fluency enhances students' capacity to become flexible and independent learners who can respond effectively to the evolving demands of technology-driven environments.

Self-regulated Learning. The findings revealed that self-regulated learning significantly influences science students' adaptive performance. This confirms that self-regulated learning enables students to develop problem-solving skills (Asare et al., 2025) by adapting to changing learning conditions, managing their cognitive processes, and strategically applying appropriate approaches to overcome academic challenges. For example, goal-setting, self-monitoring, and reflection help students become more capable of adjusting their learning behaviors, utilizing available resources, and responding effectively to complex scientific tasks. In technology-enhanced environments, self-regulated learners are also better equipped to independently explore digital tools, evaluate information sources, and integrate emerging technologies such as AI into their usual routine. Likewise, self-regulated learning remains a critical competency in AI-supported classrooms because learners must actively regulate how they use digital and generative AI tools rather than passively depend on them (Fütterer et al., 2026; Xu et al., 2026).

Collaborative AI Metacognition. It was observed that collaborative AI metacognition was directly influential to students' self-regulated learning and adaptive performance. Metacognition is an essential component of self-regulated learning (Yan et al., 2026), as it enables learners to monitor, evaluate, and adjust their thinking processes. Students' effectiveness as learners is not determined solely by their consistent use of advanced learning strategies; rather, it is reflected in their ability to improve their methods according to the demands and conditions of the environment (Tempelaar et al., 2025). Clearly, collaborative AI metacognition allows students to develop greater awareness of how they interact with AI tools by critically assessing AI-generated outputs, determining appropriate strategies, and making informed decisions during learning tasks. For example, science students who use AI-assisted platforms may not simply accept AI-generated explanations but evaluate the accuracy of information, improve their queries, and combine AI feedback with their own scientific reasoning to solve complex problems. This shows that AI metacognition strengthens students' capacity to become reflective, adaptive, and independent learners in technology-driven settings.

The findings of this study should be placed at the forefront of efforts to address the demands of future industries, particularly within the context of evolving social and technological landscapes. The modern society is calling for the continuous improvement of the education system to address the increasing demands brought about by technological advancement, globalization, and changing workforce expectations. The increasing complexity of employment demands and the need for individuals to remain competent throughout extended working lives highlight the importance of developing adaptable and responsive education systems. Vocational and professional education should not be limited to enhancing individual employability outcomes but must also contribute to broader workplace innovation, organizational development, and socioeconomic progress.

This study suggested that building students' readiness and competence in a technology-driven society requires skills that extend beyond technical proficiency. It necessitates the development of digital fluency, self-regulated learning, critical thinking, and adaptive capabilities that enable learners to effectively engage with emerging technologies. As digital environments continue to evolve, students must be equipped with the ability to evaluate information, utilize technological tools responsibly, and adjust their learning process in response to changing demands. These competencies are essential in preparing learners to navigate future academic, professional, and societal challenges shaped by technological innovation.

Beyond developing personal competencies, education must cultivate individuals' capacity to adapt to changing workplace practices, introduce innovative solutions, and support sustainable professional environments. In the contemporary era, where occupational requirements and technological advancements continue to evolve, preparing learners with adaptive skills and a capacity for continuous learning has become essential for addressing workforce demands and achieving wider economic and societal goals.

5. Conclusions

The study emphasized that preparing students for a technology-driven society requires the development of competencies that promote adaptability, independence, and effective engagement with emerging technologies. The results revealed that digital fluency, self-regulated learning, and collaborative AI metacognition contributed significantly to students' ability to navigate digital environments, manage learning processes, and perform complex problem-solving tasks. Digital fluency emerged as a critical foundation that supported students' interaction with technological tools, evaluation of information, and adjustment to changing learning demands. Meanwhile, self-regulated learning strengthened students' capacity to monitor their learning behaviors, apply appropriate strategies, and respond effectively to academic challenges. Collaborative AI metacognition further enhanced students' awareness of their interactions with AI by encouraging critical evaluation, responsible use, and strategic application of AI-supported resources.

