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The Relationship between Students' Study Strategies and their Academic Performance in an Introductory Engineering Course with Standards-Based Grading*

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The current study explored the relationship between engineering students' study strategy use and their academic performance in an introductory engineering course. Mediation analyses informed by preceding correlational analyses were conducted on data emanating from 179 engineering students. The results revealed that problem set performance functions as a full mediator between study strategy use and final course scores, which held true for both study strategies and the most relevant five strategies. In other words, employing the relevant study strategies led to a similar relationship pattern, which did not change the nature of the relationship among study strategy use, problem set performance, and final course scores. Consequently, these findings indicate that the use of study strategies that specifically encourage self-regulated learning (e.g., reviewing past performance, seeking help) relates to a higher academic performance in an introductory engineering course with standards-based grading.

Keywords: academic performance; engineering education; first-year engineering; self-regulated learning; standards-based grading; study strategies

1. Introduction

The first college year is a critical transition period for students since they need to navigate the shift from high school to college and develop their study habits and perseverance for college-level courses. Earlier research has shown that almost 20% of engineering students drop out in their first year of college [1]. The factors related to the first-year engineering students' academic performance, especially students' prior academic performance (e.g., high school GPA and standardized test scores), have been abundantly discussed in previous literature, e.g., [2, 3]. However, prior academic performance is not sufficient to explain engineering students' academic performance: Even though engineering students typically start college life with good academic credentials [4], they may not perform well accordingly. Hence, it is essential to further explore the factors related to engineering students' academic performance. This study examined the relationship between engineering students' academic performance and their study strategies which are considered one of the key predictors of first-year college students' success, e.g., [5, 6].

Task or study strategies are an important component of self-regulated learning (SRL), especially for the social cognitive approach, e.g., [7, 8]. SRL is critical for academic achievement in higher education, where students would be more actively involved and have more autonomy regarding their learning [9], which applies to engineering education. Informed by the social cognitive SRL perspective, e.g., [7, 8], we need more research exploring engineering students' SRL activities, focusing on their study strategies and their relation to academic performance in introductory courses. Once identified, such study strategies can be integrated into introductory engineering courses to encourage their use among students. Using them early on can have more long-term effects on their academic performance.

To this end, the present study explored the study strategies employed by first-year engineering students in an introductory engineering course with a standards-based grading regime as they relate to problem set performance and final course scores. Exploring the relationship between engineering students' study strategy use and academic performance in the first college year can help us better understand the need to encourage engineering students' acquisition and use of study strategies, which would enhance their SRL.

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1.1 Self-Regulated Learning

While self-directed learning serves the overall learning process at a macro level (e.g., deciding on learning tasks), SRL works at a micro-level (e.g., monitoring, self-assessment), focusing on specific learning components, including learning tasks [10]. According to Zimmerman [7, p. 65], self-regulation is a "self-directive process by which learners transform their mental abilities into academic skills," and learning is an activity students undertake proactively for and by themselves, not as a result of their "reaction to teaching." In other words, SRL requires learners' proactive involvement in their learning rather than being passive receivers of information, which can enrich learning beyond formal education, thus serving life-long learning. However, these insights do not lessen the importance of help-seeking for SRL since help-seeking is an essential part of it, e.g., [7, 11].

At the college level, SRL encourages students to actively participate in their learning and control it by themselves [9]. This is why SRL is vital for college students to become independent learners. Previous work revealed that SRL activities and interventions are related to academic achievement at the higher education level, e.g., [9, 12–18] and lower levels, e.g., [19, 20] or both, e.g., [21]. According to Jansen et al. [9], the impact of SRL on implementing cognitive learning strategies explains the relationship commonly found between SRL and higher academic performance by earlier reviews. Previous reviews also indicated that it is possible to enhance SRL activity through interventions at different educational levels, including primary and secondary schools, e.g., [22] and higher education, e.g., [13]. All these insights suggest that SRL interventions can enhance SRL activity that, in turn, would contribute to academic performance.

