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The Influence of Digital Self-Efficacy on Students' Learning Outcomes in a Programming Course

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Abstract: This study examines the role of digital self-efficacy (DSE) in students' learning outcomes in a programming course. An eight-week programming course with a modular instructional design was conducted with a total of 53 students. The aim of this course is to facilitate students' data analysis skills by learning programming concepts. Before the class, students were divided into high and low-DSE groups based on a questionnaire (denoted as HDSE and LDSE, respectively). Pre-test and post-tests were administered, and ANCOVA was used to examine the interaction between DSE and learning outcomes while controlling for prior knowledge. The results show that students in the HDSE group achieved significantly better learning outcomes than those in the LDSE group, even after controlling for pre-test scores. Epistemic Network Analysis in three-dimensional space (ENA 3D) further revealed that students in the HDSE group constructed more integrated cognitive structures, characterized by stronger connections between programming concepts, which aligned with the course's final challenge of integrating multiple programming modules into a data analysis solution. In contrast, students in the LDSE group exhibited more fragmented conceptual networks, with fewer and weaker connections across course modules.

Keywords: Digital Self-Efficacy, ENA

1. Introduction

With the high predominance of AI and smart mobile devices today, students' learning environments have gradually shifted toward Ubiquitous Learning, where learning activities are no longer confined to specific times and locations but extend across various digital devices and online networks (Weiser, 1991). Bell (2011) notes that in technology-saturated learning contexts, knowledge no longer resides only within the individual but is distributed within network systems composed of human and non-human technologies. Consequently, critical learning competence has shifted toward the learner's ability to identify and construct connections between concepts. Furthermore, Connectivism posits that the core of learning lies not in the accumulation of isolated knowledge points, but in the learner's capacity to effectively establish, maintain, and reorganize connections between concepts, consequently transforming dispersed information into meaningful knowledge structures (Goldie, 2016).

Whether students can effectively construct these knowledge connections in pervasive learning environments may be influenced by their self-efficacy (Bandura, 1977). Rooted in social cognitive theory, self-efficacy refers to an individual's belief in their capability to execute specific tasks, a belief that directly impacts motivation, strategy selection, and behavioral performance. First, in exploring connectivist learning within open networks, Kop (2011) noted that a learner's level of self-efficacy and confidence determines their engagement in highly autonomous networked learning activities. Research indicates that learners with low selfefficacy often remain limited to passive information aggregation and observation. In contrast, those with higher confidence and autonomy are more inclined to actively interact, share, and create content, ultimately forming denser and more stable learning connections. This suggests that self-efficacy does not merely influence tool usage; it translates into distinct differences in the capacity for and quality of network connections throughout the learning process. Therefore, to examine the effect of digital self-efficacy (DSE) on students' learning outcomes in a modular programming course and to understand students' knowledge structures, this study defined two research questions as follows:

- **RQ1:** Does digital self-efficacy influence students' learning outcomes?
- **RQ2:** How does digital self-efficacy influence students' learning outcomes, as reflected in students' post-class reflections?

2. Literature Review

Most studies have not treated DSE as a primary independent variable that directly influences learning outcomes. Instead, it is typically conceptualized as a mediating mechanism bridging "digital competence or digital literacy" and "learning outcomes," elucidating how students actually transform their digital capabilities into effective learning behaviors and performance. For instance, in the context of nursing education, Ibrahim and Aldawsari (2023) employed a cross-sectional questionnaire design to examine the relationships among digital capabilities, DSE, and academic performance (GPA). Their results indicated that self-efficacy exerts a partial mediating effect between digital capabilities and academic performance. This implies that even when students possess a certain level of digital competence, the significant manifestation of learning outcomes still relies on the enhancement of self-efficacy. These findings suggest that DSE does not directly determine learning performance; rather, it influences the extent to which students can effectively utilize digital tools to complete learning tasks. Furthermore, utilizing Structural Equation Modeling (SEM), Yuan, Yu, and Liu (2025) demonstrated that the impact of digital literacy on learning outcomes operates primarily through indirect paths. This process involves the joint action of multiple mediating variables, including "digital atmosphere," "digital technology self-efficacy," and "digital learning behavior." The study further posits that self- efficacy itself does not directly predict learning outcomes; instead, it influences students' willingness to participate in and their level of engagement with digital learning activities, which is ultimately reflected in their learning results.

