Assessing Problem-Solving Strategy Use by Engineering Undergraduates

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Abstract

Problem-solving strategies are the deliberate mental steps that a person takes to proceed in specific ways at various points during problem solution in order to analyze, solve, and reflect on a problem. Engineering undergraduates enrolled in physics and thermodynamics reported the frequency of use of problem-solving strategies, confidence in their ability to solve problems, and answered demographic questions. Measures of performance included course grades. Factor-analytic methods that were applied to students' reports of strategy use identified three types of strategies, which were labeled Execution, Planning and Looking Back, and Low Confidence in Ability. The three factors were significant predictors of course performance, based on correlation and regression methods that were applied to the data. The study provides evidence that using problem-solving strategies improves course performance and that low confidence is a hindrance to successful performance. Differences in the roles of problem-solving strategies for engineering students in physics compared to thermodynamics suggest that students use these strategies differently in those courses.

1.0 Introduction

Learning to solve problems is possibly the most prevalent skill that engineering students practice [1] [2] during undergraduate training. Especially in the first few years of undergraduate education, students spend considerable time observing instructors solve problems in the classroom, studying worked examples in textbooks, and solving problem sets for homework. Because solving basic computational problems is considered a foundation for subsequent professional preparation – e.g., capstone projects in the senior year – and because students often transfer out of science and engineering majors because of difficulties with solving problems, considerable effort has been directed towards helping students become proficient problem solvers. To assure that problem-solving skills are mastered, problem solving has become a core element in engineering curricula. In U.S. engineering education, ABET (Accreditation Board for Engineering and Technology) criteria for accrediting instructional programs treat problem solving as one of the critical learning outcomes to be achieved throughout curricula and is directly addressed in ABET Outcome 3.1 *an ability to identify, formulate, and solve complex engineering problems by applying principles of engineering, science, and mathematics* https://www.abet.org/accreditation/accreditation-criteria/criteria-for-accrediting-engineering-programs-2019-2020/#GC3. This ABET criterion rightly specifies the outcome students should achieve regarding problem-solving ability, and it leaves questions about the curriculum that will get them there to institutional discernment and discretion, including selection of textbooks, the nature of instruction, and the organization of the classroom. It is in this diverse and varied context that we pose the present questions of psychological processes, specifically of thinking and reasoning associated with problem solving, which are the focus of this paper.

On current views, skilled problem solving involves "a systematic approach…including complete and well-conceived problem formulation, generation of a solution, and careful assessment of the solution" [3]. It involves selecting appropriate problem-solving steps, using diagrams as solution aids, and planning and monitoring the process of finding a solution [4]. In this paper, we refer to the mental steps that a person takes to analyze, solve, and reflect on textbook problems as problem-solving strategies. Through the application of strategies, students think conceptually and critically about the problems they are solving. The identification of strategies that students use to solve problems, and the effects of applying strategies on problem-solving performance, are the topics of the present research. The engineering research literature also stresses student confidence [5] [6] [7] [8], therefore problem-solving confidence is also assessed. Finally, prior knowledge [9] and interest [10] are also known to affect student engagement, therefore students' familiarity and interest in the course material are also assessed.

The research questions are as follows:

- How frequently do students apply problem-solving strategies when solving textbook problems?
- Do the strategies cluster into types of strategies?
- Does frequent application of strategies correlate with better course performance?
- Do confidence, familiarity, and interest affect course performance?

2.0 Background and Literature Review

One of the most influential models for problem-solving is Polya's [11] 4-step model: 1) Understand the problem, 2) Develop a plan, 3) Carry out the plan, and 4) Look back. Polya's further elaboration of the steps depicted an active and inquisitive problem solver. Polya proposed visually representing the problem ("Draw a figure"), clarifying the problem ("What is unknown"), applying strategies ("Try to think of a similar problem"), and reflecting on the outcome ("Can you derive the solution differently?").

Early attempts to sketch out didactic methods for engineering instructors for promoting the development of problem-solving skill were undertaken by Woods [6], Wankat and Oreovicz [7], Stice [12], and others. Wankat and Oreovicz drew on Woods' work, as well as on the extensive problem-solving literature available to them, in order to develop a problem-solving method that all students could apply. More recently, Gray and colleagues [13] authored a textbook that implemented a structured approach that students could use in order to solve any problem they encountered in statics and dynamics. The benefits of structured problem-solving approaches have been documented using tests of problem-solving skills, course grades, student perceptions of learning, and success after graduation, e.g., [14] [15]. Other research has examined the cognitive processes that students actually apply when solving problems, e.g., [16]. Griggs and Benson [1] developed an elaborate coding scheme to analyze problem-solving deficiencies in first-year students. Several of the categories in their coding scheme are identical to those in earlier didactic models: Planning, Evaluating, Monitoring, Revising. A survey that includes a number of the strategies of interest in the present study, but which are situated in the context of physics problem solving, is the Colorado Learning about Science Survey [17].

