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Unraveling the Nexus: Engineering Student Effort, Coding Protocols, and Academic Performance

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Abstract

This paper explores the intricate interplay between engineering student effort and its impact on academic performance, building upon and refining existing research (Christensen et al., 2019; Douglas & Alemanne, 2007). The study explored the effectiveness of a 3-point coding scheme created by the research team to assess perceived effort. Additionally, it utilizes statistical analyses, including correlations and linear regression, to investigate the complex interplay between perceived effort and exam performance.

While previous research has emphasized the significance of student participation in academic contexts, measured through various metrics like attendance, discussion posts, emails, and learning management system interactions (Bekkering & Ward, 2021; Christensen et al., 2019; Douglas & Alemanne, 2007), the exploration of effort during actual exams in relation to student success remains largely uncharted.

This exploratory study aimed to bridge this knowledge gap by meticulously examining the correlation between effort and performance in engineering exam questions. Our hypothesis aligns with the findings of Christensen and colleagues (2019), positing that students who invest greater effort, as quantified by the thorough documentation in their testing booklets, will yield more favorable outcomes compared to their counterparts who exert minimal effort.

Introduction

In the realm of engineering education, understanding the factors that influence student academic performance is of paramount importance. One such factor that has garnered increasing attention in recent years is student effort. Effort, defined as the exertion of mental or physical energy towards achieving a goal, is often considered a crucial determinant of academic success (Hwang & Sohn, 2018). However, the intricate interplay between engineering student effort and its impact on academic performance remains a complex and understudied area within the field.

Efforts to quantify and assess student effort have led to various approaches, ranging from self-reported measures to qualitative assessments (Saeed & Zyngier, 2012) and objective evaluations (Christensen et al., 2019; Douglas & Alemanne, 2007). While previous research has examined the significance of student participation in academic contexts, measured through metrics like attendance, discussion posts, emails, and learning management system interactions (Bekkering & Ward, 2021; Christensen et al., 2019; Douglas & Alemanne, 2007), the exploration of effort during actual exams in relation to student success remains relatively unexplored.

This paper aimed to address this gap in the literature by delving into the intricate relationship between engineering student effort and academic performance. Specifically, we focused on the context of exam performance, where engineering students' efforts were put to the test in a controlled and high-stakes environment. By examining the correlation between effort and performance in engineering exam questions, we sought to uncover insights into the effectiveness of effort in shaping student success in engineering education.

To achieve this objective, our study employed a multifaceted approach, combining qualitative and quantitative methodologies. We compared the effectiveness of different coding schemes for qualitative perceived effort assessment and utilized statistical analyses, including correlations and Linear regression, to investigate the relationships between perceived effort and exam performance.

In our study, we distinguish between two forms of effort: self-reported and perceived effort. When discussing self-reported effort, we refer to the subjective evaluation provided by individual participants regarding the energy or commitment they believe they've dedicated to completing a task or problem. This assessment typically relies on personal perception and introspection, where individuals rate or describe their perceived level of effort based on their interpretation of the task's difficulty, complexity, or demands. On the other hand, perceived effort refers to the subjective assessment made by others regarding the challenges, obstacles, or cognitive load inherent in the task, expressed and experienced by the participants.

Through this comprehensive examination, we aim to contribute to a deeper understanding of the role of effort in shaping student success in engineering education. By elucidating the complex dynamics between student effort and academic performance, our findings have the potential to inform educational practices and interventions aimed at enhancing student learning outcomes in engineering disciplines.

Background

Student effort is a multifaceted and dynamic aspect of the educational experience, encompassing the energy, time, and dedication that students invest in their learning pursuits (Berland & Steingut, 2016). It extends beyond the completion of assignments and examinations, encapsulating a range of activities and behaviors that contribute to the depth and quality of the educational journey (Khachikian et al., 2011). Comprehending and acknowledging the subtleties of student effort is essential for educators, researchers, and institutions seeking to elevate the overall quality of the educational experience.