Theoretically speaking, SRL consists of three phases, forethought (i.e., task analysis in the form of goal setting and planning, and self-motivation), learning/performance (e.g., self-control and metacognitive self-monitoring), and self-reflection (i.e., self-judgment and self-reaction) based on a cyclical social cognitive model of SRL, e.g., [7, 8, 23, 24]. In other words, SRL emphasizes self-directed efforts spent on being successful at each phase, which would lead to success iteratively at the following phases through learners' active participation. As a component of the performance phase under self-control, task strategies help learners decompose a learning task into its essential subparts and rearrange them in a meaningful way [7]. The task strategies are also referred to as learning strategies, e.g., [17], and they also include "study strategies, such as note-taking, test preparation, and reading for comprehension, as well as performance strategies, such as writing techniques, elocution, and problem-solving" [23, p. 19].

In line with all the insights into SRL above, focusing on cognitive learning strategies, Weinstein et al. [25, p. 46] pinpointed that "all theories of strategic and self-regulated learning include the use of learning strategies." Karabenick and Dembo [11] stated that even though help-seeking is another crucial self-regulatory learning strategy, it is also unique since college students may avoid using it due to possible concerns related to looking incompetent. As a result, engineering students' SRL activity, driven explicitly by their study or learning strategies, including help-seeking, would relate closely to their academic performance even in the absence of explicit SRL interventions.

1.2 Study Strategies and Academic Performance

Previous studies have indicated that prior academic performance is a key predictor of students' academic success in college, e.g., [26]. To illustrate, Geiser and Santelices [27] yielded that the students' high school GPA (HSGPA) was the best predictor of their college academic performance. Similarly, other studies, e.g., [28–30], showed that standardized test measures are also good predictors of students' college academic performance. Given engineering schools' stringent admissions process, students already come into the engineering discipline with good academic credentials, including good HSGPA and scores in a standardized test such as SAT [31]. Despite this high level of prior academic performance and cognitive abilities, the U.S. engineering graduation rate remained around 50% [32, 33], suggesting that almost half of the engineering students either drop out or change the major. Therefore, it is reasonable to explore other factors that can impact engineering students' academic performance.

In this sense, students' study strategies have been identified as one of the factors responsible for the academic success of first-year college students, including engineering majors, e.g., [5, 6], which makes study strategies crucial for further investigation. Despite a large body of literature on the study strategies and their relationship with students' academic performance, there is still a lack of consensus on their definition [34], and *learning strategies* have been an alternatively used expression. Researchers generally consider study strategies as students' behavior and activities related to learning, such as taking notes, organizing information, seeking help, and so on [34, 35]. Seabi [31] indicated that study strategies are significant contributors to first-year students' academic performance within the engineering education literature. Similarly, Fowler et al. [36] suggested that study strategies can closely relate to academic performance and lifelong learning capacity during undergraduate years.

The research-based insights above refer to the importance of study strategies for all college students' academic performance, including that of engineering students, which covers the first college year as well. Further, learning objectives themselves covered in engineering courses can guide students' study strategies by providing specific insights into the extent to which their academic performance would satisfy learning objectives or not. Consequently, grading techniques such as standards-based grading, which works in relation to learning objectives, e.g., [37], may inform both engineering students and their instructors about students' academic performance based on course learning objectives.

1.3 Standards-based Grading

Light [38] asserted that curriculum design is a critical factor enhancing students' learning experiences. To improve the first-year students' engagement and learning experiences, previous research has stressed the need for redesigning the curriculum, e.g., [39, 40]. Several universities have redesigned their first-year engineering curriculum and witnessed a significant improvement in student success, leading to better student retention [40]. Therefore, it is important to investigate different instructional models that can help instructors and instructional designers in designing an engaging and robust course.

