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Knowledge visualization to improve writing performance in undergraduate engineering courses

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ABSTRACT

Over-reliance on generative artificial intelligence (AI) for writing tasks can have negative effects on engineering education. Despite growing concerns over generative AI's impact on authentic writing skills, limited research has critically examined alternatives that integrate between self-regulated learning (SRL) theories with knowledge visualization tools to foster monitoring and evaluation processes in engineering education. This exploratory study addresses this gap by exploring how machine learning-based text analytics can scaffold SRL, extending prior frameworks on information processing. Thirty participants were recruited from two sections of an engineering technology course. As a course task, participants wrote essays using the knowledge visualization system over a semester. SRL skills were measured through a survey, and final course grades served as a measurement of learning performance (LP). First, there were no noticeable relationships between students' SRL, LP, and writing performance (WP). Second, regression analysis showed that SRL and course grades do not significantly predict WP. Third, engineering students' WP significantly increased over time. Lastly, there were no differences in WP changes over time between high and low SRL or LP groups. However, there is a main effect of LP on WP, and an interaction effect of LP and time was observed in the evaluating component.

Keywords: engineering education, writing performance, generative AI, knowledge visualization, self-regulated learning

INTRODUCTION

With the growing emphasis on communication skills in the engineering field, it is unsurprising that engineering courses are incorporating writing and communication into their curricula (Hanson & Williams, 2008). The advent of generative artificial intelligence (AI), specifically ChatGPT, an advanced language model developed by OpenAI, has notably transformed writing practices in both K-12 and higher education.

In K-12 education, generative AI serves as a tool for enhancing students' writing. By providing a revised version of a student's input in real-time, with immaculate grammar, syntax, and style, it assists with assignments, homework, and writing tasks. This immediate assistance allows students to submit various types of writing, including essays, explanations, summaries, and more. Furthermore, with generative AI's ability to generate prompts and ideas, students do not have to spend time creating their own stories, making writing tasks a lot less daunting.

In higher education, generative AI can synthesize information from diverse sources and presenting coherent summaries. This ability not only aids in the initial stages of research but also helps students analyze and integrate the information provided. Generative AI can assist in drafting essays and papers, offering suggestions for improvement and helping students achieve higher grades in academic writing tasks. This technological aid is particularly beneficial for non-native English speakers, who can use the tools to overcome language barriers and enhance their academic performance.

The integration of generative AI into writing practices raises important considerations about academic integrity and the development of independent writing skills. While the tools offer substantial benefits, it also poses challenges related to plagiarism and over-reliance on AI. When a student depends solely on generative AI, their opportunity to mastery language and writing conventions can be lost. Thanks to the innovation of AI technology, large language models may excel at producing grammatically correct sentences; however, they may not always capture the delicate nuances of language or context-specific conventions. Writing proficiency involves more than just stringing words together; it requires an understanding of syntax, vocabulary, style, and rhetorical strategies. By relying on AI to generate text, students miss opportunities to refine their language skills and develop their unique voices as authentic writers. Over time, heavy reliance on generative AI can lead to regression in linguistic proficiency, hindering learners' ability to communicate effectively in academic and professional settings.

While generative AI offers immediate grammatical and structural aid, it often bypasses critical cognitive processes essential for developing authentic writing proficiency, such as those outlined in the self-regulated learning (SRL) framework (Zimmerman, 2002), which emphasizes monitoring and self-evaluation. Existing studies highlight SRL's role in writing improvement (e.g., Graham et al., 2005; Teng & Zhang, 2018), yet they rarely integrate knowledge visualization as a scaffold for engineering students' monitoring processes, particularly in countering AI over-reliance. This study bridges this gap by examining a knowledge visualization tool grounded in SRL theory, challenging the dominant focus on generative AI and extending empirical work on text analytics in science, technology, engineering, and mathematics (STEM) education (Ifenthaler, 2014).