How does problem-solving skill emerge? Early in skill development, when students lack insight or knowledge in a problem, they fall back on general heuristics that are applied to superficially similar situations [18]. These heuristics have been described as a *purely rote strategy* [4], a *plug and chug* method [3], and *working backwards* [2] [14]. Zajchowski and Martin [19] describe working backwards as "the use of specific formulae or algorithmic procedures with little understanding” (p. 460). Working backwards involves a mental search for equations that will solve the problem, but with little conceptual understanding of the nature of the problem, little strategic decision-making, and little metacognitive self-reflection and regulation of the solution process. Wasson [20] described plug-and-chug as “a traditional engineering teaching model in which students *Plug* a value into an equation and *Chug* out an answer.” Truax [21] suggests that “The plug and chug approach to completing assignments does not require the student to really understand what they are doing, and even protects their limited knowledge of the subject from being exposed.”

The present study was motivated by the question of whether and when engineering undergraduates apply strategies that involve conceptual understanding, that is, whether students take time to understand a problem before trying to solve it, whether they engage in regulation of the solution process when generating and solving equations, and whether they reflect on the solution after they solve the problem. This question was addressed by identifying and testing problem-solving strategies discussed in the engineering education literature.

In summary, solving problems is a ubiquitous academic activity that is used for developing skill and competence in engineering. Can undergraduate students get by with simply applying rote strategies, or are they aided by thinking conceptually and critically about the textbook problems they regularly solve? The identification of strategies that students use in solving problems and the effects of strategy use on course performance are the topics of the present research.

3.0 Selecting and Developing the Problem Solving Strategies

The selection of strategies to include in the survey was strongly influenced by Polya [11] and followers, who laid out a basic framework of planning, executing, checking, and reflecting back. Engineering educators have filled in the details of how that might be carried out by engineering students by prescribing methods to be taught and practiced. A review and consideration of the problem-solving steps in Woods [5] [6], Stice [12], Gray et al. [13], Litzinger et al. [16], Wankat and Oreovicz [7], and Mettes et al. [15], provided a rich base from which to select strategies for the present survey. The consistency in recommendations across these sources aided in the selection of potentially relevant and significant strategies. Confidence, although not a strategy per se, has been a point of emphasis in discussions of problem-solving in the engineering education literature [5] [6] [7] [8]. One of the members of the present research team, an instructor in physics, noted that students more readily expressed anxiety over problem solving, rather than confidence. Therefore the three items in the survey that were ultimately classified as related to confidence, are phrased in terms of helplessness and anxiety. The instructors and researchers in the present study drafted and discussed multiple versions of the survey before settling, through consensus, on the version tested here. The selection and phrasing of questions was guided by related questions in the Colorado Learning about Science Survey [17]. Several additional questions were included in the questionnaire at the end of the present survey, including one related to familiarity with the course topic (cf., Table 1 Q25) and one related to interest in the course topic (cf., Table 1 Q26), which were included on the recommendation of the physics instructor in the present study. There was also a question about overall GPA for science courses (cf., Table 1 Q29) and a question about the student’s expected final grade in the course (cf., Table 1 Q32). GPA for science courses tested the generalizability of strategy use beyond the courses in which strategy use was measured in this study. Students' expected course grade tested the correlation between students' judgments of their course grade and actual grade.

3.1 Participants

Participants for this study were students enrolled in Principles of Physics II (N = 227) or in Engineering Thermodynamics I (N = 233) at a public Research I (Carnegie classification) in southwestern U.S. Both courses are included in the curricula for engineering majors. Principles of Physics II typically enrolls engineering majors and is calculus based. In the Mechanical Engineering curriculum, enrollment in Principles of Physics II precedes enrollment in Engineering Thermodynamics I. Of the 460 participants, 93% indicated that they were majoring in engineering, 81% were male, 3% were classified as freshmen, 44% as sophomores, 37% as juniors, and 16% as seniors. The mean college credits completed by Physics II students was 60.85 (SD = 48.41) and by Thermodynamics I students was 66.88 (SD = 24.63). The present analyses focused on students beyond their freshman year with the expectation that these students had developed at least modest problem-solving strategies. Including the two courses provided a range of ability and strategic practices in problem solving, which, in part, would help bolster the robustness of the statistical outcomes of the survey analyses, but importantly, could begin to reveal changes in development as students advanced deeper into their curricula.