Earlier research also revealed that students feel lost when they may not understand the course structure and assessment, which could hamper their academic performance and, sometimes, lead to dropping out of the discipline. For instance, Fink [41] argued that the alignment of the learning factors with the learning goals, environment, feedback, and assessment methods is imperative for better student learning experiences. Therefore, inspired by Wiggins's [42] backward instructional design, Fink [41] proposed an instructional model that aligned these factors to help the instructor design an effective and engaging course. Fink [41] further suggested that the instructor must begin with clarifying learning goals rather than course content. In other words, instructors need to define desired learning objectives first and work backward to design relevant content and assessment in line with the learning objectives.

Standards-based grading (SBG) is an assessment technique based on the backward design, predominantly used in K-12 education to evaluate student achievement relative to teachers' defined learning objectives [37]. The earlier work discussed SBG under different terminologies [43], such as objective-dive, criteria-based, and competence-based, but Marzano [44] standardized the terminology as SBG. SBG has proven to be an effective assessment strategy because it gives students meaningful feedback regarding learning objectives and helps students recognize their weaknesses [45]. Also, SBG brings fairness and transparency in the evaluation because it provides actionable information for students' learning and self-evaluation [46].

SBG has been implemented in numerous engineering classes, thus becoming more common in the field. For instance, Lee et al. [47] studied engineering faculty's perception of students' gains based on SBG: The faculty reported that developing self-regulated and self-evaluated learning among students can be helpful. Diefes-Dux [48] also explored the effects of courses with SBG on students' access and use of resources and feedback. Results showed that students' use and access increased significantly in the courses with SBG. Similarly, Post [49] implemented SBG in two undergraduate engineering courses to study academic performance and found that students performed better in the SBG aligned course compared to its counterpart with a summative score grading system. The study also found that SBG provides a better assessment of student achievement than the traditional summative score system.

Overall, given (a) the relationship between study strategies and academic performance concerning SRL and SBG at the higher education level; and (b) the relative lack of insights into that relationship in introductory engineering courses with SBG, it appears prudent to examine the relationship between study strategy use and academic performance in first-year engineering courses with SBG, which can provide a rich context in which students' SRL capacity can be cultivated. As a result, the present study has examined the relationship between study strategy use and academic performance in an introductory engineering course that implemented SBG, thus addressing the following research questions:

- How does engineering students' study strategy use relate to their academic performance in an introductory engineering course employing standards-based grading?
  - What are the study strategies that are relevant to the students' academic performance?
  - How does the relationship between the students' study strategy use and academic performance change depending on the relevant study strategies?

2. Methods

2.1 Study Setting

This study was conducted in a large public U.S.

university located in the Midwest region. The data collection source was an introductory and required engineering course taken in the second semester of the first college year. The course was part of a more extensive engineering undergraduate program consisting of required and elective courses and is aimed at developing students' technical skills ranging from data visualization and analysis to integrating programming into engineering problems. Broadly, the topics covered in this course are data visualization and analysis, engineering design, ethics, programming concepts using MATLAB software, and mathematical models. Typical of an engineering class, the students were assessed based on their design projects, assignments, class participation, problem sets, and exams. The instructional team designed all these course activities in line with the learning objectives. Lastly, the course was designed around a flipped classroom idea to a certain extent, including online videos on the course content that students need to watch and examine at home.

2.2 Participants

The participants were 179 undergraduate engineering students taking the course for the first time. There were 116 male students (64.81%), 56 female students (31.29%), and seven students (3.91%) who preferred not to disclose sex or gender information. Table 1 displays the race or ethnicity information of the participants.

2.3 Instruments

2.3.1 Study Strategies

Informed by Diefes-Dux and Castro [43], the study strategies survey included ten questions asking students whether they had used a specific study strategy or not as it relates to a problem set. The questions were of a *yes* or *no* nature, and they were repeatedly asked eight times during an academic semester regarding each problem set. Specifically, the questions were about different strategies ranging from whether the students checked their problem set performance compared to their prior performance to asking others for help and feedback. Students were asked whether they implemented the following study strategies: (a) referring to learning objectives; (b) using the help function in MATLAB; (c) Googling for help; (d) trying the exploration activities; (e) looking at the solutions to the previous problem set; (f) using performance assessment based on learning objectives related to earlier problem sets; (g) watching and taking notes on the online modules; (h) reviewing performance based on learning objectives related to previous problem set; (i) asking instructional team questions; and (j) asking classmates or study group questions.