In response to the growing need of competent individuals, future education systems must move beyond developing technical proficiency alone and focus on cultivating adaptive competencies necessary for rapidly changing academic, professional, and social environments. As digital transformation continues to reshape industries and workplace expectations, individuals must be prepared with skills that enable continuous learning, innovation, critical thinking, and responsible technology use. Future directions in education should prioritize learning environments that integrate digital technologies and AI while strengthening students' ability to evaluate information, collaborate with intelligent systems, and adjust to emerging challenges. Finally, developing these competencies will support the preparation of learners who are capable of contributing to future industries, responding to technological changes, and addressing broader societal demands.

Acknowledgment

The author wishes to thank North Eastern Mindanao State University for supporting this study.

The author would also wish to acknowledge the use of ChatGPT (open AI) in the preparation of this paper. The tool was utilized solely for grammar refinement and formatting assistance. All the ideas, analyses, interpretations, and conclusions presented herein are the authors' own and represent their original scholarly work.

Conflict of interest

The authors declare she have no conflicts of interest.

Funding

The author received funding from North Eastern Mindanao State University.

References

Banda Perez, J. W., Banda Sanchez, D. R., & Mendoza Banda, T. Y. (2025). Effective Strategies for Online Education: A Systematic Literature Review. Minerva, 6(18), 148–156. https://doi.org/10.47460/minerva.v6i18.249

Barnard-Brak, L., Paton, V. O., & Lan, W. Y. (2010). Profiles in self-regulated learning in the online learning environment. International Review of Research in Open and Distributed Learning, 11(1), 61–80.

Asare, B., Yaa Nchor, E., & Dissou Arthur, Y. (2025). Moderating effect of cognitive ability on the nexus between self-regulated learning and problem-solving ability among university students. Research in Mathematics, 12(1), 2554423.

Yan, Z., Mendoza, N., Zhan, Y., & Wu, Y. T. (2026). Individual-level mechanisms of SRL in digital learning environments: motivational, metacognitive, and behavioural dynamics. Educational Psychology, 46(3), 341-349.

Tempelaar, D., Giesbers, B., Rienties, B., Bátori, A., & Mihai, A. (2025). Combining dispositional and behavioural facets of SRL, and the role of students' growth orientation. Educational Psychology, 1–22. https://doi.org/10.1080/01443410.2025.2592750

Blanc, S., Conchado, A., Benlloch-Dualde, J. V., Monteiro, A., & Grindei, L. (2025). Digital competence development in schools: A study on the association of problem-solving with autonomy and digital attitudes. International Journal of STEM Education, 12, Article 13. https://doi.org/10.1186/s40594-025-00534-6

Calzada, K. P. D., Chavez, J. V., Legarde, M. A. A., Berry, E. B., Batucan, N. A., Marquina, R. L., ... & Ajijul, A. J. (2026). Can AI aid teachers to motivate inventiveness of learners in ICT, Math, Science, and TechVoc Areas. *Journal of Daoist Studies*, *19*(S3), 1134-1147.

Chai, C. S., Lin, P.-Y., Jong, M. S.-Y., Dai, Y., Chiu, T. K., & Qin, J. (2021). Perceptions of and behavioral intentions towards learning artificial intelligence in primary school students. Educational Technology & Society, 24(3), 89–101.

Charbonnier-Voirin, A., & Roussel, P. (2012). Adaptive performance: A new scale to measure individual performance in organizations. Canadian Journal of Administrative Sciences/Revue Canadienne Des Sciences de l'Administration, 29(3), 280–293.

Chin, W. W. (1998). The partial least squares approach to structural equation modeling. In Modern methods for business research (pp. 295–336). Psychology Press.

Demir, K., & Odabaşı, H. F. (2022). Development of digital fluency scale: Validity and reliability study. Themes in eLearning, 15, 1–20.

Duhaylungsod, A. V., & Chavez, J. V. (2023). ChatGPT and other AI users: Innovative and creative utilitarian value and mindset shift. *Journal of Namibian Studies: History Politics Culture*, *33*, 4367-4378.

ElSayary, A. (2024). Integrating generative AI in active learning environments: Enhancing metacognition and technological skills. Journal of Systemics, Cybernetics and Informatics, 22(3), 34–37.