3.2 Materials

The materials consisted of two forms (Form A and Form B) of a paper-pencil survey consisting of 22 5-point Likert questions concerning strategies and confidence while solving word problems (Q3-Q24), followed by ten background questions (Q25-Q35). The five Likert options were *Never, Rarely, Sometimes, Most of the Time, Always*. The five Likert options for Question 25 (Familiar) and Question 26 (Interest) were *Not at All, Marginally, Somewhat, Very, Extremely*. The questions are shown in Table 1. Form A and Form B differed only in the random order in which the 22 questions were presented. The background questions were always presented at the end of the survey and in the same order on both forms. Written instructions at the top of the form were as follows:

> *INSTRUCTIONS: The purpose of this activity is to learn more about the methods you use to solve problems in this course. There are no right or wrong answers. Answer honestly and to the best of your ability. Do not answer in a way that you think would please the instructor. Rather, answer according to your own problem solving beliefs and practices.*
>
> *Use the bulleted scale provided with each question. Simply put an **X** through the response that best reflects your behavior. All the items are about solving problems assigned in this course, except demographic questions at the end.*

Table 1. Survey Questions	**CFA Factors***
Q3 **Before writing down equations for a homework problem, how often do you construct a mental model for the problem – that is, try to visualize in your mind what the problem involves?	
Q4 Before writing down equations for a homework problem, how often do you consider alternative solution methods or equations?	F2

Q5 How often do you plan an overall solution strategy?	F2
Q6 I think about the physical principles associated with the problem, before selecting equations for that problem.	F1
Q7 How often do you start by thinking about real-life situations that relate to the problem?	F2
Q8 When I solve a problem, I start by searching textbook examples.	
Q9 When I solve a problem, I try to imitate the instructor's examples.	
Q10 How often do you use cues in the problem statement or the problem figure as a guide to solving the problem?	F1
Q11 How often do you monitor your problem solving process – i.e., ask yourself if you are on track to solve the problem?	F1
Q12 I try to explain the problem to myself as I solve it.	
Q13 How often do you check the accuracy of your solution?	
Q14 Do you compare your answer to common sense?	F1
Q15 Do you trust your calculations more than common sense, when there is a conflict?	
Q16 If I can't find a particular equation needed to solve a homework problem, there is not much I can do to come up with it.	F3
Q17 If I am solving a problem and I am not making progress, I go back and reconsider my approach to the problem.	F1
Q18 I like to set goals while I am solving a problem.	F2
Q19 How often do you reflect on what you have learned, after you have reached a solution to a problem?	
Q20 Do you consider how to solve a problem differently in the future, after you have solved it?	F2
Q21 After you have reached a solution to a problem, how often do you ask yourself whether the solution is applicable to other problems?	F2
Q22 I enjoy solving physics/engineering problems.***	
Q23 If I get stuck solving a problem, there is no chance, I'll figure it out on my own.	F3
Q24 Homework that involves problem solving makes me nervous.	F3
Q25 How familiar are you with the topic of this course?	
Q26 How interested are you with the topic of this course?	
Q27 Major	
Q28 Completed college credits, including transfer credits.	
Q29 My overall GPA is	
Q31 My GPA for science courses is	
Q32 My expected final grade in this course is	
Q33 Gender	
Q34 Age	
Q35 Ethnicity	

Notes. *See Sections 4.1 and 4.2 for more details on these factors: F1: Execution Strategies; F2: Planning and Looking Back Strategies; F3: Low Confidence in Ability. **Q1 and Q2 were filler questions; Q3 – Q24 are the 22 questions in the survey. *** "physics" was used for students in Physics II; "engineering" was used for students in Engineering Thermodynamics I.

3.3 Procedure

The survey questions were presented to students in Physics II as an online homework assignment near the end of the semester. Online distribution of homework was the typical way that the instructor distributed weekly homework assignments to those students. Students in Thermodynamics I completed a paper-pencil version of the survey as an attachment to a test near the end of the semester. Students in both courses received comparable credit for completing the survey. The respective instructors recommended the chosen methods in order to encourage full class participation in the survey through a method consistent with typical course operation.