Table 1. Race or Ethnicity Information for Students

Race/Ethnicity	***n***
White	127 (70.95%)
Asian	18 (10.06%)
Underserved/Underrepresented Minority*	8 (4.47%)
International Students (of any race or ethnicity)	13 (7.26%)
Prefer not to disclose	13 (7.26%)
Total number of students	179

Note. * Underserved/Underrepresented Minority category includes any indication of American Indian or Alaska Native, Black or African American, Hispanic or Latino, or Native Hawaiian/Other Pacific Islander.

2.3.2 Problem Sets

There were eight problem sets employed in the present study. Each set included multiple questions, addressing the basic content covered until that point in the semester. The questions aligned with course learning objectives and purported to enhance students' performance based on course learning objectives. For example, one of the problem sets question was:

> *You must write a MATLAB script that will simulate an exercise with daily exercise minutes. The schedule must follow these guidelines: (1) Assign a 40-minute run to every odd-numbered day, (2) Assign a 55-minute run to every even-numbered day, (3) One day every two weeks will have a 100-minute sports day that replaces the scheduled run. The first instance will happen in the first week, and (4) One day per week will be a rest day replaces the scheduled run.*

2.4 Procedures

2.4.1 Data Collection

The current research data set was collected in the spring 2018 semester. An online version of the study strategies survey was developed and delivered to students. Students were asked to complete the study strategies survey right after completing each problem set. The instruction team determined these strategies to introduce the new commonly used strategies to the students and, at the same time, explore their effects on the student's performance.

2.4.2 Data Preparation

A careful data preparation procedure was followed. Initially, there were 212 participants; however, a data cleaning process, including the elimination of duplicate cases, led to 179 participants. 5% trimmed means did not indicate any problematic outliers or cases to be removed. Moreover, the first four problem sets were thematically related and consti-

Table 2. Descriptive Statistics (N = 179)

	Possible Minimum	Minimum	Possible Maximum	Maximum	*M*	*SD*
Total study strategy use	0	0	80	68	37	12
Total problem set performance	0	22	96	93	79.2	11.03
Final course scores	0	710	1000	974.30	885.24	46.12

tuted the first problem set session, while the thematically relevant next four problem sets also formed the second problem set session. Consequently, total use ratings for each study strategy per each problem set session were calculated and added to each other, thereby leading to each study strategy total use. For the final scores, the study combined all the students' performance data (e.g., attendance, exams, and quizzes). Finally, most of the research data violated the normality assumption, and transformations did not work, which led to keeping the data set as it was.

2.4.3 Data Analysis

This study employed relevant correlational and mediation analyses to examine the relationships between study strategy use, problem set performance, and final course scores achieved as part of the requirements for an engineering course. Mediation analysis was also used to check the relationships between the use of the most relevant study strategies, problem set performance, and final course scores. Specifically, mediation analyses were based on Hayes's [50] statistical mediation analysis through PROCESS macro for SPSS [51]. Finally, relevant non-parametric tests were used to determine the effects of the use of study strategies on students' problem set performance.

3. Results

This section reports the current study results examining the relationships between total study strategy use, total problem set performance, and final course scores achieved in an engineering course.

3.1 Descriptive Findings

Table 2 displays the descriptive findings.

Table 2 suggests that students achieved quite a high total problem set performance on average, which is also the case for final course scores.

3.2 Correlational Analysis

Table 3 presents Pearson's (r) and Spearman's rho (rs) correlations since total problem set performance data violated the normality assumption.