At its core, student effort involves the commitment and diligence demonstrated by students in their academic endeavors (Shu, 2022). This commitment manifests in various forms, including time spent on studying, engagement in coursework, active participation in class discussions, and the pursuit of additional learning opportunities (Khachikian et al., 2011; Shu, 2022). The quantitative dimension of student effort is often reflected in the number of hours dedicated to academic tasks, the thoroughness of preparation, and the consistency of work habits (Berland & Steingut, 2016, 2016).

Moreover, student effort encompassed qualitative aspects that go beyond the mere allocation of time. It involves the depth of understanding, critical thinking, and intellectual curiosity demonstrated by students in their approach to learning (Barkley & Major, 2020; Berland & Steingut, 2016). Qualitative student effort is evident in the ability to connect concepts, apply knowledge to real-world scenarios, and actively seek a deeper understanding of the subject matter (Bradberry & De Maio, 2019). It is not solely about the quantity of work but also about the cognitive engagement and reflective practices that contribute to meaningful learning experiences (Fink, 2013).

The concept of student effort is closely tied to the idea of self-regulated learning, wherein students take an active role in managing their own learning processes (van Gog et al., 2020; Zimmerman & Martinez-Pons, 1988). This includes setting goals, monitoring progress, seeking feedback, and adapting strategies to achieve optimal learning outcomes (Ford et al., 1998; Schunk, 2007; Zimmerman & Martinez-Pons, 1988). Students who exhibit strong self-regulation skills are often more resilient, adaptable, and capable of navigating the challenges presented by their academic journey (McClelland et al., 2018).

Educational contexts often vary, and the expectations regarding student effort may differ across disciplines and levels of study (Berland & Steingut, 2016; Eklund-Myrskog, 1998). In practical terms, student effort involves the completion of assignments, preparation for examinations, active participation in class activities, collaboration with peers, and the pursuit of additional resources or opportunities for enrichment (Berland & Steingut, 2016; Shu, 2022). It also extends to the development of skills beyond the curriculum, such as effective communication, teamwork, and problem-solving (Barkley & Major, 2020; Berland & Steingut, 2016).

The relationship between study time and student performance has been studied for years with mixed results (Patron & Lopez, 2011). Early studies showed a positive but moderate link, while later studies had varied findings (Patron & Lopez, 2011). For example, Schuman et al. (1985) and more recently Christensen and colleagues (2019) found no significant connection, but subsequent studies challenged this, citing sample selectivity and specification errors. Other studies found positive relationships, considering additional variables (Michaels & Miethe, 1989; Rau & Durand, 2000).

Methods

The participants in this study were selected from a larger research pool, resulting in a sample size of 51 individuals between Fall 2018 and Spring 2019. Among them, 18 were female-identifying and 33 were male-identifying engineering students. Demographic data were gathered through questionnaires distributed to students enrolled in engineering courses at Mountain West University. Note that while the research team asked about non-binary identities, no participant self-selected this choice. This study examined a static engineering exam consisting of 15 questions, carefully designed by the course instructor. The questions were categorized into conceptual and analytical items, with the first six questions focusing on conceptual understanding followed by a series of questions continuing in the same vein.

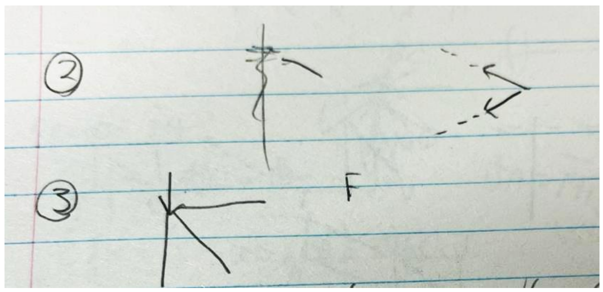
Data was gathered in the week preceding the Fall 2018 and Spring 2019 midterm exams, with daily study and office hours held. Each day featured morning and afternoon data collection sessions, allowing engineering students flexibility to take the practice exam at their convenience. Although the course offered three midterms (M1, M2, M3), only M2 data was used in this study.

