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# The Ability to Solve Realistic Problems is a Competency that Should Be Scaffolded

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# The Ability to Solve Realistic Problems is a Competency and Should Be Scaffolded


## Abstract

Real-world problem-solving is consistently emphasized as a key outcome in engineering education. Yet, the problems students encounter in the classroom differ fundamentally from those they will face in practice. These differences take the form of simplifications and assumptions performed on behalf of the student by an expert, instructor, or textbook. In fact, the ability to perform these operations is the hallmark of a real-world problem solver. When problems are overly bound, they remove the development of abstract thinking skills. When problems are not sufficiently bounded, they provoke negative student outcomes. Determining the balance of these factors is paramount to developing real-world problem-solving skills in an engineering curriculum, and this determination cannot be made without understanding the role of abstraction in engineering problem-solving.

This study operationalizes abstraction as a problem-level, observable construct and examines its relationship to problem-solving self-efficacy (PSSE) in a sophomore-level statics course. An abstraction rating scale is developed from the mathematical and representational features of statics problems and applied to homework assignments across a semester, for which student teams reported PSSE after each submission. The results support two hypotheses: more realistic problems produced lower PSSE, and students acclimated to realism contingent on mastery of the underlying content rather than exposure alone. A year-over-year comparison additionally finds that dedicating structured class time to team-based problem-solving with instructor support was associated with meaningful improvements in PSSE across all measured dimensions, even as lecture time decreased. Together, these findings argue that the ability to solve realistic problems is a competency that must be explicitly scaffolded: introduced carefully relative to content mastery, and supported through structured social learning.


## Introduction

Engineering work rarely begins with an equation sheet and a problem statement. More often, engineering begins with a physical context that must be interpreted, assumed about, and measured. Problem-solving, as a pedagogical study, does not have a clear set of descriptions of *why* real problems differ from those seen in the classroom. A common description of problems is in terms of complexity and structuredness [1]. A real-world problem is ill-structured and complex, while a textbook problem is well-structured and simple. However, these descriptions are ill-suited for curriculum development, as they describe the wrong construct. Structuredness and complexity are determined by the problem's solution and solution paths, rather than by the problem's characteristics.

The construct developed in this paper, abstraction, relates real-world problems to textbook problems. Abstractions are the simplifications and assumptions required to transform a real system into a mathematically solvable one. The fewer abstractions a problem contains, the more realistic it is (throughout this paper, higher abstraction corresponds to lower realism). For example, a real-world system contains friction. An abstraction of the system would be to neglect friction, which results in a less realistic representation. Another abstraction would be treating the system as a 2D object rather than a 3D object. After repeated abstractions, the representation will be simpler and solvable with the given information. Understanding the types and importance of abstractions is an important skill in engineering, especially for mathematical modeling. When judging the quality of models, it is these same abstractions that are analyzed [2], [3], [4].

This creates a fundamental tension in engineering education. In practice, abstraction precedes solution, necessarily so [5]. An engineer must first decide what to ignore before they can begin to calculate. But in the classroom, solution must precede abstraction. A student cannot make principled decisions about what to simplify until they understand what the solution structure demands. The sequencing is inverted between the real world and the curriculum, and this inversion has direct consequences for how realistic problems should be introduced to students. Specifically, a negative feedback loop can form if realistic problems are introduced before mastery of the solution. If a student does not understand the problem's solution structure, they cannot develop a suitable representation of the problem. Without a suitable representation, solution skills cannot be utilized. The student is asked to abstract before they can solve, but they need to solve before they can abstract. This dynamic is reflected in statics textbooks, in which a recent review found that fewer than 2% of problems were ill-structured and required non-algorithmic/logical thinking [6].

Real-world problem-solving is a key outcome for students [7], but implementing realistic problems requires careful consideration of timing, content mastery, and scaffolding. This study addresses both the measurement and the mitigation of that challenge. First, we develop an abstraction rating scale for a sophomore-level statics class as part of a multi-year project focused on the explicit instruction of abstraction skills. Abstraction characteristics of homework problems are compiled across a semester, for which groups indicated their problem-solving self-efficacy (self-evaluation of their problem-solving skills). This analysis quantifies the effect of problem realism on self-efficacy using a method directly tied to the problem's observable characteristics. We test two hypotheses: (H1) when homework problems contain fewer abstractions, students will initially report lower self-efficacy; and (H2) for repeated exposure to problems with similar abstractions, students will acclimate and report increased self-efficacy. In addition, we examine how course-level scaffolding moderates this relationship. By comparing cohorts across years, we find that dedicating structured class time to team-based problem-solving with instructor support produced statistically significant improvements in self-efficacy.

## Conceptual Framing

### A Simple Problem-Solving Model

Problem-solving can be decomposed into two steps: abstraction, which transforms a real system into a solvable representation, and solution, which applies that representation to find an answer.