Table 3 refers to a very strong relationship between problem set performance and final course scores. Further, there was a small, positive, and statistically significant correlation between students' study strategy use and problem set performance. These findings suggest that total problem set performance would function as a mediator between study strategies and final course scores, thus explaining the relationship between the two. This possibility was further supported by the decreased value of the correlation between study strategies and final course scores when problem set performance was controlled for, pr = –0.092, n = 179, p = 0.110. To further examine these relationships, we conducted two mediation analyses.

Table 3. Correlational Statistics (N = 179)

	1 r (r_s)	2 r (r_s)	3 r (r_s)
Total study strategy use (1)	–		
Total problem set performance (2)	0.211* (0.198*)	–	
Final course scores (3)	0.100 (0.090)	0.752* (0.761*)	–

Note. * p < 0.01 (1-tailed).

3.3 Mediation Analyses

To address the main research question, we consecutively conducted data analyses in which we (1) explored the relationship between total study strategy use and academic performance through a mediation analysis; (2) examined the effects of total study strategy use on problem set performance; and (3) checked the effects of problem set performance on final course scores. The latter two analyses were complementary to the first main mediation analysis. In the second round of data analysis, we addressed the complementary research questions by (1) determining the study strategies that are most relevant to problem set performance through a correlation analysis; (2) testing the relationship between the use of relevant study strategies and academic performance through a mediation analysis; and (3) checking the effects of relevant study strategy use on academic performance, which was complementary to the second main mediation analysis.

3.3.1 The First Mediation Analysis

Fig. 1 shows the results of the first mediation analysis.

Fig. 1 indicates that problem set performance functioned as a full mediator between study strate-

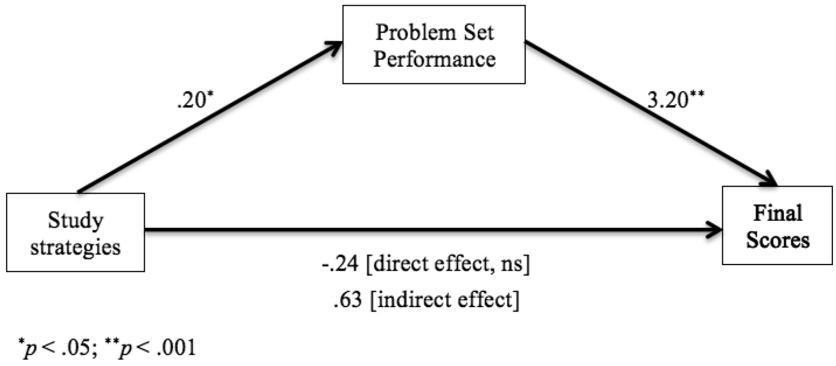

Fig. 1. The First Mediation Analysis.

gies and final course scores, thereby accounting for the relationship between the two. Namely, study strategy use did not relate directly to final course scores; however, there was an indirect relation between them through problem set performance.

Then, we divided study strategy use into high ($Md = 44$, $n = 89$) and low ($Md = 29$, $n = 90$) groups through a median split procedure. A Mann-Whitney U test confirmed a statistically significant difference between the participants who indicated more use and those who indicated less use of study strategies, $U = 8010$, $z = 12$, $p < 0.001$. A second Mann-Whitney U showed that there was no problem set performance difference between the participants who used study strategies more ($M = 80.5$, $SD = 10$) and those who used them less ($M = 78$, $SD = 12$), $U = 4600$, $z = 1.62$, $p > 0.05$. Likewise, problem set performance scores were divided into low ($Md = 74$, $n = 90$) and high ($Md = 87.2$, $n = 89$) groups through a median split procedure. A Mann-Whitney U test showed a statistically significant problem set performance difference between these low and high groups, $U = 8010$, $z = 12$, $p < 0.001$. A final Mann-Whitney U test showed that participants with a higher problem set performance achieved higher final course scores ($M = 913.2$, $SD = 31.25$) than those with a lower problem set performance ($M = 858$, $SD = 42$), $U = 7000$, $z = 9$, $p < 0.001$, $r = 0.70$.