LITERATURE REVIEW

Generative AI has emerged as a promising tool for enhancing writing education by providing opportunities for creative expression, feedback, and language exploration (e.g., Fu et al., 2019). However, this contrasts with evidence showing over-reliance can undermine critical thinking and synthesis, which is core to writing as a multifaceted process (Leahy et al., 2014; Van Ockenburg et al., 2019; Wade, 1995). For instance, while Burrows et al. (2001) demonstrated writing's role in improving engineering quiz performance through reflection, Smith and Colby (2007) argue that outsourcing synthesis to AI erodes deep learning, which is consistent with a concern amplified in engineering where writing fosters field contributions (Berdanier & Alley, 2023). This tension also highlights a gap: prior studies focus on AI's ethical dilemmas (e.g., plagiarism) but lack critical integration with SRL frameworks, which posit monitoring as key to avoiding complacency.

Writing facilitates critical engagement with course material, encourages curiosity, and fosters independent thinking. In the generative AI era, students risk missing out on opportunities to grapple with complex concepts, form connections between ideas, and develop a deeper understanding of the subject matter.

The Need for Writing Support Tools

In the context of generative AI, there is a growing recognition of the necessity to incorporate writing support tools (e.g., guides or scaffolds) rather than tools that automate or revise entire pieces. These tools are crucial for students with diverse linguistic backgrounds, varying levels of proficiency, and different learning preferences. They provide essential scaffolding throughout the writing, offering targeted assistance in grammar, syntax, vocabulary, and organization. For instance, grammar checkers and proofreading software provide real-time feedback on grammatical errors and stylistic inconsistencies, helping students refine their writing mechanics and adhere to standard conventions (McCarthy et al., 2019). Similarly, outlining tools and mind-mapping software aid in organizing and structuring ideas, enabling students to create coherent and well-structured compositions (Fu et al., 2019). Although tools like grammar checkers and mind-mapping software provide targeted scaffolding, they often overlook engineering-specific challenges and fail to integrate SRL's metacognitive elements. This leaves a void in AI-supported writing that prioritizes self-evaluation over automation. Specifically, engineering students have more complicated sentence structures than practitioners do as engineering students' writing often contained features that could negatively impact engineering practice, whereas practitioners' writing was characterized by clear, precise language, minimal errors, and structured, logical organization, especially in technical memos (Conrad, 2017).

While writing support tools may contribute significantly to accessibility in engineering education by addressing diverse student needs and preferences, there remains limited investigation into how AI technology can be effectively utilized with pedagogical and theoretical considerations in writing tasks in engineering education. The integration of AI technology in writing instruction calls for pedagogical approaches that integrate technology seamlessly, balancing traditional methods with innovative tools designed to enhance learning experiences.

Self-Regulated Learners in Writing Tasks

We argue that self-regulated learners would benefit more from a writing support tool than those who are not. Self-regulated learners are less likely to overly rely on AI tools because they actively monitor their learning processes. If they find themselves copying-and-pasting using a generative AI tool, they recognize the lack of genuine learning.

The monitoring process of learning progress, or metacognition, plays a critical role specifically in enhancing STEM learning (Mayer, 2016). We can effectively use writing as a metacognitive tool in engineering courses, allowing students to evaluate their understanding of technical content and self-assess whether they have sufficient knowledge to apply it in new engineering contexts (Hanson & Williams, 2008). Self-reflection also promotes increased learning effectiveness when learners monitor their current knowledge (Zimmerman, 2002). Therefore, understanding and monitoring one's own knowledge structure, a part of knowledge representation, are crucial for succeeding in the next learning cycle in STEM education as learners' knowledge is effectively conveyed through their writing (Verhoeven & Van Hell, 2008).

There is evidence that SRL is directly and indirectly impacts writing. Graham et al. (2005) found that students who received SRL strategy development instruction wrote longer, more complete, and higher-quality stories and persuasive essays compared to a control group. Cuenca-Carlino et al. (2018) also noted improvements in opinion essay writing quality and word count after SRL strategy development instruction, highlighting a functional relationship between SRL strategy development instruction and enhanced essay components.

These findings align with Zimmerman (2002) SRL model, where metacognition drives writing improvements, yet they challenge assumptions in STEM contexts by revealing motivational regulation's mediating role (Shen & Bai, 2024; Teng & Zhang, 2018), underscoring the need for tools that enhance monitoring without fostering dependency. Teng and Zhang (2018) explored the role of motivational regulation in SRL and its impact on English-as-a-foreign-language writing performance (WP). They found motivational regulation strategies significantly affect WP and are closely linked to cognitive and metacognitive SRL strategies. This underscores the foundational role of motivational regulation in using SRL strategies to improve WP. Shen and Bai (2024) further supported these findings with a partial mediation model showing direct and indirect paths from motivational regulation strategies to WP.