This partition is not unique to this framework. Problem framing and problem solving have been recognized as distinct cognitive steps across the engineering problem-solving literature [8]. In addition, a similar partition can be identified in major problem-solving frameworks, as shown in Table 1.

| **Problem Solving Framework** | **Steps** |
|---|---|
| Mathematical Modeling Cycle [9] | **Understanding; Simplifying**; Mathematizing; Mathematical Work; Interpretation; Validation |
| PROCESS [10] | **Problem Definition; Represent the Problem**; Organize Information; Calculations; Evaluation; Solution Communication; Self-Assessment |
| Formal Approach to Cognition of Problem Solving [11], [12] | **Define and represent the problem**; Search solution goals and paths; Generate solutions; Select solutions; Represent problem-solving results |
| Problem Solving for Well-Structured Problems [1] | **Represent the problem**; Search for solutions; Implement solutions |

Table 1: Stepwise Problem-Solving Description

While these frameworks use different terminology, the representational step (bolded in each) is consistently identified as the cognitive crux that precedes and enables everything that follows. What the two-step model adds is a name for that step and a connection to the engineering practice of mathematical modeling. In statics, this boundary is demarcated by the free-body diagram (FBD). A student who has constructed a correct FBD has completed the abstraction step and can proceed to apply equilibrium equations. A student who has not cannot begin. This makes steps observable and assessable rather than inferred.

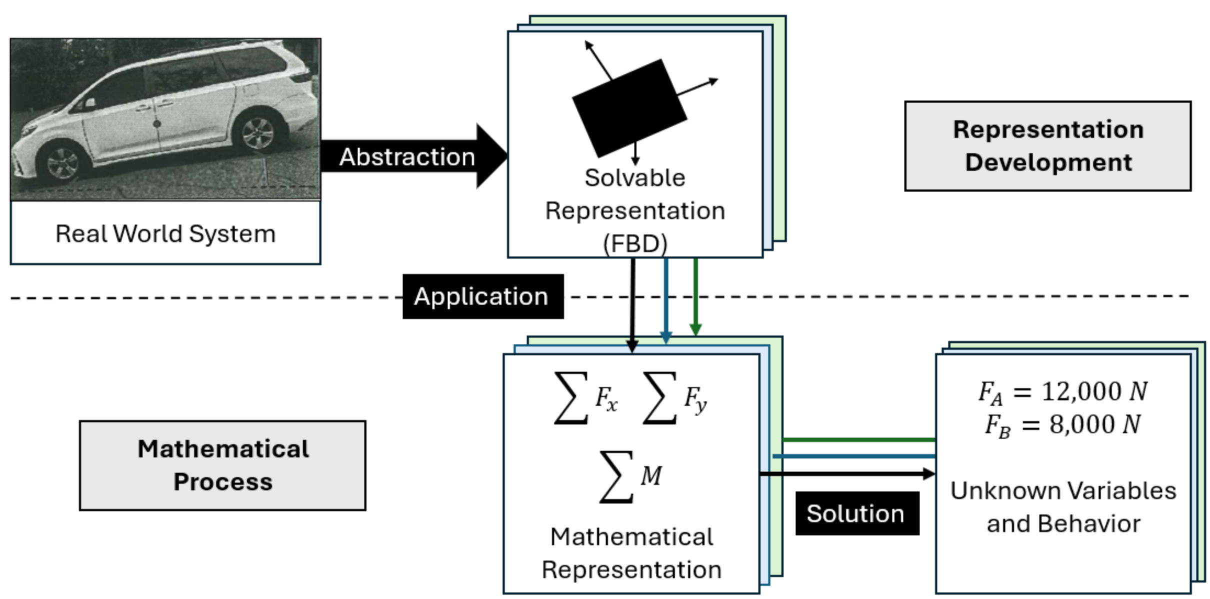


Figure 1: Two-Step Problem Solving Process

Figure 1 represents an example of this process for a statics problem. It is important to note that multiple feasible representations can be derived from a real-world system. As a result, there is a breakpoint in the abstraction process at which the system becomes well-structured rather than ill-structured. The possible solutions expand from a singular solution that *must* be true to an unbounded number of solutions that *may* be true. Ill-structured problems require inductive reasoning, while well-structured problems require deductive reasoning. The differences between these two regimes of thought and their effects on students are vast, but must be leveraged to develop real-world problem-solving skills [13].

### Cognition and Self-Efficacy

The value of the two-step model lies in its ability to isolate a difference in cognitive processes. Abstraction requires a range of meta-cognitive and domain-specific skills. Decisions must be made about which representation is appropriate, and these decisions precede and enable later algorithmic and logical thinking [14]. The choices made during abstraction are consequential, as the representation of a problem determines how and whether it can be solved [15].

To correctly abstract a problem, one must project the future solution path. Consider a problem that asks a student to find the minimum coefficient of friction between a car and a driveway required to hold the car still on a slope. Solving for this value requires treating all four wheels as a single contact point. Without this assumption, or an explicit assumption about weight distribution, the problem is statically indeterminate. Many representational choices a student might make will produce an unsolvable system or require knowledge beyond the scope of the course. The student must develop a representation in order to solve the problem, but must first determine whether that representation is appropriate and solvable. The inherent uncertainty in this loop is doubly problematic when considering the multiplicity of representations and external pressures in the classroom.

The ability to create mathematical representations is a competency that requires instruction and meta-cognitive reflection [16], not unlike other engineering competencies. However, teaching abstraction is complicated by a sequencing constraint: it must be scaffolded *after* the underlying technical skills have been established. Realistic problems are complex, and constructing a model can only be effective if the problem solver possesses the necessary technical knowledge [17], [18]. Problems must be simplified to aid learning, but simplified models reduce the range of abstraction decisions a student must make. This is the core tension that motivates the study's design.