4.0 Statistical Methods

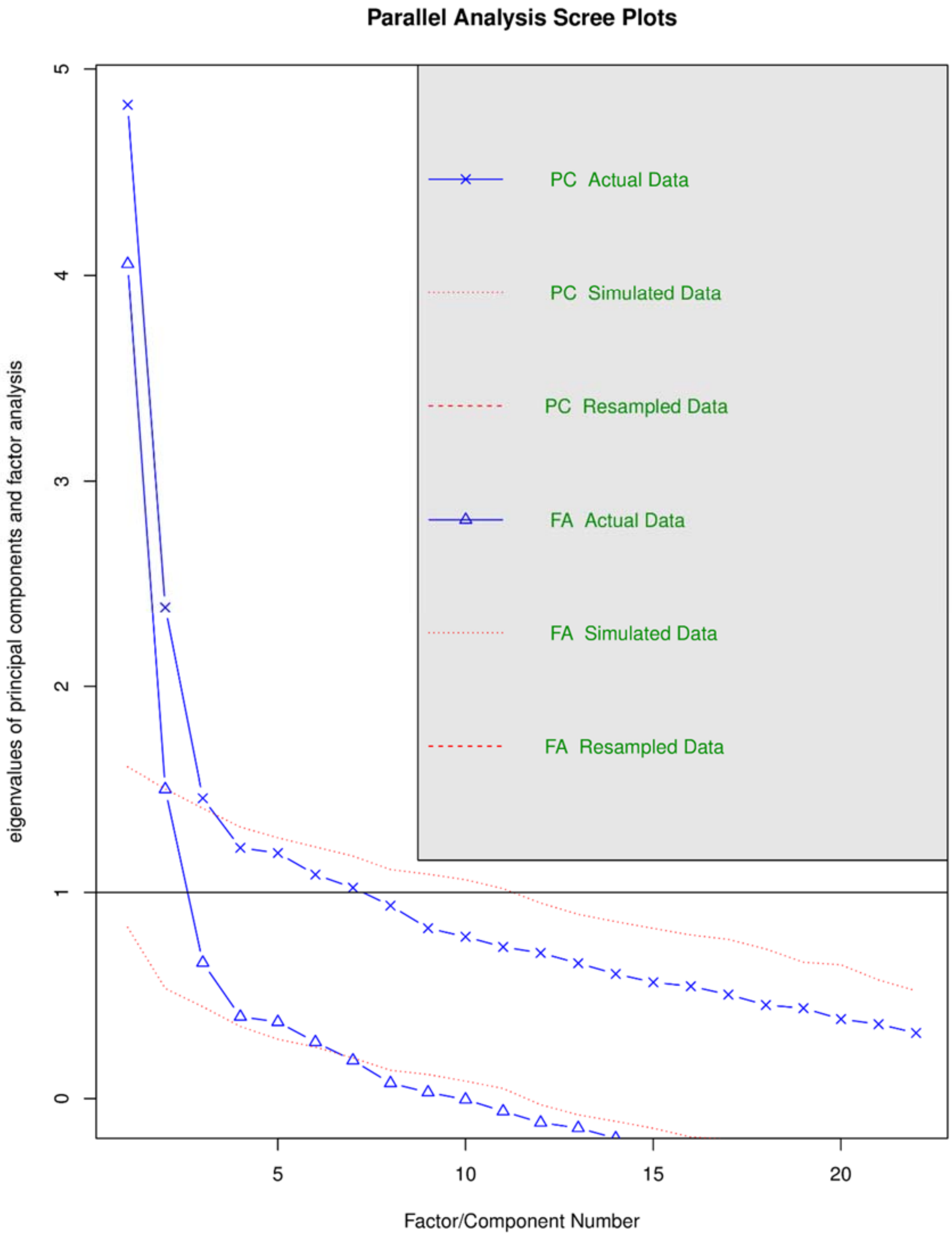
All completed surveys were used for the analyses reported here. The survey responses were analyzed using several statistical methods. Separate analysis of each of the 22 questions for each course would be difficult to interpret. Forty-four separate statistical outcomes would also inflate the possibility of Type I statistical error when testing the association of students' use of strategies with their course performance. Therefore, data reduction methods were applied first, specifically, exploratory factor analysis followed by confirmatory factor analysis. The purpose of factor analysis was to identify strategies that clustered together into factors (i.e., types). Factor analysis allowed the elimination of redundant questions and questions that did not clearly fit into a type. The factors that were extracted from these analyses were used to assess the associations between students' use of strategies and their course performance (Tables 4-7) using standard correlation methods. Finally, correlation analyses examined the association between familiarity with the course topic, interest in the course topic, and expected course grade with actual course performance (Tables 8-9).