Evans, C., Kay, W., Amici-Dargan, S., González, R. D. M., Donert, K., & Rutherford, S. (2024). Developing a scale to explore self-regulatory approaches to assessment and feedback with academics in higher education. Frontiers in Psychology, 15, 1357939.

Fornell, C., & Larcker, D. F. (1981). Structural Equation Models with Unobservable Variables and Measurement Error: Algebra and Statistics. Journal of Marketing Research, 18(3), 382. https://doi.org/10.2307/3150980

Fütterer, T., Bardach, L., Kuhn, J., Keller, S. D., & Gerjets, P. (2026). Enhancing school students' self-regulated learning through generative AI support: A randomized controlled trial. Educational Psychology Review, 38, Article 42. https://doi.org/10.1007/s10648-026-10133-8

Geisser, S. (1974). A predictive approach to the random effect model. Biometrika, 61(1), 101–107.

Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021). Partial least squares structural equation modeling (PLS-SEM) using R: A workbook. Springer.

Helsper, E. (2021). The digital disconnect: The social causes and consequences of digital inequalities.

Hirschi, A., Nagy, N., Baumeler, F., Johnston, C. S., & Spurk, D. (2018). Assessing key predictors of career success: Development and validation of the career resources questionnaire. Journal of Career Assessment, 26(2), 338–358.

Ishaque, M. F., Ishaaq, A., & Nazim, M. (2026). Overdependence on AI Supported Learning and Critical Thinking: Investigating Opportunities and Risks in Modern Education at Higher Educational Level. Inverge Journal of Social Sciences, 5(2), 242–255. https://doi.org/10.63544/ijss.v5i2.263

Jafarli, R., Jafarli, G. F., Özperçin, A., & Adıgüzel, E. (2026). Scaling Project-Based Learning with Artificial Intelligence-Powered Parametric Feedback—A Model for Nakhchivan State University. ELECTRICA, 26, 1–15. https://doi.org/10.5152/electrica.2026.26054

Kock, N. (2017). WarpPLS user manual: Version 6.0. ScriptWarp Systems: Laredo, TX, USA, 141, 47–60.

Kock, N., & Lynn, G. S. (2012). Lateral collinearity and misleading results in variance-based SEM: An illustration and recommendations. Journal of the Association for Information Systems, 13(7), 2.

Laupichler, M. C., Aster, A., Schirch, J., & Raupach, T. (2022). Artificial intelligence literacy in higher and adult education: A scoping literature review. Computers and Education: Artificial Intelligence, 3, 100101. https://doi.org/10.1016/j.caeai.2022.100101

Long, D., & Magerko, B. (2020). What is AI literacy? Competencies and design considerations. 1–16.

Marzuki, A. G., Huriyah, H., Triassanti, R., Kencanawati, D., M. Nur, M. D., & Ulfah, U. (2026). Enhancing EFL Speaking Fluency and Reducing Anxiety through Mobile-Assisted Language Learning. International Journal of Interactive Mobile Technologies (iJIM), 20(05). https://doi.org/10.3991/ijim.v20i05.58509

Ng, D. T. K., Leung, J. K. L., Chu, S. K. W., & Qiao, M. S. (2021). Conceptualizing AI literacy: An exploratory review. Computers and Education: Artificial Intelligence, 2, 100041. https://doi.org/10.1016/j.caeai.2021.100041

Oktaviani, H. I., & Kuswandi, D. (2024). Trends in Self Regulated Learning (SRL) in Indonesia Based on Web of Science (WOS) Data. Edcomtech: Jurnal Kajian Teknologi Pendidikan, 9(1), 14–26. https://doi.org/10.17977/um039v9i12024p14-26

Santoso, H., Abdinagoro, S. B., & Arief, M. (2019). The Role of Digital Literacy in Supporting Performance Through Innovative Work Behavior: The Case of Indonesia's Telecommunications Industry. International Journal of Technology, 10(8), 1558. https://doi.org/10.14716/ijtech.v10i8.3432

Siddiq, F., & Scherer, R. (2016). The relation between teachers' emphasis on the development of students' digital information and communication skills and computer self-efficacy: the moderating roles of age and gender. Large-scale Assessments in Education, 4(1), 17.