Problem-Solving Self-Efficacy (PSSE) is an appropriate construct for examining how abstraction influences problem-solving. Self-efficacy concerns beliefs about one's capability to organize and execute the courses of action needed to achieve an outcome [19], [20], which directly mirrors the cognitive demands of abstraction. These beliefs also affect persistence and self-regulation [19], [21], making PSSE consequential for course design: a student whose confidence collapses when encountering a realistic problem is less likely to persist through the representational uncertainty that abstraction requires. This paper posits that uncertainty about how a system should be represented is transferred to students, producing measurable changes in PSSE. Conversely, as self-efficacy is responsive to mastery experiences [20], the same abstraction demand is expected to incur diminishing PSSE costs as students develop fluency with the underlying representations.

### Abstraction in Statics

Moving from a theoretical definition of abstraction to a practical rating scale requires anchoring to something concrete. Figure 2 illustrates the abstraction process for a single statics problem: calculating the reactions applied by a tree trunk to support a branch. The real system (a photograph of an actual tree branch) contains no abstractions. Each subsequent row introduces additional simplifications: measurement choices that assume constant density, geometric idealizations that reduce the branch to primitive shapes, and load idealizations that model the distributed weight as a mathematical function along a 1D object. The final row is the free-body diagram (FBD), the most abstracted representation, in which the branch has been isolated from the tree, and all forces are explicitly shown. Only at this stage can static equilibrium be applied and the problem solved.

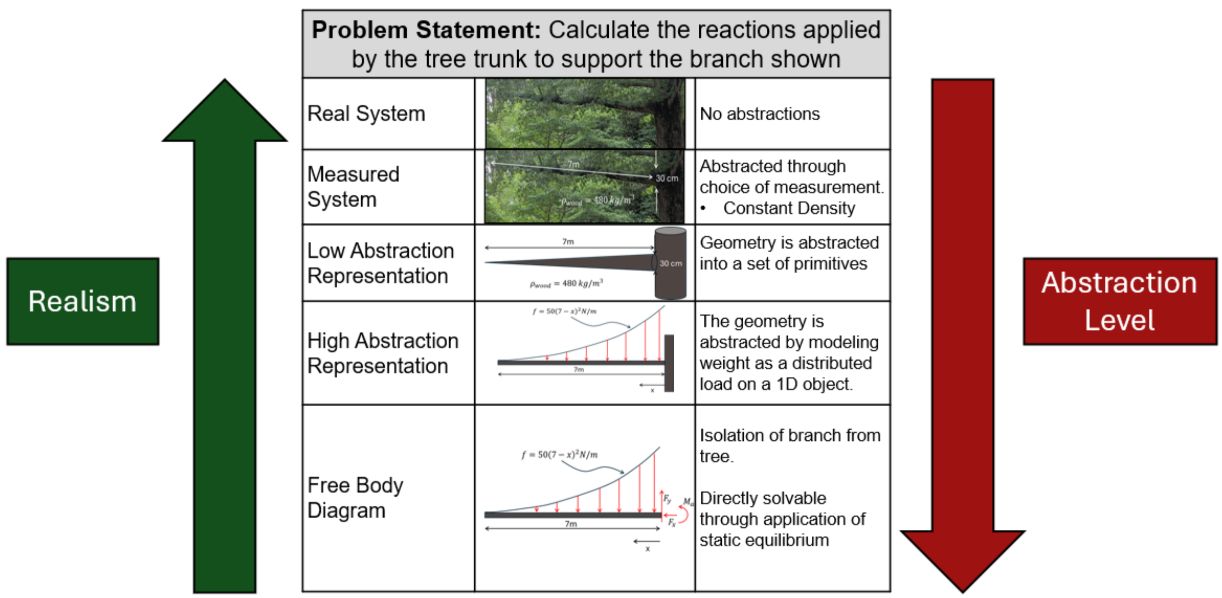


Figure 2: The abstraction process for a single statics problem. Realism (left axis) and abstraction level (right axis) run in opposing directions. Each row introduces additional simplifications until the system is represented as a free-body diagram, at which point static equilibrium can be applied directly. The abstraction rating table (Table 2) operationalizes the observable differences between these representations.

Abstraction is a sequential decision process. The branch can be treated as a 1D or 3D object (equilibrium dimensionality). Its weight can be modeled as a distributed load or a point mass (load idealization). The subsystem to analyze can be specified or left implicit (isolation). Each of these choices corresponds to a row in the abstraction rating table, and each can be varied independently of the others. A problem in which all of these choices have been made for the student is maximally abstracted and minimally realistic. A problem in which none of them have been made is the *referent*: the most complex problem that is still fully solvable within the epistemic boundaries of the course [22]. The referent concept matters because courses cannot fully model reality. A statics course defines a learnable slice of reality by holding more advanced topics constant as background assumptions. Material behavior is treated as rigid, not because deformation is unimportant, but because integrating it would displace more fundamental skills. The referent is therefore not the most realistic problem imaginable: it is the most realistic problem that remains inside the course's scope. The referent is to a course what a controlled experiment is to nature: the maximum realism that the epistemic instruments can actually resolve. By establishing a referent, a consistent baseline is created from which to describe problem-to-problem differences in abstraction.