Furthermore, within the contexts of STEM and blended learning, relevant research has indicated that the relationship between DSE and learning outcomes is non-linear. Integrating learning analytics, Le, Lawrie, and Wang (2022) noted that students with high digital literacy or self-efficacy did not consistently exhibit higher overall grades; however, they demonstrated distinct behavioral patterns in resource usage and learning strategies within the Learning Management System (LMS). These findings suggest that DSE is more likely to influence "learning approaches" rather than "final grades," further supporting its theoretical positioning as a control variable. Moreover, in studies focusing on non-traditional learning outcomes, the mediating role of DSE is even more pronounced. Using an online entrepreneurial education course as a case study, Primario, Rippa, and Secundo (2022) found that the integration of digital technologies could significantly enhance the entrepreneurial self-efficacy of STEM students, thereby influencing their entrepreneurial intentions. Similarly, this study did not treat self-efficacy as a direct outcome, but rather as a crucial psychological mechanism explaining how digital learning designs affect high-level learning achievements.

Overall, the existing literature suggests that within digital learning contexts, DSE predominantly plays a mediating or conditional role. Its primary function is to influence how students respond to the learning environment rather than serving as a directly manipulable instructional treatment variable.

3. Methodology

3.1 Participants

The participants in this study were primarily recruited from a Computer Programming course designed to cultivate fundamental computational skills. One class comprising 53 students was enrolled. More than half of these were international students with diverse backgrounds spanning the humanities, social sciences, and information fields. The course content covered topics ranging from basic syntax (such as variables and loops) to the implementation of data visualization. In this course, students' weekly reflections were collected using the following prompt: "*What did you learn this week, and which parts of this section were manageable or unmanageable?*" A total of 1,921 sentences were collected over the eight-week learning period.

3.2 Learning Activities

This study spanned eight weeks. Prior to the course, students completed a DSE questionnaire and were stratified into high digital self-efficacy (HDSE) and low digital self-efficacy (LDSE) groups based on the results. This grouping did not involve any actual instructional differentiation or treatment; rather, it was utilized solely for subsequent analysis and the verification of interaction effects. A pre-test was administered in Week 1, and a post-test was conducted in Week 8. Both assessments were paper-based examinations primarily evaluating the programming syntax knowledge covered in the course, including basic control structures such as for-loops, if-else statements, and while-loops.

Weeks 2 through 7 constituted the primary instructional intervention phase. The instructor sequentially introduced various programming syntax concepts employing a modular instructional design. Taking 'if- else' as an example, the instructional content was deconstructed into conceptual modules such as 'if', 'if- else', and 'if-elif-else' to assist students in progressively comprehending syntax structures and logical relationships. Post-class assignments required students to assemble different syntax modules to complete more comprehensive programming tasks, for instance, combining for-loops with if-else logic to implement the bubble sort algorithm. Each weekly session lasted three hours, comprising two hours of conceptual module instruction followed by one hour of hands-on practice and programming exercises, thereby supporting students in transforming conceptual understanding into practical programming proficiency.

3.3 Measurement

Recent research has further indicated that in data-driven and highly digitalized learning contexts, students' DSE significantly influences their tool manipulation, information evaluation, and depth of reflection (Ulfert-Blank & Schmidt, 2022). Consequently, to address the first research question, this study employed the DSE scale developed by Ulfert-Blank and Schmidt (2022). The scale was administered at the beginning of the course, and students were stratified into HDSE and LDSE groups based on their mean scores.

3.4 Analysis

In this study, we applied Epistemic Network Analysis (ENA) to reveal students' cognitive structures. Traditional ENA typically relies on a predefined coding schema and a human-based coding process. However, in this study, we employed TopicENA, an ENA-based analytic pipeline integrated with BERTopic, a topic modeling technique that enables automated concept labeling. Specifically, BERTopic was used to automatically identify the concepts present in students' reflective texts and to assign each sentence to one or more topic categories. These topics corresponded to the programming concepts taught in the course and served as the input for subsequent ENA modeling. ENA, as a co-occurrence-based analytic method, captures not only which conceptual categories appear in students' reflections but also the strength of connections between these categories within a single reflective artifact.

4. Results and Discussion

4.1 DSE and Learning Outcomes

To answer the RQ1 (*Does digital self-efficacy (DSE) influence students' learning outcomes?*), this study compared students' learning outcome across different groups. The t-test analysis reveals that there was no significant difference in pre-test scores between the HDSE and LDSE groups prior to the commencement of the course (t=-0.063, p=.95), indicating that the two groups possessed a high degree of equivalence regarding their prior knowledge.

Table 1 presents the results of the Analysis of Covariance (ANCOVA) after controlling for pretest scores, revealing that DSE had a significant impact on post-test scores. Specifically, the post-test scores of students with HDSE were significantly higher than those of students with LDSE (p=.014). This finding demonstrates that even when prior knowledge is taken into account, DSE remains effective in differentiating students' learning outcomes. Furthermore, pre-test scores significantly predicted post-test performance (p=.014) with a medium level of explanatory power (partial η2=0.116), suggesting that prior knowledge and DSE play distinct yet complementary roles in learning outcomes.