Sidra, S., & Mason, C. (2026). Generative AI in human-AI collaboration: Validation of the collaborative AI literacy and collaborative AI metacognition scales for effective use. International Journal of Human–Computer Interaction, 42(7), 5084–5108.

Su, J., & Yang, W. (2023). Unlocking the power of ChatGPT: A framework for applying generative AI in education. ECNU Review of Education, 6(3), 355-366.

Sun, W. (2025). Human-Agent Interaction and Collaboration in Education: A Review and Future Research Prospects. 262–267.

Taudien, A., Walzner, D. D., Fuegener, A., Gupta, A., & Ketter, W. (2024). Know thyself: The relationship between metacognition and human-AI collaboration.

Van Laar, E., van Deursen, A. J., van Dijk, J. A., & De Haan, J. (2019). Determinants of 21st-century digital skills: A large-scale survey among working professionals. Computers in Human Behavior, 100, 93–104.

Vial, G. (2019). Understanding digital transformation: A review and a research agenda. The Journal of Strategic Information Systems, 28(2), 118–144. https://doi.org/10.1016/j.jsis.2019.01.003

Wang, B., Rau, P.-L. P., & Yuan, T. (2023). Measuring user competence in using artificial intelligence: Validity and reliability of artificial intelligence literacy scale. Behaviour & Information Technology, 42(9), 1324–1337. https://doi.org/10.1080/0144929X.2022.2072768

Westerman, G., Bonnet, D., & McAfee, A. (2014). Leading digital: Turning technology into business transformation. Harvard Business Press.

Xu, J., Luo, Y., Wang, C., Wang, M., & Wu, Y. (2026). AI support in self-regulated learning: A decade of technological evolution and meta-analysis. British Journal of Educational Technology.

Zhai, X., Chu, X., Chai, C. S., Jong, M. S. Y., Istenic, A., Spector, M., ... & Li, Y. (2021). A Review of Artificial Intelligence (AI) in Education from 2010 to 2020. Complexity, 2021(1), 8812542.

Zimmerman, B. J. (2008). Investigating Self-Regulation and Motivation: Historical Background, Methodological Developments, and Future Prospects. American Educational Research Journal, 45(1), 166–183. https://doi.org/10.3102/0002831207312909

Ismail, N. F., Jafri, R., & Abd Aziz, S. (2025). Empowering Leadership as a Catalyst for Adaptive Performance: A Systematic Review and Future Research Directions. International Journal of Research and Innovation in Social Science (IJRISS), 9(14).

Honra, J. R., & Monterola, S. L. C. (2025). Forecasting cognitive flexibility through academic resilience in design thinking-enhanced biology lessons. Journal of Education and Learning (EduLearn), 19(3), 1368-1374.

Korabayev, S., Ergashev, O., Mahsudov, S. A., & Mamatova, S. (2024). Exploring common technical issues in modern technology. In BIO Web of Conferences (Vol. 145, p. 03016). EDP Sciences.

Castro, E. A. G. (2024). EMPLOYABILITY, CAREER ADAPTABILITY, AND FUTUREORIENTED EMOTIONAL RESPONSES TO WORK TRANSITION OF COLLEGE GRADUATING STUDENTS OF A PHILIPPINE HEI: POST COVID-19 STUDY. MOJEM: Malaysian Online Journal of Educational Management, 12(3), 54-72.

Mensah, S., Asare, B., & Aboagye, S. K. (2026). Modelling University Students' Problem-solving Ability: The role of Self-regulated Learning, Peer-assisted Learning, and Cognitive Ability. Asian Journal of Education and Social Studies, 52(6), 812-830.

Zulkefli, N. H., & Ismail, H. H. (2025). The Impact of AI on ESL Writing Autonomy: A Systematic Review. Malaysian Journal of Social Sciences and Humanities (MJSSH), 10(8), e003555. https://doi.org/10.47405/mjssh.v10i8.3555