With a referent established and the rating categories illustrated, abstraction in statics can be operationalized as variation in the representations (FBDs) that a student must develop before equilibrium can be applied. That variation is documented across three clusters: (1) mathematical modeling demands, which describe the complexity of the representation the student must target, (2) representational cues provided by the problem statement, which describe how much scaffolding the problem offers toward that representation, and (3) perceptual features, which describe how readily the physical situation can be interpreted. The full rating table is shown in Table 2. Each homework problem was rated by the first author using this table. While inter-rater reliability is a necessary next step, the ratings are grounded in observable artifacts of the problem statement and expected solution rather than holistic judgment, which limits the scope for subjective variation.

| Mathematical Modeling | | |
|---|---|---|
| **Abstraction Category** | **Criteria** | **Rating Categories** |
| Equilibrium Dimensionality | Maximum dimensionality of equilibrium equations required | $N = 1, 2, 3$ |
| Geometric Idealizations | Maximum dimensionality of geometric idealizations used in the system | $N = 0, 1, 2, 3$ |
| Mixture of Idealizations | Multiple geometric dimensionalities are used within the same analysis | Yes, No |
| Mass and Inertia | The system model includes mass and/or inertia effects | No, Mass, Inertia, Both |
| Friction | Contact between subsystems includes frictional effects | No, Yes |
| Shear and Bending | The system considers shear/bending for a rigid body | No, Yes |
| Decomposition | Number of distinct subsystems that must be isolated and analyzed | 1,2,3+ |
| Load Idealization | Dimensionality of the region that the load affects the system | $N = 0, 1, 2$ |
| *Representation Provided by the Problem* | | |
| **Abstraction Category** | **Criteria** | **Rating Categories** |
| Pictorial Dimensionality | Dimensionality communicated by the provided diagram | 2D, in-plane 3D, multiple 3D, single 3D |
| Geometric Primitives | The system is depicted using explicit geometric primitives | Yes, No |
| Reaction Forces | Reaction forces are indicated through text/symbols | Vector, Symbols, Text, Not Indicated |
| External Loads | External loads are indicated through text or symbols | Vector, Text, Not Indicated |
| Reference Frame | Coordinate axes or reference directions are provided | Shown, Stated, Not provided |
| Entity Labeling | Key points, bodies, or members are labeled | Yes, No |
| Geometry Annotation | Required geometric quantities are explicitly given | On diagram, In text, Not Provided |
| Isolation | The prompt specifies what subsystem to isolate | Done, Indicated, Not Indicated |
| Representation Requirement | Explicit deliverables required by the prompt | Rep., Rep. and Value, Value only |
| *Perceptual Effects* | | |
| **Abstraction Category** | **Criteria** | **Rating Categories** |
| Embodiment | The system is used or affected by a person | Yes, No |
| Affordance | Intended use or behavior is made perceptually clear | Represented, Described, Unclear |

Table 2: Abstraction Rating Table

# Methodology

## Course Context and Structure

This study was conducted as part of a three-year project to redesign a sophomore-level civil engineering statics course around the explicit instruction of abstraction skills. The course enrolled 48 students, 39 of whom were civil engineering majors, with the remainder drawn from programs including bioengineering.

Homework, projects, and tests all included team-based components. Teams of four students, formed based on availability, were the primary unit for assignments and reflective exercises. The most recent iteration of the course (Fall 2025) substantially increased the proportion of class time devoted to guided in-class problem-solving, with students completing most homework and project work on designated problem-solving days under instructor supervision and with peer support. This structural change is central to the year-over-year scaffolding analysis presented later in the paper.

The course was organized into four modules: point equilibrium, rigid body equilibrium, structures, and internal forces. For analysis purposes, the structures and internal forces modules were grouped into a single section, as only one homework set was assigned for internal forces. This three-part partition (point equilibrium, rigid-body equilibrium, structures and internal forces) forms the basis for the temporal analysis.

### Reflective Exercise

Problem-Solving Self-Efficacy (PSSE) was measured using a brief reflective exercise completed by each team after submitting each homework set. Teams responded to five PSSE prompts and one grade-estimation prompt for each problem in the set, shown in Table 3.

| **Question Text** | **Tag** | **Rating Scale** |
|---|---|---|
| Our group had the knowledge and mathematical skills needed to solve this problem | Knowledge | 0-10 |
| We felt hurried or rushed when completing the problem* | Rushed | 0-10 |
| We could successfully complete a similar problem to this in the future | Future Work | 0-10 |
| We put in a lot of effort to complete this problem* | Effort | 0-10 |
| We felt insecure, discouraged, irritated, or stressed while solving this problem* | Emotions | 0-10 |
| Estimate your grade for each problem in this homework set | Est. Grade | 0-20 |

Table 3: Homework Reflection Questions

The prompts were rated on a 0-10 scale to reduce ceiling effects and produce more sensitive measures [23]. Items phrased negatively (starred) were reverse-scored by subtracting the response from 10, so that higher scores consistently correspond to higher self-efficacy across all items. The grade estimation item was included as an independent check on self-efficacy and is analyzed separately where relevant.