Factor analyses were carried out using the statistical package MPlus version 7 [22]. The data were analyzed in two steps: 1) categorical Exploratory Factor Analysis (EFA) on the 22 strategy questions, and 2) categorical confirmatory factor analysis (CFA). The purpose of the EFA was to identify the latent structure in students' responses. The purpose of the CFA was to confirm that the latent structure found in the EFA was not due to chance and had good construct validity. To carry out the EFA and CFA, the data were randomly split in half (n = 230). A sample size of 230 is well above the minimum sample size of 110, based on Streiner [23], of 5 times the number of variables being tested. It was determined that both Bartlett's test of sphericity was significant for both datasets, and the Kaiser-Meyer-Olkin measure of sampling adequacy was above the cutoff level of .5 [24] [25] for both datasets. These results suggested that both datasets were appropriate for factor analysis. Significance was based on an alpha of .05.

4.1 Exploratory Factor Analysis

Exploratory factor analysis was applied to the first set of 230 randomly-selected responses using oblique rotation. The scree-plot suggested that a three-factor model should be retained, and this was verified by a parallel analysis conducted in R using the Psych package [26]. The parallel analysis plot is shown in Figure 1. The rotated factor loadings are shown in Table 2. To maintain simple structure, variables Q3, Q8, Q9, Q12, Q13, Q15, Q19, and Q22 were eliminated from further consideration. These variables did not meet the inclusion criteria. For a variable to have

Figure 1



been chosen for further consideration in the CFA it must have had a rotated loading of .45 or above on one and only one factor in the EFA. A loading of .45 was chosen because it is considered the cutoff of a fair loading by Comrey and Lee [27]. The three-factor solution also made theoretical sense due to the factors being easily describable. Factor 1 could be described as involving Execution Strategies (Q6, Q10, Q11, Q14, Q17). Factor 2 relates to Planning and

Reflecting-Back Strategies (Q4, Q5, Q7, Q18, Q20, Q21). Factor 3 is best described as Low Confidence in Ability (Q16, Q23, Q24).

Table 2. Rotated Factor Loadings for all Variables Used in EFA for Three Factor Solution

	Factor 1	Factor 2	Factor 3
Q3	0.358	0.284	-0.140
Q4	0.064	0.515	-0.054
Q5	0.240	0.475	0.145
Q6	0.755	-0.061	-0.017
Q7	-0.050	0.547	-0.210
Q8	-0.003	0.196	0.254
Q9	0.084	0.149	0.302
Q10	0.674	-0.040	0.007
Q11	0.558	0.232	0.327
Q12	0.207	0.284	-0.026
Q13	0.167	0.421	0.023
Q14	0.499	0.107	-0.127
Q15	-0.271	0.174	0.179
Q16	-0.058	-0.247	0.702
Q17	0.538	-0.004	-0.152
Q18	0.008	0.606	0.116
Q19	0.269	0.397	0.046
Q20	0.006	0.553	0.000
Q21	-0.031	0.635	-0.092
Q22	0.143	0.362	-0.051
Q23	0.009	-0.203	0.744
Q24	-0.160	0.006	0.677