Explicit instructions were provided during participant recruitment, advising them to abstain from caffeine, smoking, alcohol, illegal drugs, and dental visits on the study day. Participants on metabolic medications were requested to disclose this information to identify potential outliers in the dataset if physiological signals appeared irregular. All instructions, practice exams, and self-reports were delivered in a computer-based format to facilitate data collection, consistent with the instructor's examination format using the library testing center for computer-based exams.

Additionally, supplementary measurements were concurrently gathered, including salivary data and electrodermal activity, although these metrics are not the primary focus of the present study. The examination itself was conducted via a computer-based interface, featuring multiple-choice questions and systematically time-stamped for analysis. Participants were equipped with standard blank testing booklets, meticulously tailored to accommodate handwritten computations typically encountered in engineering examinations. While the majority of questions were multiple-choice in format, it is noteworthy that a significant portion, if not all, necessitated manual and calculator-based computations for accurate responses.

At the end of the experiment, the computer-based system automatically collected performance results from students. Additionally, average values for conceptual questions (Q1-Q6) and analytical questions (Q7-Q15) were computed respectively. A blue booklet with empty sheets was given to the students to support their calculations as they answered their multiple-

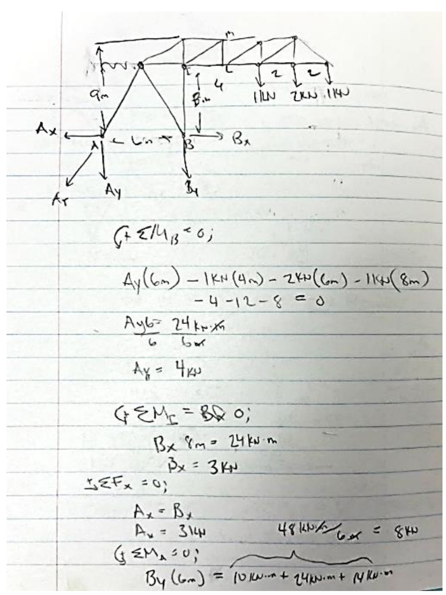
Figure 1.
A coding example of a score of One for the perceived effort.



Note. Something written in the test booklet, but incoherent and possibly only meaningful to the Participant.

choice exam questions. The entries that the student hand-annotated in these booklets were collected by the research team, who custom-created and face-validated a 3-point coding process to allow the team to categorize the effort students spent on select exam questions. In this study, each question was meticulously analyzed on a scale ranging from zero to two (Christensen et al., 2019).

Figure 2.
A coding example of a score of Two for the perceived effort.



Note. Adequate work is shown and can easily be followed through to a final answer.