Supporting Learners' Monitoring Process Through Text Analytics

One effective method to encourage students' SRL monitoring process is knowledge visualization using text analytics. Text analytics, also known as text mining, is a subfield of natural language processing that serves as a pivotal tool for extracting knowledge and discerning patterns within unstructured textual data (Ittoo & van den Bosch, 2016). It involves the extraction of concepts, relationships, and implicit knowledge from texts. Text analytics is a rapidly growing field that suggests approaches to revealing a straightforward and visually appealing visualization method for text, such as word cloud (Heimerl et al., 2014) and knowledge graphs (Zenkert et al., 2018) with different algorithms.

By leveraging machine learning for entity recognition and summarization (Ittoo & van den Bosch, 2016), text analytics can extend SRL theory by visualizing knowledge structures (Heimerl et al., 2014; Zenkert et al., 2018), potentially addressing Ifenthaler (2014) call for unexplored knowledge representation in STEM, though empirical tests in engineering writing remain sparse.

This Study

The primary objective of this study is to scaffold engineering students' knowledge monitoring process through a knowledge visualization supporting system. While prior research underscores the importance of knowledge visualization, addressing the current challenges of knowledge representation in STEM learning remains largely unexplored (Ifenthaler, 2014). To bridge this gap, we developed and implemented the knowledge visualization intelligence system (KVIS). We seek to elucidate the potential and challenges of the knowledge visualization tool with the overarching goal of promoting engineering students' SRL and learning performance (LP). This addresses a critical void in the literature, where SRL and knowledge visualization are discussed separately but rarely synthesized in engineering education, extending Fischer et al. (2002) information processing framework to AI-supported contexts.

As an exploratory study, this research aims to investigate the relationships between SRL, LP, and WP when supported by machine learning-based text analytics for knowledge visualization, guided by the following research questions (RQs).

RQ1: What are the relationships between students' SRL, LP, and WP?

RQ2: What are the effects of SRL and LP on learners' WP?

RQ3: How do undergraduate engineering students' WP change while using machine learning-based text analytics for knowledge visualization?

RQ4: What are the similarities and differences in WP changes over time between high and low SRL or LP?

METHODS

This research employed an exploratory study design (Fraenkel et al., 2023) within a regular course setting. No experimental treatment was applied in the research. While this design suits preliminary exploration, it lacks a control group, limiting causal inferences, and relies on a small sample (N = 30) from one institution, constraining generalizability, which issues we address critically in the discussion.

Context and Participants

Participants were recruited from two sections of an engineering technology course offered at a public university in the Southern USA. The course focused on computer networking, and both sections were taught by the same instructor. Experiential learning activities, including problem-solving tasks, group projects, and discussions that required experience and reflection (Kolb, 2014), were adopted into the course.

Before recruitment, researchers introduced the study information and process to potential participants in the course. An online link to the Institutional Review Board-approved informed consent form was emailed to potential participants, accompanied by detailed explanations of the research procedure. The study did not require a certain number of participants because the nature of this study was exploratory rather than statistically experimental. Researchers clarified during the recruitment process that participation was voluntary and that the research was exploratory in nature. Participation in the research was not contingent upon course credit or any other form of compensation.

After excluding students who did not consent to participate in the research and did not fully complete the study's measurements including writing tasks, data from 30 students were finally analyzed for the research.

Procedure

Participants were asked to review each content area along with its sub-content regions in their course materials to prepare for writing a selected topic essay (i.e., a summary of the topic). The topic selection was discussed with the researchers and the course instructor. While writing their essays using KVIS, the system provided real-time knowledge visualization of their writing. The essay writing process using KVIS was repeated six times throughout the semester with the measurement of their WP. Students' writing tasks were scored based on participation; upon submission, they received the full