4.2 Confirmatory Factor Analysis

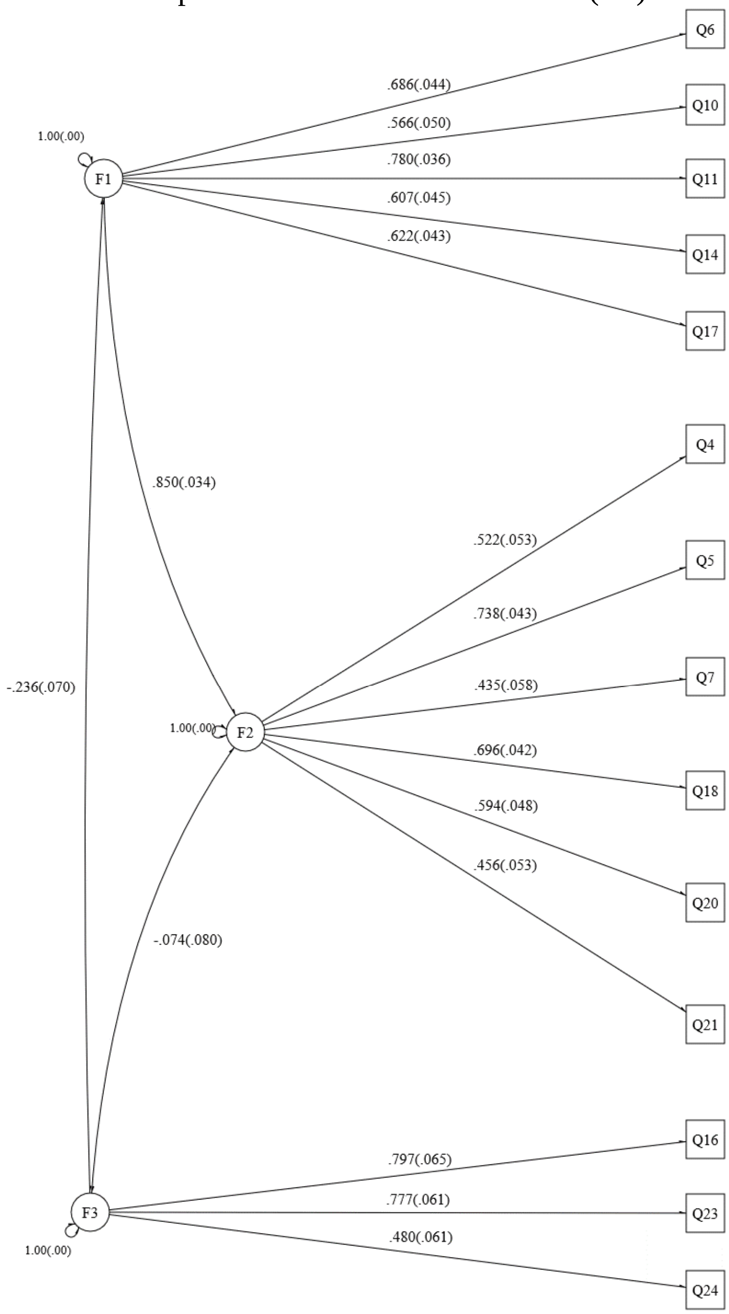
The questions that were retained in the EFA were tested using CFA. Loadings were freely estimated in the CFA, the variance of all latent variables was set to 1, and the factors were allowed to correlate. The internal consistency of the factors in the model was tested using composite reliability (CR) estimators: coefficient alpha and coefficient omega. All factors showed acceptable reliability (F1 Omega = .79 & Alpha = .73, F2 Omega = .75 & Alpha = .70, F3 Omega = .73 & Alpha = .71) above .7 [28] [29].

In addition to internal consistency, the model also showed good construct validity. First, all manifest indicators loaded significantly onto their respective latent factors ($p < .001$ for all variables). The proposed model also fit the data well according to accepted standards, with both RMSEA (RMSEA = 0.059, 90% confidence interval = .043, .075) and CFI (CFI = .953) showing good model fit [30] [31]. Additionally, as suggested by Tomarken and Waller [32], the model was compared against a plausible nonequivalent competing model in which all variables were loaded onto a single factor. In this competing model, fit dropped noticeably, with CFI = .672, and RMSEA = .154, 90% confidence interval = .141, .167, further strengthening the claim that the proposed model is valid. Overall, the results of the EFA and CFA verified the factor structure in the 22 survey questions.

Factor loadings for the survey questions are shown in Figure 2. All indicators load significantly onto their associated factors. The correlation between F1 (Execution) and F2 (Planning and Looking Back) is positive and significant, indicating that individuals high in planning and reflection are also high in affirming execution strategies. In contrast, the correlation between F1 and F3 (Low Confidence in Ability) is negative and significant, indicating that anxiety and helplessness associated with problem solving are associated with lower affirmation of execution strategies. The correlation between F2 and F3 was not significant.

In order to rule out the possibility that Physics II had a different factor structure than that derived from the combined course, additional EFA analyses were conducted. The results showed that the factor structure for Physics II alone was similar to the original structure found across all classes.

Figure 2. Standardized Path Model for the Confirmatory Factor Analysis (Standardized loadings are outside of parentheses and standard errors (SE) are inside parentheses.)