### Analysis Methods

PSSE responses vary substantially across teams due to baseline differences in confidence and prior experience. The analysis is designed to emphasize *changes* in PSSE rather than absolute levels, isolating the effect of problem characteristics from stable between-team differences. To accomplish this, PSSE values were normalized within each team using a Z-score:

$$Z_{i,j} = \frac{X_{i,j} - \mu_j}{\sigma_j}, \tag{1}$$

where $X_{i,j}$ is the PSSE response for problem $i$ from team $j$, and $\mu_j$ and $\sigma_j$ are that team's mean and standard deviation across the semester for the same PSSE item. This produces a within-team metric: a positive Z-score indicates that a problem elicited higher self-efficacy than that team's typical response, and a negative Z-score indicates lower. Normalized responses were then averaged across teams for each problem. Duplicate responses from a single team were averaged, and missing entries were excluded.

Three complementary analyses were then conducted. First, to test whether PSSE differed systematically across abstraction levels within each category, single-factor ANOVAs were conducted for each pairing of abstraction category and PSSE item. Because abstraction categories contain different numbers of levels, a bias correction was applied to prevent categories with more levels from being artificially advantaged in significance testing. Second, to estimate the direction of these effects (whether more realistic problems increase or decrease PSSE), Spearman rank correlations were computed between ordered abstraction levels and normalized PSSE. Lower ratings correspond to more abstracted problems and higher ratings to more realistic ones, so a negative correlation indicates that realism reduces PSSE. We refer to the magnitude and sign of this correlation as the *PSSE resilience* of a category: a less negative (or more positive) correlation indicates that PSSE is more resilient to increases in realism within that category. Third, to evaluate whether students' PSSE responses to realism change across the semester, correlations were recomputed within each course module, and differences between adjacent modules were tested using two-tailed t-tests, accounting for the differing number of problems per module.

## Results

Before discussing how problem characteristics influence PSSE, it is important to establish the interrelationship between PSSE items. Figure 3 displays Pearson correlation coefficients for the normalized class average response on the reflective activity completed after homework submission.

| **PSSE Items** | Knowledge | Rushed | Future Work | Effort | Emotions | Est. Grade |
|---|---|---|---|---|---|---|
| Knowledge | | | | | | |
| Rushed | 0.26 | | | | | |
| Future Work | 0.83 | 0.32 | | | | |
| Effort | 0.63 | 0.36 | 0.69 | | | |
| Emotions | 0.82 | 0.40 | 0.91 | 0.75 | | |
| Est. Grade | 0.10 | 0.32 | 0.02 | 0.12 | 0.07 | |

Figure 3: Pearson Correlation Coefficients between Items on Reflective Activity

For all items in the reflective exercise, an increase in one measure of self-efficacy, on average, results in increases in the other measures of PSSE. Questions about future work, effort, knowledge, and emotions are highly correlated, suggesting strong internal consistency. Emotions related to self-efficacy are the most predictive of other PSSE categories. The question related to feelings of being rushed correlates to a statistically significant degree but more weakly, suggesting it may capture a more generalized sense of course load than problem-specific self-efficacy. In previous work, a natural disaster occurring mid-semester caused a statistically significant increase in responses to this item [24], consistent with the interpretation that it reflects environmental context rather than problem difficulty.

### Abstraction Levels and PSSE

To examine the impact of abstraction categories on PSSE, single-factor analyses of variance (ANOVA) were conducted for each pairing of abstraction category and PSSE item. The resulting p-values are presented in Table 4.

| **Abstraction Categories** | Knowledge | Rushed | Future Work | Effort | Emotions | Est. Grade |
|---|---|---|---|---|---|---|
| Equilibrium Dimensionality | 0.25 | 0.03 | 0.19 | 0.02 | 0.06 | 0.40 |
| Geometric Idealizations | 0.25 | 0.06 | 0.29 | 0.03 | 0.09 | 0.56 |
| Mixture of Idealizations | 0.03 | 0.62 | 0.05 | 0.17 | 0.14 | 0.55 |
| Mass and Inertia | 0.40 | 0.20 | 0.72 | 0.50 | 0.70 | 0.40 |
| Friction | 0.87 | 0.13 | 0.63 | 0.37 | 0.50 | 0.80 |
| Decomposition | 0.02 | 0.34 | 0.03 | 0.24 | 0.09 | 0.48 |
| Load Idealization | 0.22 | 0.05 | 0.46 | 0.58 | 0.54 | 0.19 |
| Pictorial Dimensionality | 0.09 | 0.88 | 0.38 | 0.27 | 0.18 | 0.04 |
| Geometric Primitives | 0.78 | 0.51 | 0.74 | 0.68 | 0.74 | 0.46 |
| Reaction Forces | 0.50 | 0.92 | 0.72 | 0.87 | 0.86 | 0.91 |
| External Loads | 0.52 | 0.83 | 0.88 | 0.54 | 0.96 | 0.50 |
| Shear Force | 0.22 | 0.08 | 0.79 | 0.79 | 0.29 | 0.08 |
| Reference Frame | 0.46 | 0.18 | 0.54 | 0.45 | 0.47 | 0.49 |
| Entity Labeling | 0.11 | 0.23 | 0.29 | 0.63 | 0.37 | 0.42 |
| Geometry Annotation | 0.42 | 0.79 | 0.38 | 0.63 | 0.52 | 0.94 |
| Isolation | 0.21 | 0.45 | 0.11 | 0.07 | 0.09 | 0.56 |
| Representation Requirement | 0.01 | 0.19 | 0.07 | 0.00 | 0.01 | 0.06 |
| Information Gathering | 0.23 | 0.28 | 0.07 | 0.01 | 0.17 | 0.56 |
| Embodiment | 0.92 | 0.32 | 0.72 | 0.68 | 0.96 | 0.85 |
| Affordance | 0.07 | 0.53 | 0.04 | 0.10 | 0.10 | 0.98 |