3.3.2 The Second Mediation Analysis

The second mediation analysis examined the relationship between the use of relevant study strategies and academic performance, the following attempt was to determine the most relevant study strategies for students' academic performance. To this end, because research data violated the normality assumption, Spearman's rho (rs) correlations were run between the use of each study strategy and problem set performance (Table 4).

Table 4 reveals that only the use of five study strategies was positively related to problem set performance. Because final course scores came after both study strategies and problem set implementations, and problem set performance happened between study strategy use and final course scores, a mediation analysis was conducted to see whether problem set performance could function as a mediator. Fig. 2 displays the results of this mediation analysis.

In line with Fig. 1, Fig. 2 suggests that problem set performance functions as a full mediator between the use of most relevant study strategies and final course scores. Namely, even though the

Table 4. Correlations between Study Strategy Use and Problem Set Performance ($N = 179$)

Study Strategy	Total problem set performance
Referring to learning objectives	0.015
Using the help function in MATLAB	0.082
Googling for help	0.141*
Trying the exploration activities	0.023
Looking at the solutions to the previous problem set	0.113
Using performance assessment based on learning objectives related to earlier problem sets	0.173*
Watching and taking notes on the online modules	0.180**
Reviewing performance based on learning objectives related to previous problem set	0.265**
Asking instructional team questions	0.099
Asking classmates or study group questions	0.147*

Note. *$p < 0.05$ (1-tailed). **$p < 0.01$ (1-tailed).

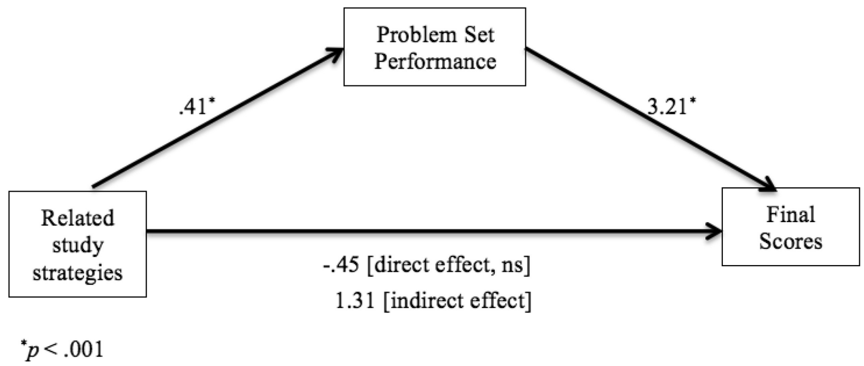

Fig. 2. The Second Mediation Analysis.

most relevant study strategies were not directly related to final course scores, they did so indirectly through problem set performance. Next, the total use of the five most relevant study strategies was turned into high (*Md* = 28, *n* = 84) and low (*Md* = 19, *n* = 95) groups through a median split procedure. A Mann-Whitney U test examining the difference between these high and low strategy groups confirmed that these high and low groups were different from each other, $U = 8000$, $z = 12$, $p < 0.001$. Another Mann-Whitney U test examined the effects of the use of these most relevant study strategies on problem set performance. Results yielded that high-study strategy use ($M = 81.3$, $SD = 9$) group achieved a statistically significantly higher level of problem set performance compared to their low-study strategy use ($M = 77.34$, $SD = 12.33$) counterparts, $U = 4800$, $z = 2.3$, $p < 0.05$, $r = 0.17$.

4. Discussion

The current study explored the relationships between engineering students' academic performance and their use of study strategies in an introductory course based on standards-based grading. The analyses and results provided insights into those effective study strategies linked to problem set performance most closely. To this end, our exploratory results showed that the use of study strategies was directly linked to students' problem set performance but not to final course scores, which seems to partly align with previous research indicating a relationship between study strategies and academic performance, e.g., [31, 36]. On the other hand, problem set performance was directly related to final course scores. In other words, problem set performance functioned as a full mediator between study strategies and final course scores, which held true for both all study strategies and the five most relevant ones. This is quite understandable given that (a) problem set performance contributed to the participants' final course scores, and (b) solving problem sets or problem set performance preceded final course scores in time. Fig. 3 summarizes this overarching finding.