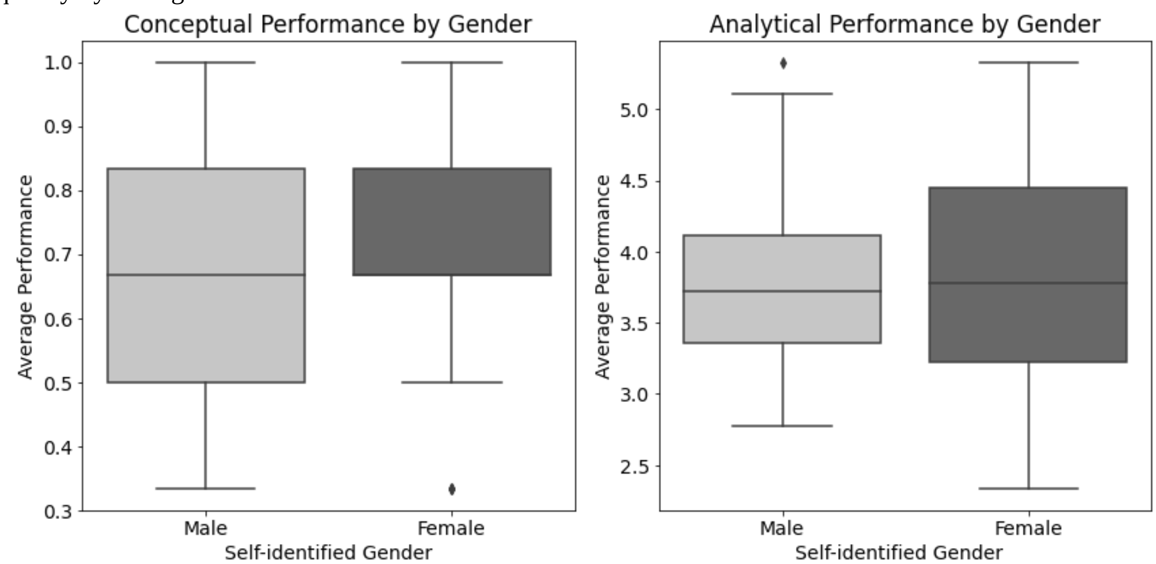
A score of zero indicated that nothing was written in the testing booklet for that particular question. A score of one denoted that something was written, but it was incoherent and possibly only meaningful to the participant. On the other hand, a score of two indicated that adequate work was shown, and the solution could be easily followed through to the final answer.

Results

Participants were categorized by self-identified male and female and academic year (freshman, sophomore, junior, senior). Among the 51 engineering students surveyed, the majority (37) were sophomores, followed by juniors (10), seniors (2), and freshmen (2). In terms of gender distribution, there were 18 female students and 33 male students in the sample. Figure 3(a) illustrates the distribution of participants by gender and academic year, while Figure 3(b) illustrates that most of both male and female students were sophomores.

Figure 3.

Student Demographics: Year in College Frequency Distribution (a) Frequency of College Year by Gender (b) Frequency by College Year.



(a) (b)

Note. (a) Student Demographics for Year by Self-identified Gender and (b) Student Demographics for overall frequencies for Year in College.

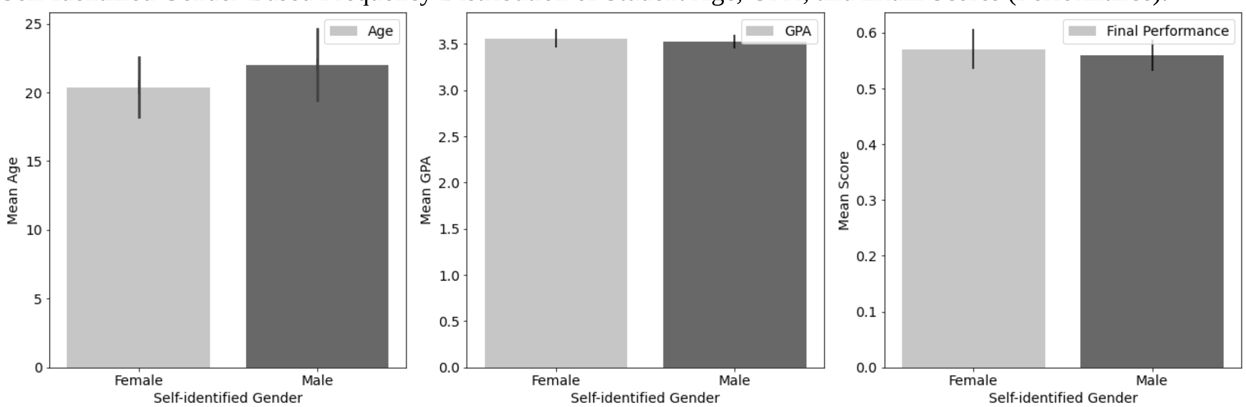
Regarding the age distribution (see Figure 4), male-identifying students in this population were slightly older than female-identifying students. The mean age for female-identifying participants was 20 years (SD = 2.25), while male-identifying participants had a mean age of approximately 22 years (SD = 2.62). In terms of GPA, female-identifying participants showed a slightly superior performance, with a median GPA of 3.56 (SD = 0.42), compared to 3.52 (SD = 0.40) for male-identifying participants. Furthermore, female-identifying participants demonstrated slightly better overall performance during the exam compared to male-identifying participants, achieving scores of 0.57 (SD = 0.15) and 0.56 (SD = 0.16) respectively, Figure 4.