Table 4: Single-Factor, Bias-Corrected ANOVA p-values for ratings of problem abstraction and the resulting normalized PSSE class averages

Significant values are presented in green, with a threshold of .05, and values close to significance in light orange, at less than .1. Mathematical characteristics of the model and the problem's representational scaffolding comprise the majority of significant values. Decomposition, mixture of idealizations, and representation requirements all exhibit statistically significant associations with PSSE. These categories share a common feature: they relate to knowing *what* to do rather than *how* to do it. This is consistent with the feedback loop described in the introduction, as uncertainty about the solution path transfers directly to the student. Notably, diagramming features such as entity labeling and reference frame provision did not significantly change PSSE. While these steps are necessary for a correct FBD, they do not clarify the solution path and therefore do not appear to carry the same representational burden. To estimate directionality, Spearman rank correlations were computed between ordered abstraction levels and normalized PSSE measures, shown in Table 5.

| **Abstraction Categories** | Knowledge | Rushed | Future Work | Effort | Emotions | Est. Grade |
|---|---|---|---|---|---|---|
| Equilibrium Dimensionality | **-0.235** | **-0.298** | **-0.308** | **-0.350** | **-0.351** | -0.183 |
| Geometric Idealizations | **-0.235** | **-0.298** | **-0.308** | **-0.350** | **-0.351** | -0.183 |
| Mixture of Idealizations | **-0.261** | -0.047 | **-0.286** | -0.199 | **-0.228** | 0.014 |
| Mass and Inertia | -0.196 | 0.006 | -0.163 | -0.151 | -0.134 | -0.187 |
| Friction | 0.067 | 0.187 | 0.151 | -0.112 | 0.130 | -0.079 |
| Decomposition | **-0.280** | -0.149 | **-0.253** | -0.168 | **-0.233** | -0.141 |
| Load Idealization | **-0.221** | **0.315** | -0.106 | 0.020 | -0.038 | 0.097 |
| Pictorial Dimensionality | 0.060 | 0.007 | 0.078 | 0.073 | 0.097 | -0.163 |
| Geometric Primitives | 0.011 | 0.099 | -0.005 | -0.007 | -0.001 | -0.021 |
| Reaction Forces | 0.013 | -0.027 | 0.040 | 0.068 | 0.106 | -0.067 |
| External Loads | -0.167 | 0.036 | -0.124 | -0.136 | -0.094 | 0.073 |
| Shear Force | **-0.227** | **-0.269** | -0.050 | 0.043 | **-0.232** | **-0.228** |
| Reference Frame | -0.025 | 0.126 | -0.069 | -0.048 | -0.051 | -0.140 |
| Entity Labeling | **-0.235** | 0.152 | -0.137 | 0.030 | -0.100 | 0.175 |
| Geometry Annotation | 0.079 | 0.044 | 0.141 | -0.063 | 0.071 | -0.082 |
| Isolation | 0.109 | -0.007 | 0.023 | 0.005 | 0.115 | -0.102 |
| Representation Requirement | **-0.382** | -0.176 | **-0.362** | **-0.409** | **-0.423** | -0.061 |
| Information Gathering | -0.171 | -0.015 | **-0.272** | **-0.371** | **-0.210** | -0.053 |
| Embodiment | 0.020 | 0.106 | 0.023 | -0.026 | -0.029 | 0.036 |
| Affordance | **0.255** | 0.074 | **0.327** | **0.240** | **0.26** | -0.007 |

Table 5: Spearman Rank Correlations

For the majority of categories, reducing abstraction (that is, making problems more realistic) decreases problem-solving self-efficacy, consistent with H1. The effect is largest for categories related to model complexity: equilibrium dimensionality, geometric idealizations, decomposition, and representation requirement. These are precisely the categories that determine whether a student knows what representation to build, rather than whether they can execute it. Load idealization is an exception, showing a positive correlation with PSSE, which is attributable to a narrow concentration of distributed load problems within a single homework set rather than a general trend. The affordance category also shows a positive correlation, which is a known confound discussed in the limitations.