Table 1. A writing performance measurement rubric

Category	0	1	2	3	4	5
Evaluating		Minimally determined the significance or relevance of information needed for the writing task		Partially determined the significance or relevance of information needed for the writing task		Completely determined the significance or relevance of information needed for the writing task
Interpreting		Inaccurately provided meaning to the topic, made inferences, or extracted key points from the information		Provided meaning to the topic, made inferences, or extracted key points from the information with errors		Accurately provided meaning to the topic, made inferences, or extracted key points from the information
Manipulating, transforming (extent)		Minimally converted information from one form to another		Partially converted information from one form to another		Completely converted information from one form to another
Manipulating, transforming (accuracy)		Inaccurately converted information from one form to another		Converted information from one form to another with errors		Accurately converted information from one form to another

Table 2. Descriptive statistics of all measures

Measure (max)	WP					SRL (7)	LP (1,000)
	Evaluating (5)	Interpreting (5)	Manipulating & transforming		Total (20)		
			Extent (5)	Accuracy (5)			
Mean (standard deviation)	4.16 (.59)	4.01 (.65)	3.80 (.71)	3.78 (.69)	15.76 (2.40)	5.08 (.64)	877.05 (48.26)

Table 3. WP: Mean and standard deviation

	T1	T2	T3	T4	T5	T6
Evaluating	4.07 (.75)	4.03 (.62)	4.00 (.62)	4.17 (.62)	4.23 (.34)	4.47 (.41)
Interpreting	4.08 (.79)	3.78 (.74)	3.97 (.66)	3.95 (.63)	3.97 (.49)	4.33 (.46)
Extent	3.15 (.73)	3.77 (.73)	3.80 (.68)	3.80 (.55)	4.11 (.55)	4.15 (.53)
Accuracy	3.71 (.86)	3.55 (.81)	3.72 (.70)	3.73 (.57)	3.87 (.54)	4.12 (.52)
Total	15.02 (2.84)	15.13 (2.71)	15.48 (2.46)	15.65 (2.18)	16.18 (1.74)	17.07 (1.78)

credit for writing participation. Thus, students WP did not affect their final course grades.

Data Collection

Firstly, SRL skills were measured through a survey administered at the end of the semester. The survey utilized the motivated strategies for learning questionnaire (MSLQ) developed by Pintrich and De Groot (1990), a widely used instrument for assessing learners' SRL (e.g., Puzziferro, 2008; Van den Boom et al., 2007). The MSLQ consists of 44 items measuring learners' motivational orientations (i.e., self-efficacy, intrinsic value, and test anxiety) and their use of different learning strategies (i.e., cognitive strategy uses and self-regulation) on a 7-point scale, ranging from 1 (not at all true of me) to 7 (very true of me).

Secondly, for measuring students' WP, we adopted the systematically designed information processing rubric with validity and reliability checks (Reynders et al., 2020), which is based on Fischer et al.'s (2002) framework as shown in **Table 1**.

Lastly, students' final course grades served as a measurement of LP.

Data Analysis

For **RQ1**, descriptive and correlation analyses were employed to identify relationships between the constructs. For **RQ2**, a regression analysis was conducted to investigate the impact of the constructs on learners' WP. For **RQ3**, a one-way repeated measure analysis of variance (ANOVA) was conducted to examine changes in WP over time. For **RQ4**, a two-way repeated-measure ANOVA was used to analyze changes in WP over time between high and low levels of SRL or LP groups.

RESULTS

RQ1. What are the relationships between students' SRL, LP, and WP?

Here are the descriptive statistics of the constructs, SRL, WP, and LP: SRL (mean [M] = 5.08, standard deviation [SD] = .64), WP (M = 15.76, SD = 2.40), LP (M = 877.05, SD = 48.26). Descriptive statistics can be found in **Table 2**.

The WP is not correlated with SRL ($r = .029$, $p = .880$), and LP ($r = .287$ $p = .124$). SRL and LP are not correlated with each other ($r = .135$, $p = .477$).

RQ2. What are the effects of SRL and LP on learners' WP?

A regression analysis reveals that SRL and LP do not significantly predict learners' WP, $R^2 = .083$, $F(2, 27) = 1.215$, $p = .312$.

RQ3. How do undergraduate engineering students' WP change while using machine learning-based text analytics for knowledge visualization?

The participants' WP changed over the semester. Using an ANOVA with repeated measures with a Greenhouse-Geisser correction, the mean scores for WP over the semester were statistically significantly different, $F(4.082, 118.364) = 5.243$, $p < .001$, with an effect size (partial eta squared) of .153. The mean and standard deviation of each measurement period can be seen in **Table 3**.