The exam was designed in such a way that consisted of 15 questions. The questions were The exam comprised 15 questions, all of which were multiple-choice. However, the first 6 questions were of a conceptual nature, requiring minimal computation but demanding a deeper understanding and critical thinking from the students. The remaining questions were analytical, necessitating computational skills to derive solutions. These analytical questions were intentionally designed to be more challenging, demanding greater effort from the students. Figure 5 illustrates the performance and perceived effort of students across these question categories.

Interestingly, students achieved better overall performance in the analytical questions compared to the conceptual ones. Despite the analytical questions being designed to require more effort, it appears that engineering students were more adept at finding solutions in this category rather than relying solely on their knowledge and instincts for conceptual questions. As expected, the mean average effort reported for analytical questions was lower compared to conceptual questions, reflecting the greater cognitive demand of the latter (see Figure 5).

Figure 4.

Self-identified Gender-Based Frequency Distribution of Student Age, GPA, and Exam Scores (Performance).

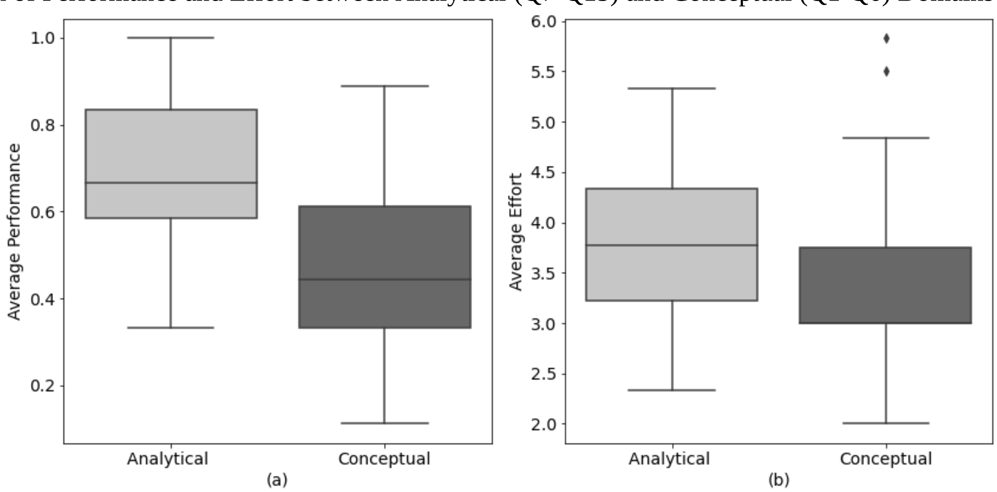


Note. (a) Gender-Based Frequency Distribution for Age, (b) Gender-Based Frequency Distribution for GPA, and (c) Gender-Based Frequency Distribution for Score or Performance.

Upon analyzing the conceptual questions (Q1-Q6), it becomes evident that students consistently demonstrated a higher level of performance compared to the effort they reported for these specific questions. However, exceptions were noted for Q6 and, to a lesser extent, Q4,

Figure 5.

Comparison of Performance and Effort between Analytical (Q7-Q15) and Conceptual (Q1-Q6) Domains



Note. (a) Conceptual vs Analytical Performance, and (b) Analytical vs Conceptual Effort.

where the reported effort slightly aligned with the performance outcomes.