4.3 Correlation and Linear Regression Analyses with Course Performance

Given the success in identifying reliable factors, analyses were undertaken to assess the strength of association between the factors, course performance measures, and science-course GPA.

Scores for each factor for each student were computed by calculating the mean rating of the questions comprising the factor. Descriptive statistics are shown in Table 3.

Table 3. Means (standard deviation) by Course

Measures	Physics II	Thermodynamics I
f 1	3.74 (.60)	3.84 (.60)
f 2	3.19 (.60)	3.31 (.61)
f 3	2.58 (.71)	2.78 (.76)
Science GPA*	3.19 (.49)	3.29 (.47)
Familiarity	3.22 (.78)	3.14 (.82)
Interest	3.21 (.99)	3.44 (.90)
Expected Grade	2.85 (.74)	2.96 (.80)

Note. GPA is on a 4-point scale.

An examination of Table 3 shows that mean ratings for the measures were comparable for the two courses. The measures for f1 (Execution Strategies) and f2 (Planning and Looking-Back Strategies are above the neutral rating of *Sometimes*, and mean ratings for f3 (Low Confidence in Ability) is below the neutral rating. Mean Familiarity and Interest ratings are above the neutral value of *Somewhat.*

Summary grades were provided by instructors, however, they were not identical for the two courses (Thermodynamics I: weighted course grade; Physics II: average exam grades; final exam), therefore, the analyses were conducted separately for the two courses.

In a preliminary analysis, correlations were calculated between f1-f3 and course performance measures for Physics II (Table 4) and Thermodynamics I (Table 5). Correlations for f1 were positive and significant, indicating that the more frequently students applied Execution Strategies the higher was their course performance. Correlation of f2 with course performance was not significant for Physics II, but it was positive and significant for Thermodynamics I. Correlations for f3 were negative and significant, indicating that students with Low Confidence in Ability had lower course performance.

Table 4. Physics II Pearson Correlation Coefficients (p-values in parentheses)
N = 223

Factors	Course Exams (excl. Final)	Course Final Exam	GPA Science Courses
f 1	**.168** (.006)	**.131 (.026)**	**.297 (.001)**
f 2	-.056 (.203)	-.104 (.061)	.060 (.185)
f 3	**-.281** (.001)	**-.259** (.001)	**-.199** (.001)

Notes. One-tailed *p*-values. Significant correlations are bolded.

Table 5. Thermodynamics I Pearson Correlation Coefficients (p-values in parentheses) N = 216		
Factors	Course Grade	GPA Science Courses
f 1	**.259** (.001)	**.216** (.001)
f 2	**.256** (.001)	**.139** (.021)
f 3	**-.270** (.001)	**-.230** (.001)
Notes. One-tailed *p*-values. Significant correlations are bolded.		

In the next analyses, linear regression was employed in order to control for the interdependence between factors. For Physics II (see Table 6), f1 remained a significant positive predictor of course performance, based on standardized Beta coefficients. f2 and f3 were both significant and negatively related to course performance. These results suggests that Low Confidence in Ability has a detrimental effect on performance, as has already been shown in the correlation analyses. Similarly, application of Execution Strategies (f1) aided performance. However, a surprising outcome was the significant negative association between Planning and Looking-Back Strategies and course performance, suggesting that applying these strategies was associated with lower course performance. We will return to this finding in the Discussion. The results for Thermodynamics I (see Table 7) were generally consistent with the correlation analyses in Table 5.

Table 6. Physics II Standardized Beta Coefficients from Multiple Regression Analysis (p-values in parentheses) N = 223			
Factors	Course Exams (excl. Final)	Course Final Exam	GPA Science Courses
f 1	**.191** (.011)	**.177** (.019)	**.317** (.001)
f 2	**-.174** (.018)	**-.213** (.004)	-.106 (.145)
f 3	**-.252** (.001)	**-.237** (.001)	**-.133** (.044)
Notes. Two-tailed *p*-values. Significant coefficients are bolded.			

Table 7. Thermodynamics I Standardized Beta Coefficients from Multiple Regression Analysis (p-values in parentheses) N = 216		
Factors	Course Grade	GPA Science Courses
f 1	.130 (.085)	**.159** (.042)
f 2	**.171** (.021)	.043 (.577)
f 3	**-.233** (.001)	**-.197** (.003)
Notes. Two-tailed *p*-values. Significant coefficients are bolded.		