RQ4. What are the similarities and differences in WP changes over time between high and low SRL or LP?

SRL. For the main effect of SRL, the Huynh-Feldt estimate of the departure from sphericity was $\varepsilon = 1.0$. This main effect

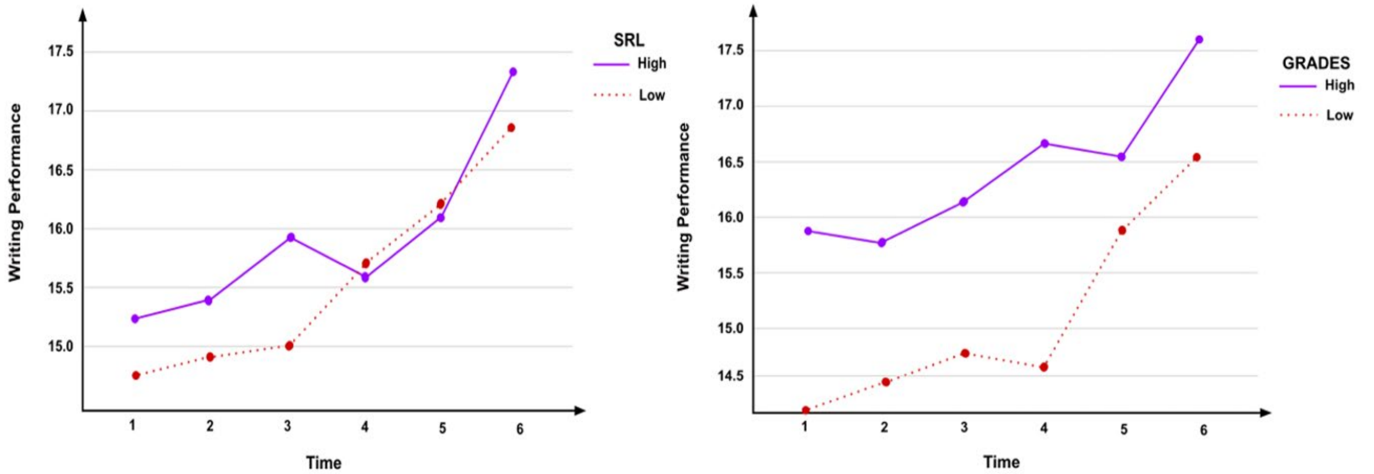

Figure 1. WP changes between high and low levels of SRL (left) & grades (right) (Source: The authors)

was not significant, F (1, 14) = .336, p = .571. When considering SRL, for the main effect of time, the Huynh-Feldt estimate of the departure from sphericity was ε = .878. This main effect was significant, F (4.392, 61.483) = 4.842, p = .001, with an effect size (partial eta squared) of .257. For the interaction, the Huynh-Feldt estimate of the departure from sphericity was ε = .952. This interaction effect was not significant, F (4.760, 66.638) = .420, p = .825. The trend of change can be seen in **Figure 1** (left).

LP. For the main effect of LP, the Huynh-Feldt estimate of the departure from sphericity was ε = 1.0. This main effect was significant, F (1, 14) = 5.170, p = .039, with an effect size (partial eta squared) of .270. When considering LP, for the main effect of time, the Huynh-Feldt estimate of the departure from sphericity was ε = 1.0. This main effect was significant, F (5, 70) = 5.006, p < .001, with an effect size (partial eta squared) of .263. For the interaction, the Huynh-Feldt estimate of the departure from sphericity was ε = .853. This interaction effect was not significant, F (4.265, 59.717) = .502, p = .746. The trend of change can be seen in **Figure 1** (right).

LP–Each component of WP. To investigate the potential interaction in terms of each component of WP since there was a significant main effect of LP.

LP–WP: Evaluating. Among the four components of WP (evaluating, interpreting, manipulating and transforming–extent, manipulating, and transforming–accuracy), there is a significant interaction effect (i.e., LP and time) in the Evaluating component. For the interaction, the Huynh-Feldt estimate of the departure from sphericity was ε = 1.0. This interaction effect was significant, F (5, 70) = 2.395, p = .046, with an effect size (partial eta squared) of .146.