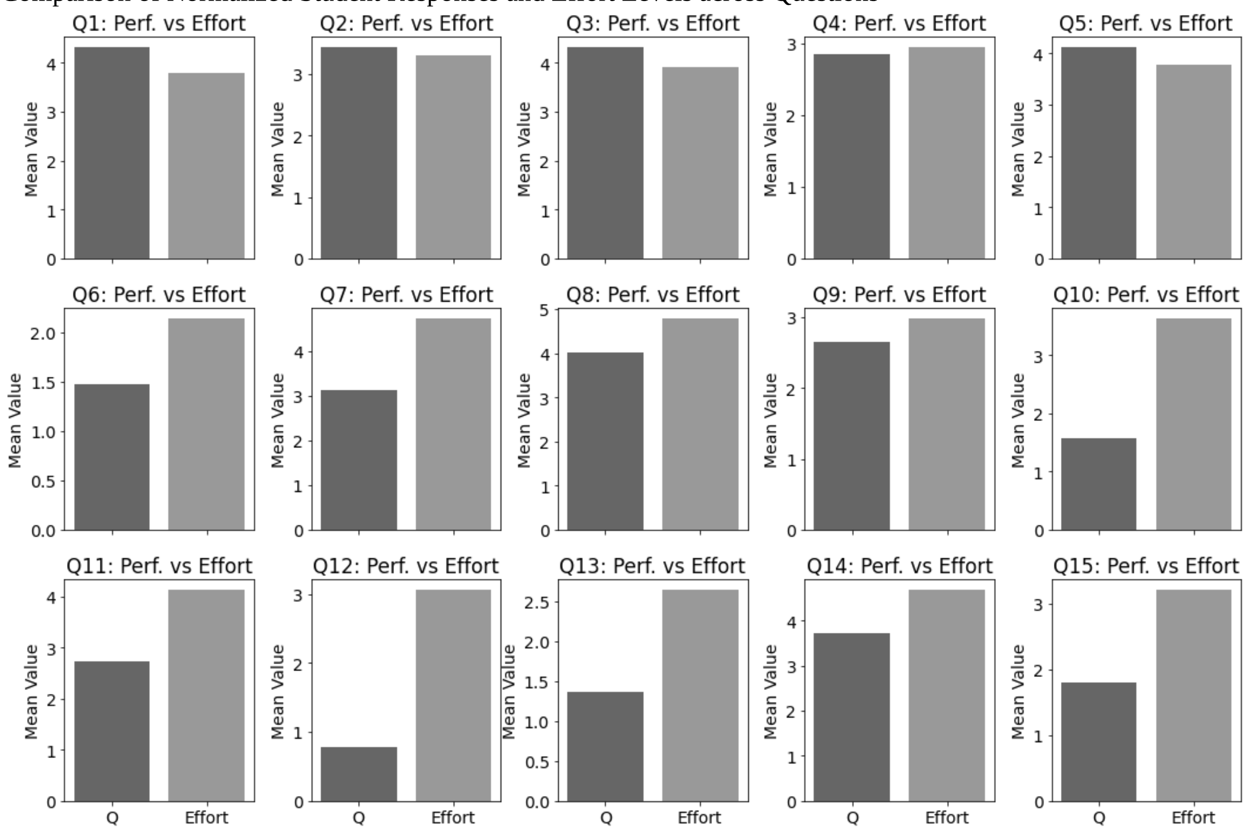
A comprehensive depiction of the intricate relationship between the types of questions – analytical or conceptual – and the perceived effort invested by students can be seen in Figure 6. To facilitate visual comparison, question performances were standardized to a scale of 5, enabling a nuanced examination alongside the corresponding perceived effort levels. Originally, questions were dichotomously marked as either correct (1) or incorrect (0).