The direct relationship between problem set performance and final course scores was quite larger than the one between study strategies and problem set performance. Likewise, relevant nonparametric tests showed that greater problem set performance is associated with higher final course scores with a large effect size based on Cohen's [52, p. 223] (1988) "criteria of 0.1 = small effect, 0.3 = medium effect, 0.5 = large effect". The current findings concerning the use of all study strategies also indicated that even though the use of study strategies is related to problem set performance, using all the strategies does not make a difference in problem-set performance. However, using the most relevant ones produced a small increase in problem set performance. In other words, although the most relevant study strategies changed the relationships above to some degree, the overall relationship pattern among study strategies, problem set performance, and final course scores with problem set

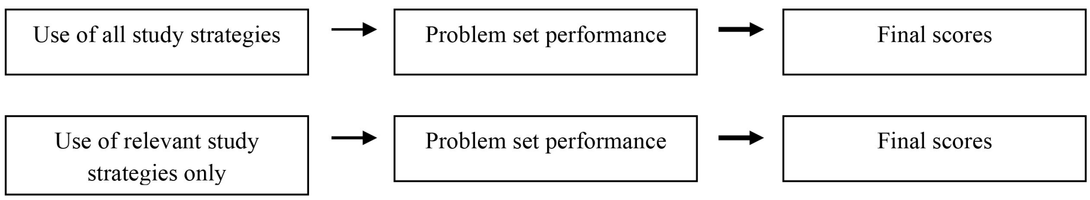

Fig. 3. The Relationship between Study Strategy Use and Academic Performance.

performance as a full mediator between the other two remained the same.

The direct link between the use of the most relevant five strategies and problem set performance was larger (thicker arrow between relevant strategies and problem set performance in Fig. 3) than the one between the use of all study strategies and problem set performance. Furthermore, the difference between all of the study strategies and the most relevant study strategies in terms of affecting problem set performance suggests that it may be enough to use the most relevant strategies, techniques, and methods that can inform student performance more in engineering courses. In other words, it may not be the number of study strategies but their relevance to academic performance that would matter more when it comes to improving student performance. Therefore, it may also be helpful to focus on these useful strategies in engineering courses to design, develop, and implement them as effectively and efficiently as possible. Namely, the current findings indicate that employing fewer study strategies that are more relevant to academic performance may be more effective and efficient than employing all existing study strategies. After all, employing fewer but more relevant study strategies would take less time on the part of students and lead to using less cognitive resources of students that could be devoted to further and other learning.

It is also important to note here that using the most relevant study strategies would not be directly related to final course performance. However, as the current findings related to the direct link between problem set performance and final course performance showed, as long as study strategies serve student performance items that are directly related to final course performance, they may also serve final course performance. This finding further implies that while examining students' study strategies employed in an engineering course, it would be better not to focus on final course performance only because, even though study strategies may not be related to final course performance, they might be related to some earlier performance. Consequently, it is also worth handling the most relevant five study strategies here since they suggest that the participating students took an active role in their learning, which aligns with learners' participation and control in self-regulated learning, e.g., [8, 9].

Specifically, the most relevant study strategy turned out to be students' reviewing their performance based on learning objectives concerning the previous problem set. In other words, the participating students reviewed their performance by using the learning objectives of the introductory engineering course. Therefore, when students are aware of what is expected of them (i.e., learning objectives) and are given a chance to review their performance based on those learning objectives, their performance may increase. This strategy is also the core of the SBG employed in this course. Hence, this finding is similar to that of Atwood et al. [45], and Sadler [46] in that SBG can be an effective strategy for students to be aware of their weaknesses and provide actional feedback to improve their academic performance.