To break down this interaction, contrasts compared high and low grades to their timeline. There are significant differences between high and low grades in time #2, F (1, 14) = 7.256, p = .017, with an effect size (partial eta squared) of .341; time #5, F (1, 14) = 6.387, p = .024, with an effect size (partial eta squared) of .313.

The trend of changes in the four components can be seen in **Figure 2**.

DISCUSSION

This study addresses issues surrounding engineering students' writing tasks in the generative AI era. As generative AI technologies become increasingly sophisticated, concerns about over-reliance, ethical use, and potential misuse have gained prominence in our society. Addressing challenges related to authenticity, feedback quality, bias, and digital literacy is essential for realizing the full potential of generative AI in engineering education and ensuring equitable access to learning opportunities for all students. This study explored how to support engineering students' WP using text analytics-based knowledge visualization considering learners' monitoring process.

The results show mixed outcomes. First, there were no noticeable relationships between engineering students' SRL, LP, and WP. Second, regression analysis also shows that SRL and course grades do not significantly predict learners' WP. Third, throughout the semester, engineering students' WP changed over time. Lastly, there were no significant differences in WP changes over time between high and low self-regulated learners or LP groups.

Although there was no main effect of SRL on WP, there is a main effect of LP on WP. Contrary to expectations from SRL theory (Zimmerman, 2002), which posits strong links between self-regulation, monitoring, and performance, our non-significant correlations between SRL, LP, and WP suggest contextual factors in engineering education may moderate these relationships. This challenges prior findings (e.g., Cuenca-Carlino et al., 2018; Graham et al., 2005) where SRL instruction directly boosted writing, possibly because our tool focused on visualization rather than explicit strategy training, or due to the small sample's power limitations (N = 30), which may have masked subtle effects. Extending Teng and Zhang (2018), motivational aspects of SRL might be less predictive in technical writing tasks, highlighting a need for domain-specific SRL models in STEM.

In addition, a detailed analysis of each component of WP revealed a significant interaction effect of LP and time only in the evaluating component among the four components of WP measurement. This aligns with Schunk (1996) emphasis on