Conversely, when scrutinizing the analytical questions, an inverse relationship between perceived effort and performance emerged. Across the board, students reported exerting greater effort than reflected in their performance on these questions, indicating a perceived challenge that exceeded their actual achievement.

Further insights gleaned from Figure 6 revealed specific question nuances. Notably, Q10, Q12, and Q13 emerged as particularly challenging for students, as evidenced by their lower performance scores. Conversely, Q7, Q11, and Q14 surfaced as questions perceived by students to demand the most substantial effort for resolution.

Figure 6.

Comparison of Normalized Student Responses and Effort Levels across Questions



Note. Questions Q1 to Q15 were of the multiple-choice type, with Q1 to Q6 categorized as conceptual and Q7 to Q15 as analytical. Conceptual questions typically required minimal calculations for a proper answer, whereas analytical questions often necessitated the use of calculators or scratch paper.

Moreover, upon conducting a Pearson correlation analysis between performance metrics and perceived student effort data, numerous significant relationships among the variables emerged. For instance, Table 1 illustrates a robust positive correlation ($r = 0.819$, $p < 0.001$) between Average Effort and Conceptual Effort. Analytical Effort displayed a statistically significant and moderate positive correlation with Average Effort ($r = 0.578$, $p < 0.001$), mirroring a similarly significant and strong positive correlation with Final Performance ($r = 0.784$, $p < 0.001$).

Likewise, Final Performance demonstrated a moderate positive correlation with Conceptual Effort ($r = 0.294$), and a robust positive correlation with Analytical Performance ($r = 0.892$), both significant at the $p < 0.05$ level. Analytical Performance exhibited strong positive correlations with both Analytical Effort ($r = 0.891$) and Final Performance ($r = 0.892$), both of which were highly significant at the $p < 0.001$ level. However, no significant correlations were found between Conceptual Performance and any other variables at the 0.05 level.

Table 1.
Correlation Analysis: Student Performance Metrics vs. Student Effort

		Average Effort	Conceptual Effort	Analytical Effort	Final Performance	Analytical Performance
Average Effort	Pearson Correlation	1				
	Sig. (2-tailed)					
	N	51				
Conceptual Effort	Pearson Correlation	.819**	1			
	Sig. (2-tailed)	0.000				
	N	51	51			
Analytical Effort	Pearson Correlation	.578**	.354*	1		
	Sig. (2-tailed)	0.000	0.011			
	N	51	51	51		
Final Performance	Pearson Correlation	0.255	.294*	.784**	1	
	Sig. (2-tailed)	0.071	0.036	0.000		
	N	51	51	51	51	
Analytical Performance	Pearson Correlation	0.248	0.242	.891**	.892**	1
	Sig. (2-tailed)	0.080	0.087	0.000	0.000	
	N	51	51	51	51	51
Conceptual Performance	Pearson Correlation	0.123	0.212	0.169	.634**	0.218
	Sig. (2-tailed)	0.388	0.135	0.236	0.000	0.124
	N	51	51	51	51	51

Notes. ** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).

Furthermore, we conducted a simple linear regression to predict students' exam performance based on their perceived analytical effort. The regression analysis revealed a significant relationship ($F(1,14) = 25.925$, $p < .000$)), with an R^2 of 0.649. The predicted performance of participants can be expressed as -.046 + .162 (Analytical Effort). Notably, the results indicate that for each unit increase in analytical effort, student performance is expected to increase by .162 points (percentage).

Subsequently, a similar regression analysis was performed to predict students' exam performance based on their perceived conceptual effort. This analysis also yielded a significant relationship ($F(1,49) = 4.630$, $p = .036$), albeit with a smaller R^2 of 0.086. The predicted performance of participants is given by -.054 + .087 (Conceptual Effort), suggesting that for each unit increase in conceptual effort, student performance is expected to increase by .087 points (percentage).