In the same vein, another most relevant study strategy was using performance assessment based on learning objectives related to earlier problem sets. The similarity between these two strategies suggests that it is not enough to assess their performance for engineering students: they also need to review their performance as it relates to learning objectives, which also points to the importance of self-evaluation. Unsurprisingly, the study strategy that requires just referring to learning objectives did not become one of the most relevant strategies. The two most relevant strategies above appear to refer to a high level of self-regulated and reflective learning, which is in line with self-monitoring and self-assessment, e.g., [10] as well as self-directive and proactive aspects of SRL, e.g., [8]. All these insights further align with the importance of students' use of course resources and feedback to improve their learning in courses designed with SBG, e.g., [48].

Watching and taking notes on the online modules was also one of the most relevant study strategies. This study strategy also required active participation on the part of students since they not only watched but also took notes regarding the online learning content, including videos. It is highly likely that taking notes would have let the participating students more actively process the learning content through SRL since Zimmerman [7] claimed that task strategies, which are part of self-control involved in SRL, comprised study strategies including note-taking. Likewise, the other most relevant study strategy, asking classmates or study group questions, also underlines the importance of students' learning efforts spent on seeking help that is important for SRL, e.g., [11]. The last strategy seems to incorporate both SRL and collective learning, thus pointing to their importance for engineering students' academic performance.

The final most relevant strategy was using Google for help, which also refers to the participating students' search for relevant information and help-seeking efforts. The participating students needed to look for further help and used the Google search engine for this purpose. The finding that it relates significantly to students' performance suggests that this strategy did serve students' academic performance to a certain degree. Further, it is also possible that this strategy contributed to learners' SRL in that they looked for relevant information by themselves in addition to collaborating with and seeking help from their peers. Of note, the two other study strategies related to seeking help (i.e., asking instructional team questions and using the MATLAB help function) were not among the most relevant strategies. This finding further suggests that help sources may also be important for engineering students to seek help with, for instance, peers being preferable compared to instructional teams. As a result, the present findings pertaining to the most relevant five study strategies strongly suggest that self-regulated study strategies can be quite helpful for engineering students even in introductory courses, supporting the relationship between SRL and academic performance in higher education, e.g., [12, 13].

Readers should pay attention to some limitations while interpreting the present findings, though. First, even though this study used some non-parametric tests, it is basically relational without robust insights into any cause-and-effect relationship between the use of study strategies and academic performance. Therefore, we need further research to determine the most relevant study strategies and examine their effect on student learning. Similarly, the current research focused on problem set performance and final performance scores only. Therefore, future research would cover a larger set of academic performance items to any possible study strategies that would serve academic performance most. In the same vein, future research can employ more complex research designs such as mixed-method research to uncover the study strategies that better help students self-regulate their learning. Finally, only one introductory engineering course was involved in this study, thereby limiting generalizations of the findings. This is also why it is not clear whether students' academic performance survived in the long term or not. Further research would investigate study strategies and their use across different engineering courses and times to gain deeper insights into how the relationships identified in this study would change over time and how they would affect student performance both in the short and long terms. Despite the need for such future research, the present results provided prerequisite and initial exploratory insights that legitimize further research focusing on study strategies and self-regulated learning and how to encourage higher academic performance among students.

5. Conclusions

This study provided insights into the interrelationships among engineering students' use of study strategies, problem set performance, and final course scores in an introductory engineering course, which led to some noteworthy overarching implications and conclusions. First, active learning and self-evaluation strategies can be intertwined, and they can go hand in hand, thereby serving higher levels of academic success and self-regulated learning. Secondly, some study strategies can be much more related to academic performance than others, and their use would be more effective in increasing students' academic performance. Accordingly, engineering departments and engineering instructors would inform their upcoming students about the effective study strategies and encourage their use throughout their college education, which would lead to better SRL skills and academic performance. Further, it is also reasonable to expect such attempts to decrease student attrition since it is more likely that when students become more successful in their majors, they would be more inclined to stay and complete their degrees. Finally, SBG can be a crucial factor at this point, thus triggering the use of more active study and evaluation strategies that would enhance the mastery of specific learning outcomes.

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