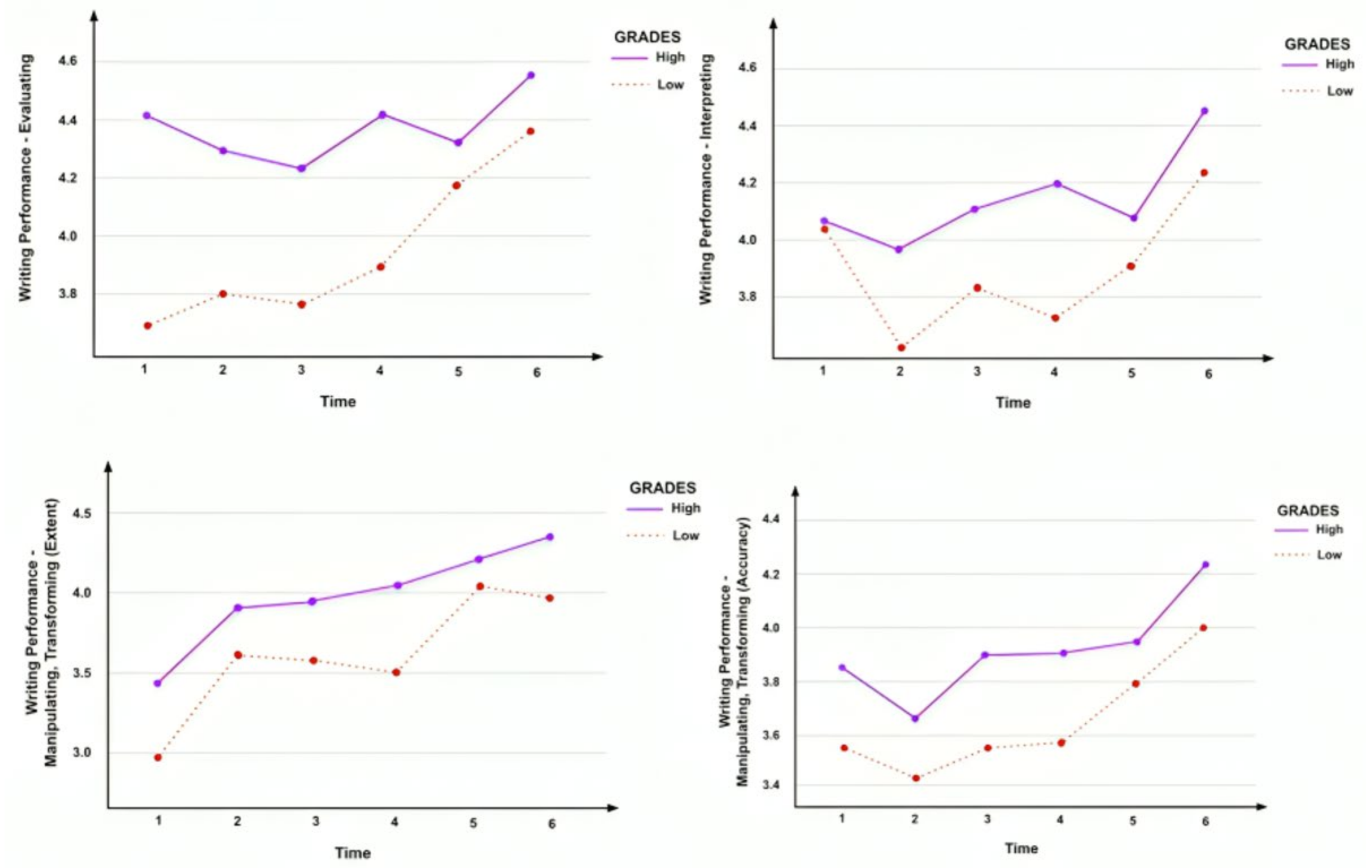

Figure 2. WP changes between high and low levels of grades: evaluating (top, left), interpreting (top, right), manipulating and transforming–extent (bottom, left), & manipulating and transforming–accuracy (bottom, right) (Source: The authors)

self-evaluation's benefits for lower performers, as low-grade students appeared to leverage visualization for self-judgment against standards, extending Kitsantas et al. (2004) by showing visualization's role in outcome-oriented goals. However, it challenges Hanson and Williams (2008) by suggesting visualization supports evaluation without traditional self-assessment assignments, potentially offering a scalable alternative in engineering curricula.

Methodologically, the absence of a control group precludes causal claims about KVIS's impact, while the small sample (N = 30) and single-institution setting limit internal validity (e.g., potential confounding from instructor effects) and external validity (e.g., generalizability beyond Southern USA engineering programs). These constraints, common in exploratory studies (Fraenkel et al., 2023), underscore the preliminary nature of our findings and call for caution in interpretation, though they provide a foundation for challenging over-reliance on generative AI through theoretically grounded tools. We acknowledge that this study is exploratory rather than experimental, and we cannot argue that the knowledge visualization support tool caused the improvement in WP. However, as the instructor specifically prohibited participants' use of generative AI tools in their writing tasks, the results of the improvements could be promising for future experimental studies.

One notable finding is the interaction effect of LP and time on the evaluating component of students' WP among the four components (i.e., evaluating, interpreting, manipulating, and transforming–extent, manipulating, and transforming–accuracy). Specifically, low-grade students increased their evaluation portion of WP more than high-grade students did. It seems that the knowledge visualization supports tool help low-grade students evaluate their writing topics and their writing itself. Our initial intention was to support learners' monitoring processes through knowledge visualization; however, it appears that knowledge visualization supported learners' (specifically, low-grade students') evaluation processes. Self-evaluation is one of the key components of SRL (Cassidy, 2011). As a form of self-judgment, self-evaluation refers to "comparisons of self-observed performances against some standard, such as one's prior performance, another person's performance, or an absolute standard of performance" (Zimmerman, 2002, p. 68).

In two studies with elementary school students, Schunk (1996) reported that self-evaluation is identified as a significant factor when it is frequent or conveys information that students may not be able to acquire by themselves. This could be relevant to the result of this study, as low-grader students might not be able to evaluate their current writing on their own, so they could benefit from the knowledge visualization support for their self-evaluation. The structural graphics of writing might provide learners with an opportunity for self-evaluation. Self-evaluation is also known to have a positive effect on student skill acquisition, particularly for students in the outcome goal condition compared to the process goal condition (Kitsantas et al., 2004). It seems that the self-evaluation of low-grade students who improved their WP in this study was supported by the knowledge visualization; eventually, their self-evaluation had a positive effect on the improvement of WP over time.