Table 1. *Group Descriptives and ANCOVA-Adjusted Post-test Means*

Group	N	Pre-test		Post-test				F	η^2
		Mean	SD	Mean	SD	Adjusted mean	Std.error		
LDSE	27	72.07	10.15	68.30	16.23	68.34	2.63	6.464^*	0.116
HDSE	26	72.31	16.13	77.92	12.13	77.88	2.68		

* p-value < 0.05

Synthesizing the analytical results presented above, it is evident that within the programming course implemented in this study, students' levels of DSE are significantly associated with their learning outcomes. The results indicate that there was no significant difference in pre-test scores between students with HDSE and LDSE group prior to the course, demonstrating a high degree of equivalence in prior knowledge between the two groups. Building on this foundation, further analysis using ANCOVA to control for pre-test scores revealed that DSE significantly predicted students' post-test performance. Specifically, the adjusted post-test scores of students with HDSE were significantly higher than those with LDSE, exhibiting a medium effect size. These findings suggest that students' DSE does not merely reflect their inherent ability levels; rather, it is closely linked to how they effectively utilize digital tools, comprehend learning tasks, and transform their learning engagement into actual performance throughout the programming learning process.

4.2 Knowledge Organization in Reflection

To answer the RQ2 (*How does digital self-efficacy influence students' learning outcomes, as reflected in students' post-class reflections?*), this study applied BERTopic on students' post-class reflections. The four clusters serve as the basis for subsequent cognitive network modeling. These topics correspond to fundamental programming concepts: Data Analysis, Data Structures, Interactive Functions, and Condition Logic.

Then we input students' post-class reflections, paired with their respective topic types into the ENA network and the results as shown in Figure2. The model is represented across three rotated dimensions: MR1 (Technical vs. Conceptual), MR2 (Data-focused vs. Logic-focused), and MR3 (Structural Complexity). In this space, the four nodes (diamond markers) represent the BERTopic-derived programming concept clusters: Data Analysis, Data Structures, Interactive

Functions, and Condition Logic. Furthermore, the positions of the nodes indicate how these concepts are situated relative to the three dimensions. The edges connecting the nodes represent co-occurrence relationships between concept pairs, where thicker lines indicate stronger connections. In other words, the more connections students made between two different concepts, the thicker the line became. For additional interpretation, the MR1 × MR2 plane can be discussed in four regions, Technical-Data (+X, +Y), Technical-Logic (+X, −Y), Conceptual-Data (−X, +Y), and Conceptual-Logic (−X, −Y).

The difference between LDSE and HDSE students becomes evident (see figure 2). These results indicate that both groups have Data Analysis as the cornerstone idea in their reflections, however the way they connected this concept with other ideas was different. For LDSE students, the network displays a relatively narrow distribution (upper-left, blue network graph) and is dominated by two constructs or topic pairs: Data Analysis vs. Interactive Functions (weight = 0.482) and Data Analysis vs. Condition Logic (weight = 0.458). This suggests that, LDSE students' reflections showed a strong step-by-step reasoning in their reflections. They recalled the information in a sequential way, instead of interconnecting concepts from different weeks together.

HDSE students, on the other hand, showed a more balanced network, with connections distributed more evenly across all constructs (bottom-left, red network graph). The analysis reveal that Data Structures appeared frequently as part of their conceptual connections, especially with Condition Logic (weight = 0.362) and Interactive Functions (weight = 0.284). This suggests that HDSE students were more likely to connect how data is organized and stored with how the program behaves, a reasoning that aligns more closely with the competencies the course sought to cultivate.

The subtraction network (Figure 2, right) shows a clear contrast between both groups. LDSE-stronger connections (blue lines) were mostly concentrated in Data Analysis vs. Interactive Functions (Δ = 0.213). On the other hand, HDSE thick edges (red lines) connected Data Structures (Δ = 0.131, 0.106, and 0.026) and Condition Logic vs. Interactive Functions (Δ = 0.028). In other words, the biggest difference between LDSE and HDSE groups lays on whether they built or not consistent bridges to data organization and how the structure interacts with logic and execution.