### Temporal Effects: Acclimation

Hypothesis 2 predicts that students will acclimate to realistic problems over the semester as they develop mastery of the underlying material. To evaluate this, Spearman rank correlations between abstraction categories and PSSE were recomputed within each course module, and changes between adjacent modules were tested using two-tailed t-tests. Significant changes are shown in Figure 4.

| | Knowledge | | Rushed | | Future Work | | Effort | | Emotions | | Est. Score | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Equilibrium Dimensionality | 0.44 | | **-0.83** | | 0.24 | | 0.37 | | 0.26 | | **-0.88** | |
| Geometric Idealizations | 0.44 | | **-0.83** | | 0.24 | | 0.37 | | 0.26 | | **-0.88** | |
| Mixture of Idealizations | | 0.06 | | 0.23 | | -0.11 | | 0.07 | | 0.03 | | -0.05 |
| Mass and Inertia | -0.23 | 0.08 | -0.14 | -0.28 | -0.11 | 0.19 | -0.26 | **0.49** | -0.22 | 0.23 | -0.21 | 0.12 |
| Friction | **-0.60** | 0.32 | **-0.70** | 0.37 | **-0.45** | 0.02 | **-0.91** | **0.67** | **-0.51** | 0.17 | -0.43 | 0.14 |
| External Loads | **-0.54** | 0.58 | -0.25 | 0.07 | -0.39 | **0.48** | -0.48 | **0.60** | -0.40 | 0.54 | -0.26 | 0.03 |
| Entity Labeling | -0.13 | -0.31 | -0.25 | -0.16 | -0.07 | -0.30 | -0.18 | 0.37 | -0.02 | -0.27 | **-0.60** | -0.17 |
| Isolation | 0.26 | -0.07 | -0.21 | **0.86** | 0.19 | -0.16 | 0.16 | 0.03 | 0.34 | 0.03 | -0.19 | 0.24 |
| Representation Requirement | 0.26 | -0.27 | 0.18 | -0.21 | 0.38 | **-0.43** | 0.28 | 0.10 | 0.38 | -0.42 | -0.02 | 0.14 |
| Information Gathering | 0.00 | 0.30 | -0.38 | 0.11 | 0.24 | -0.08 | 0.14 | -0.12 | 0.28 | 0.22 | -0.39 | 0.18 |
| Embodiment | 0.04 | -0.41 | -0.21 | -0.38 | -0.07 | -0.30 | -0.19 | 0.08 | -0.07 | -0.25 | **-0.56** | -0.12 |
| Affordance | 0.15 | -0.36 | 0.11 | -0.16 | 0.12 | -0.14 | 0.09 | -0.39 | 0.05 | -0.26 | **0.54** | -0.07 |
| | $\Delta\rho_{2/1}$ | $\Delta\rho_{3/2}$ | $\Delta\rho_{2/1}$ | $\Delta\rho_{3/2}$ | $\Delta\rho_{2/1}$ | $\Delta\rho_{3/2}$ | $\Delta\rho_{2/1}$ | $\Delta\rho_{3/2}$ | $\Delta\rho_{2/1}$ | $\Delta\rho_{3/2}$ | $\Delta\rho_{2/1}$ | $\Delta\rho_{3/2}$ |

Figure 4: Change in Spearman's Rank Correlation Coefficient between Course Modules. Abstraction categories that did not contain significant values were removed, and significant values are bolded. A positive value indicates that PSSE has increased across modules within the abstraction category, consistent with acclimation.

The evidence yields mixed results. The most significant decreases in PSSE resilience occurred between the first and second modules, whereas significant increases were more common between the second and third modules. The pattern is therefore more nuanced than simple acclimation: PSSE resilience does not rise steadily throughout the semester, but rather rises and falls with the content introduced.

A possible explanation for this behavior lies in the content of each module. The content-based categories in Figure 4 (friction, external loads, mass, and inertia) account for nearly half of the significant results, and they exhibit a consistent pattern: PSSE tends to decrease in the first comparison and then increase in the next. Module 2 introduces rigid bodies, where Module 1 had only idealized point masses, so concepts like friction are still being established and actually become more difficult. Problems involving friction are genuinely more challenging at this stage, and PSSE drops relative to realism. There is then a noticeable rebound as these concepts are consolidated in Module 3.

This same logic explains the significance of the representation requirement category. The third module focuses on structures and internal forces, where many possible FBDs can be drawn from a single system. Explicitly requesting an FBD of a specified subsystem directs the student toward a solution path and increases PSSE. As systems become more realistic and the number of plausible representations expands, guidance on what to isolate becomes critical to student confidence.

### Scaffolding and Class Time

A central claim of this paper is that the negative feedback loop between abstraction and solution can be mitigated through instructional design. The most substantive course-level change between cohorts was an increase in dedicated in-class problem-solving time, in which student teams worked on homework and project assignments with instructor support and peer discussion. This reduced the time spent on lectures but increased the time students spent vocalizing their cognitive processes and learning from one another. In Fall 2024, students spent approximately 33 percent of their time on in-person problem-solving sessions, which increased to 44 percent in Fall 2025. This time was largely taken from lectures, which decreased from 50 % to 33%. Despite the reduction in lecture time, students in Fall 2025 reported higher PSSE across all measures than in Fall 2024, as summarized in Table 6.

| PSSE | Fall 2025 | Fall 2024 | Percent Change |
|---|---|---|---|
| Knowledge | 8.82 | 7.36 | 18.0 |
| Rushed | 8.88 | 8.10 | 9.2 |
| Future Work | 8.73 | 7.12 | 20.2 |
| Effort | 3.60 | 1.80 | 66.4 |
| Emotions | 8.12 | 6.43 | 23.3 |
| Est. Grade | 18.77 | 16.41 | 13.4 |

Table 6: Year-by-Year Change in PSSE

The magnitude of these differences suggests that structured peer problem-solving time meaningfully supports the development of abstraction skills. Note that the Rushed, Effort, and Emotions items are reverse-scored, so higher values in Fall 2025 indicate that students felt less rushed, that problems required less effort, and had less negative emotions. Peer learning provides a form of support that lectures cannot: students can articulate the cognitive hang-ups associated with the development of representation in ways that instructors often cannot anticipate. These results are descriptive, and a controlled comparison is a priority for future work. Still, they are consistent with the broader argument that scaffolding abstraction through structured social learning is a productive intervention.