Finally, we employed a simple linear regression to predict students' analytical exam performance based on their perceived analytical effort. This analysis revealed a highly significant relationship ($F(1,49) = 189.061$, $p < .001$), with a substantial R^2 of 0.794. The predicted analytical performance of participants is expressed as -.432 + .244 (Analytical Effort), indicating that for each unit increase in analytical effort, student analytical performance is expected to increase by .244 points (percentage).

Discussions

In the context of engineering education, the findings of our exploratory study hold significant implications for both students and educators. Specifically, the analysis revealed an intriguing pattern regarding analytical questions, where an inverse relationship between perceived effort and actual performance was observed. Despite students reporting higher levels of effort, their actual performance on analytical questions tended to be lower. This discrepancy suggests that students perceived analytical questions as more challenging than their ability to effectively solve them, highlighting potential areas for improvement in teaching and learning strategies.

Furthermore, the detailed examination of specific question nuances offers valuable insights for educators. Analytical questions such as Q10, Q12, and Q13 emerged as particularly challenging for students, as evidenced by their lower performance scores. This information can guide instructors in identifying specific areas where students may require additional support or clarification in understanding complex concepts or problem-solving techniques. Conversely, questions like Q7, Q11, and Q14 were perceived by students to demand the most substantial effort for resolution. Understanding which questions students perceived as more effort-intensive can help educators tailor instructional approaches to provide appropriate support and scaffolding, thereby optimizing student learning experiences.

After a further review was observed that a significant relationship between students' exam performance and their perceived effort levels, particularly in analytical tasks, underscores the importance of fostering analytical skills among engineering students. This highlights the necessity for engineering programs to incorporate curriculum components and teaching methodologies that promote critical thinking, problem-solving, and analytical reasoning skills.

Moreover, the identified relationship between students' exam performance and their perceived conceptual effort emphasized the importance of understanding fundamental concepts in engineering education. It suggests that students who invest mental effort in comprehending underlying principles and theories tend to perform better in exams. Thus, engineering educators should focus on designing instructional strategies that facilitate deep conceptual understanding and encourage students to engage actively with course material.

Furthermore, the substantial impact of analytical effort on analytical exam performance highlights the significance of targeted interventions aimed at enhancing analytical skills among engineering students. Educators could implement tailored instructional approaches, such as problem-based learning, case studies, and hands-on projects, to develop students' analytical abilities and improve their performance in analytical tasks**.**

Additionally, the findings underscore the value of perceived effort as a predictor of academic success in engineering education. By acknowledging and measuring students' perceived effort levels, educators can gain insights into individual learning behaviors and tailor instructional strategies to support students effectively. This could involve providing personalized feedback, offering additional resources or support, and fostering a supportive learning environment that encourages effort and persistence.

Overall, the findings contributed to enhancing the quality of engineering education by highlighting the importance of analytical and conceptual efforts in predicting students' exam performance. By leveraging these insights, educators can design more effective instructional strategies and interventions to support students' learning and success in engineering disciplines.

Limitations

It's important to acknowledge the limitations of our study. Firstly, the findings are based on perceived student effort, which may not always accurately reflect actual effort expended. Additionally, the study focused on a specific cohort of students and may not be generalizable to broader populations. Furthermore, other factors beyond perceived effort, such as prior knowledge and study habits, may also influence exam performance. Future research could explore these factors in more depth to provide a comprehensive understanding of student success in engineering education.

Conclusions

Our study sheds light on the complex relationship between student effort, question types, and exam performance in engineering education. The findings underscore the need for targeted instructional interventions to enhance analytical skills, promote conceptual understanding, and support student learning in engineering disciplines. By understanding these dynamics, educators can design effective teaching strategies that optimize learning experiences and improve student outcomes.t effort, leveraging innovative coding protocols and advanced statistical techniques. Our findings enrich the comprehension of the intricate relationship between effort and academic achievement in engineering education, paving the way for future investigations and potential pedagogical enhancements.

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