4.4 Correlations of Familiarity, Interest, and Expected Grade with Course Performance

Using correlation analyses to test the association of familiarity and interest with course performance showed significant positive associations for both courses (See Tables 8 and 9). Students' expected course grades were also significantly and positively associated with their actual grades.

Table 8. Physics II Pearson Correlation Coefficients (p-values in parentheses) N = 223		
Questions	Course Exams (excl. Final)	Final Exam
How familiar are you with the topic of this course?	**.272** (.001)	**.226** (.001)
How interested are you with the topic of this course?	**.271** (.001)	**.225** (.001)
My expected final grade in this course is ______	**.716** (.001)	**.572** (.001)
Notes. Two-tailed *p*-values. Significant coefficients are bolded.		

Table 9. Thermodynamics I Pearson Correlation Coefficients (p-values in parentheses) N = 216	
Questions	Course Grade
How familiar are you with the topic of this course?	**.402** (.001)
How interested are you with the topic of this course?	**.339** (.001)
My expected final grade in this course is ______	**.648** (.001)
Notes. Two-tailed *p*-values. Significant coefficients are bolded.	

5.0 Discussion

The present study measured the frequency of problem-solving strategy use by undergraduate engineering students and assessed the associations of those strategies with course performance measures. Factor analyses identified three factors in the survey, which were consistent with strategies identified as being important in the engineering education literature, specifically, an execution of solution factor (f1), a planning and looking back factor (f2), and a low-confidence in problem-solving ability factor (f3). Although the proposed model fit the data quite well, and better than a plausible competing model, it should be noted that there are likely other models that may fit the data just as well—for a discussion of model fit see Tomarken and Waller [32].

Overall, the results indicate that Execution Strategies (f1), which are generally those strategies directly involved with carrying out the solution to a problem, aided students in both courses in achieving higher course grades. Application of these strategies was also associated with students' science-course GPA (self-reported), suggesting that these basic problem-solving strategies, like monitoring a problem solution, generalized to performance in other courses. These significant associations confirm the didactic recommendations for problem solving in Woods [6], Wankat [7], Stice [12], Gray and Costanzo [13], and Litzinger et al. [16] [33], which were a strong inspiration for the present study.

A second effect that was significant for both courses was a negative association between Low Confidence in Ability (f3) and course performance, including science-course GPA. Confidence, which is an affective factor in problem solving, is rarely mentioned in the engineering education literature. However, here it shows very clearly that students with low confidence in their problem-solving ability will do more poorly in the course than students with high confidence. The effect of confidence contrasts with the findings in Montfort et al. [8] where the researchers found that high confidence was in some cases associated with misconceptions in knowledge and subsequent weak problem-solving performance. Thus, high confidence may not always be a benefit to students. Confidence, of course, may not be the root source of effects on performance, and additional analyses will be required to better understand its role across the engineering curriculum.

Planning and Looking-Back Strategies (f2) had different effects in the two courses. In Thermodynamics I, f2 was positively associated with course performance, as would be expected based on past research [4] [5] [6] [34]. In Physics II, however, planning and looking back predict lower course grades. The present data do not allow a firm explanation for this unexpected result. As a matter of speculation, the nature of the course material, the nature of tests, the manner of course instruction, among other possibilities, could possibly account for why planning a solution or reflecting back on a solution, for instance, could be disadvantageous for course performance.

Overall, the success of the present study motivates further research, particularly on a wider range of problem-solving strategies, the effects of the instructor, course organization, and activities and tests on strategy use by students. The difference in f2 effects for the two courses suggests that a universal model of strategy types and use may not be feasible. Rather, attention needs to be directed towards course differences, and differences in students' academic level, in order to draw reliable conclusions about the role of strategies. Additional research may ultimately lead to recommendations for classroom practices and student development.

5.1 Limitations

The present study was based on a limited number of possible problem-solving strategies that students might employ. Further, only two cohorts of students were tested, limiting the generalizability of these results to students at other academic levels (e.g., freshman and seniors) and who are enrolled in other engineering courses. Future research could test a more complete set of engineering problem-solving strategies, as well as the generalization of the current strategies to other cohorts of students and problem-solving contexts.

6.0 Conclusions

The present survey is one of the few attempts in the engineering education literature to identify students' applications of problem-solving strategies and to relate strategy use to course achievement. Further development and confirmation of the present strategy types may eventually aid instructors in identifying group and individual strengths and weaknesses in terms of basic problem-solving practices, across a wide variety of courses.

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