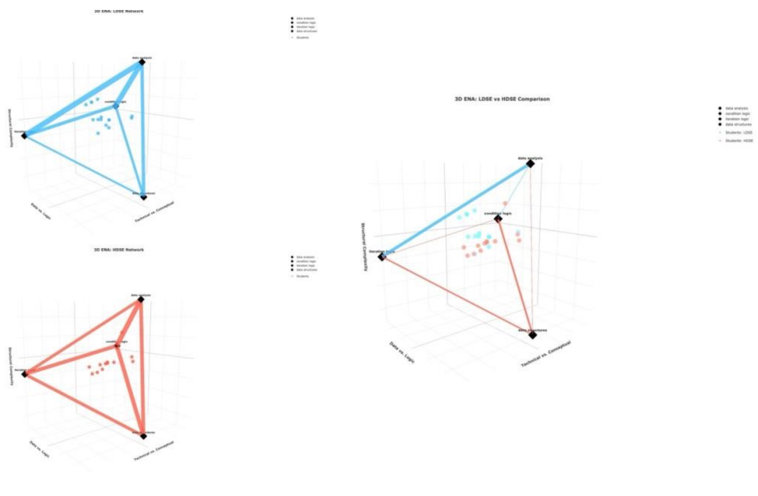

Figure 2. 3D ENA Result (blue: LDSE group, red: HDSE group).

Moreover, the 3D space provides further interpretations. Across the rotated dimensions (MR1–MR3), the LDSE and HDSE groups didn't just form different networks, they also occupied different regions of the projection space. Along MR2 (Data-focused vs. Logic-focused), LDSE students were strongly pushed toward the data side (Y = +1.23), while HDSE students drew closer to the center (Y = +0.04), suggesting a more even distribution of ideas between data and logic, in the reflections of the latter. Along MR1 (Technical vs. Conceptual), HDSE students sat further toward the technical-execution side (X = +0.896) compared with LDSE students (X = +0.019). Essentially, this indicates HDSE students reflected more directly on implementing and making decisions in coding, while still maintaining connections between concepts. The quadrant results indicate similar outcomes, half of the HDSE students appeared in the Conceptual–Logic quadrant, whereas none of the LDSE students did. Instead, about half of the LDSE students stayed in the Technical–Data quadrant. Emphasizing this way, the LDSE group recalled their programming takeaway more sequentially, rather than thinking about a broadened idea.

In response to the two research questions, the findings indicate that DSE does not directly determine students' programming performance, but it shapes how effectively students integrate programming concepts (as modules in this course and as topics in BERTopic) into coherent cognitive structures, which are in turn reflected in their learning outcomes. As for the limitation, this study employed a fixed prompt: "What did you learn this week, and which parts of this section were manageable or unmanageable?", as it may have constrained the scope of students' reflections.

Conclusion

Contextualized within a programming course, this study empirically examined the role of DSE in students' learning outcomes. The results indicate that, after controlling for prior knowledge, DSE exerts a significant interaction effect on students' learning outcomes. Specifically, students with HDSE significantly outperformed those with LDSE on the post-test. This suggests that DSE does not merely reflect students' inherent ability levels but serves as a crucial learner characteristic that influences how they respond to digital learning environments. Besides, the epistemic network analysis provided valuable insights regarding the relation of DSE and the students' ability to connect programming concepts for data analysis tasks. In this regard, the results suggest that students with LDSE relied on sequential recall, while students with HDSE demonstrated a holistic recall, this indicates the latter acquired the integrated knowledge the course attempted to build.

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References

Bandura, A. (1977). Self-efficacy: toward a unifying theory of behavioral change. *Psychological review*, 84(2), 191.

Bell, F. (2011). Connectivism: Its place in theory-informed research and innovation in technology-enabled learning. *International Review of Research in Open and Distributed Learning*, 12(3), 98-118.

Goldie, J. G. S. (2016). Connectivism: A knowledge learning theory for the digital age? *Medical teacher*, 38(10), 1064-1069.

Ibrahim, R. K., & Aldawsari, A. N. (2023). Relationship between digital capabilities and academic performance: the mediating effect of self-efficacy. *BMC nursing*, 22(1), 434.

Kop, R. (2011). The challenges to connectivist learning on open online networks: Learning experiences during a massive open online course. *International Review of Research in Open and Distributed Learning*, 12(3), 19- 38.

Le, B., Lawrie, G. A., & Wang, J. T. (2022). Student self-perception on digital literacy in STEM blended learning environments. *Journal of Science Education and Technology*, 31(3), 303-321.

Primario, S., Rippa, P., & Secundo, G. (2022). Rethinking entrepreneurial education: The role of digital technologies to assess entrepreneurial self-efficacy and intention of STEM students. *IEEE Transactions on Engineering Management*, 71, 2829-2842.

Ulfert-Blank, A.-S., & Schmidt, I. (2022). Assessing digital self-efficacy: Review and scale development. *Computers & education*, 191, 104626.

Weiser, M. (1999). The computer for the 21^{st} century. *ACM SIGMOBILE mobile computing and communications review*, 3(3), 3-11.

Yuan, N., Yu, Q., & Liu, W. (2025, August). The impact of digital literacy on learning outcomes among college students: the mediating effect of digital atmosphere, self-efficacy for digital technology and digital learning. In *Frontiers in Education* (Vol. 10, p. 1641687). Frontiers Media SA.