In engineering, proficiency in written communication is highly valued, and engineering students should progressively master skills like written communication, teamwork, and design throughout their undergraduate studies (Yalvac et al., 2007). Although institutional approaches, such as a writing center program, could offer a way to incorporate writing instruction into the engineering curriculum without compromising the emphasis on technical subjects (Walker, 2000), it can be costly. As an efficient and affordable approach, the use of writing support tools would be needed to improve engineering students' WP. Generative AI tools might be seen as shortcuts in various engineering courses, but foundational skills in writing must still be taught, helping students define their audience and build arguments before using generative AI for editing (Berdanier & Alley, 2023).

Limitations and Future Research

This study's exploratory design, lacking a control group, restricts causal inferences about KVIS's efficacy, while the small sample (N = 30) and single-institution context compromise internal and external validity, potentially inflating Type II errors in non-significant results (e.g., SRL correlations). Future research should employ randomized controlled trials with larger, multi-institutional samples to enhance rigor and generalizability, critically testing SRL integration against established frameworks like Zimmerman (2002).

There are some specific aspects that this study could not deal with, which call for further investigation. Firstly, this study could not systematically capture the comparison between participants who utilized the knowledge visualization tool and those who did not. We call for further studies in an experimental setting with a control condition and a larger sample.

Secondly, our writing support approach may need to be redesigned to specifically support each component of WP (i.e., evaluating, interpreting, manipulating, and transforming–extent, manipulating, and transforming–accuracy). Given the results of this study, knowledge visualization might support specific aspects of students' WP. The tool may need to add more functions and features to provide balanced support for students' writing components. Future research could include the design and development research approach (Richey & Klein, 2014) to examine required features to support students' WP in detail, such as AI-generated constructive feedback or writing coach/tutor (Calvo & Ellis, 2010).

Thirdly, engineering students' psychological and emotional aspects should be considered in the future research. Unmeasured variables may explain non-significant SRL correlations. For example, as previous studies (e.g., Berdanier, 2021) revealed that writing attitudes are statistically linked to factors such as perfectionism, procrastination, and intuitiveness, more student-side factors should be further investigated. This suggests future studies incorporate these to challenge or extend motivational models (Shen & Bai, 2024).

Lastly, another future direction of this research needs to include supporting learners' collaborative writing processes. Writing and collaborative learning for engineering education are more effective together, as they both promote active participation in knowledge construction, enhancing critical thinking and communication skills (Wheeler & McDonald, 2000). As the importance of collaborative learning increases, engineering students have more opportunities for collaborative tasks, projects, and assignments in their courses. The final product of many of these tasks includes a written report. Implementing a knowledge visualization tool that supports collaborative writing could be a future research topic, as could further research on the roles of AI systems in learner collaboration.

CONCLUSION

Advanced language models have significantly impacted writing practices in engineering education. Generative AI tools' real-time assistance has the potential to enhance students' writing skills, making writing tasks more engaging for engineering students, synthesizing information from various sources, presenting coherent summaries, and offering suggestions for improvement. However, the reckless integration of generative AI in writing raises serious concerns, potentially undermining academic integrity and authentic writing skill development. Educators must balance using generative AI's capabilities with ensuring students develop their writing abilities. By addressing these challenges, educators need to enhance students' WP in engineering education while maintaining academic integrity. This study demonstrated possibilities to provide engineering students with writing skill development opportunities through knowledge visualization support. We hope our approach to supporting engineering students' SRL through AI-based text analytics and knowledge visualization contributes to addressing these challenges.

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Ethics declaration: Prior to the implementation of the project, all necessary permissions were secured in accordance with IRB (Institutional Review Board) protocols (IRB2023-0471M). Informed consent was obtained via detailed forms before any participation. All personal data were immediately de-identified, stored securely with access limited to the corresponding author, and permanently deleted/destroyed after the study.

Declaration of interest: The authors declare that they have no competing interests.

Availability of data and materials: All data generated or analyzed during this study are available for sharing when appropriate request is directed to corresponding author.

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