## Discussion

### Representational Ambiguity and Uncertainty

The abstraction categories most strongly associated with PSSE are those that govern whether a student knows what to represent, not whether they can execute the representation. Decomposition, mixture of idealizations, and representation requirement (all of which relate to identifying and bounding the correct solution path) show the strongest and most consistent associations with PSSE across both the ANOVA and Spearman analyses. A student who cannot label a free-body diagram correctly has a knowledge gap. A student who does not know which body to draw has a representational ambiguity problem, and that ambiguity is what drives the feedback loop described in the introduction. This has a direct pedagogical implication. When introducing new concepts, minimize representational ambiguity until the underlying model is stable. For example, explicitly requesting an FBD for a specified subsystem is one way to accomplish this, removing uncertainty about what to target, but it still requires students to perform the abstraction process themselves. In general, decomposition tasks, mixed idealizations, and problems with implied parameters should be introduced only after students have demonstrated fluency with the underlying representations. The goal is to isolate the abstraction demand that is developmentally appropriate at each stage, rather than exposing students to the full complexity of realistic problems before they have the representational toolkit to navigate them.

### Realistic Problems Require Mastery of Unrealistic Problems

The module-level data have some support for the hypothesis that students will acclimate to realistic problems, but this relationship is complex. Students acclimate to realistic problem if they have mastered the underlying content. The dip in PSSE resilience during the Module 1 to Module 2 transition, followed by recovery in the Module 2 to Module 3 transition, maps directly onto the course's content difficulty curve and increasing realism of the problems faced. This is consistent with the theoretical framing posed in this paper: the feedback loop between abstraction and solution amplifies uncertainty when new content is introduced, because students cannot yet project the solution path that would inform their representational choices. As content stabilizes, students then begin to acclimate to increasingly realistic problems. Introducing realistic problems early in a new content module, before students have internalized the relevant representations, is likely to lower PSSE without producing the intended abstraction development.

### In-Person Team Problem-Solving

The year-over-year comparison provides preliminary evidence that the negative feedback loop can be mitigated through instructional design. The shift toward structured in-class problem-solving time (with team collaboration and instructor support) was associated with meaningful PSSE improvements across all measures despite a reduction in lecture time. This is consistent with the scaffolding argument advanced in the introduction. What students need is not more content delivery but more supported practice navigating representational ambiguity in a low-stakes environment. Peer learning is particularly well-suited to this, as students can surface and discuss the specific cognitive hang-ups of abstraction in ways that are difficult to anticipate from the instructor's perspective.

### Limitations

Several limitations bound the claims of this study. First, PSSE responses were collected at the team level, which creates ambiguity about whether responses reflect a shared team state or the perspective of the individual completing the reflection. Second, abstraction ratings were performed by a single rater. While the rating table was designed to minimize subjectivity by grounding ratings in observable problem artifacts, inter-rater reliability is a necessary next step, particularly for the ordinal assumptions required by rank-based analyses. Third, the affordance category is significantly negatively correlated with 13 of the 19 other abstraction categories, meaning that problems with unclear behavioral cues tend also to be less complex overall. This confounding makes the positive Spearman correlation for affordance difficult to interpret causally and limits what can be concluded from that category in isolation. Future work should study the effect of individual perception on the ability to find solution paths, as this may be a large source of performance variation, compounded by the factors discussed. Fourth, PSSE exhibited a statistically significant semester-level decay in knowledge and rushed items, correlating negatively with homework set number. This is likely an inevitable characteristic of any semester-long measure, but it introduces noise into the dataset and may partially confound the acclimation analysis. Future work should administer a repeated content quiz at multiple course stages to separate schedule effects from problem-specific abstraction effects. Finally, the year-over-year scaffolding comparison is descriptive rather than inferential, as individual-level data and controlled conditions were not available for a formal between-cohort test.

## Conclusion

This study operationalizes abstraction as a construct to describe the realism of problems and relates it to students' problem-solving self-efficacy. By naming and categorizing the observable ways in which problems *don't* reflect reality, curricula can be designed to mitigate uncertainty and foster real-world problem-solving skills. In this study, the abstraction categories most strongly associated with PSSE are those related to representational ambiguity (decomposition, mixture of idealizations, and representation requirement) rather than those describing diagram or visual details. The cognitive cost of realistic problems lies primarily in knowing what to represent and where to focus attention, not in carrying out the representation once defined.

Repeated exposures to realistic problems lead to acclimation. However, this is contingent on mastery of the underlying content. In this study, the data showed that resilience decreased during the transition to more demanding content, then recovered as that content was mastered. Carefully managing the types of abstractions introduced to students, such as moving from 2D to 3D problems, is crucial in terms of fostering self-efficacy, but is enabled by establishing these categories as a fundamental aspect of those problems.

Finally, year-over-year comparison provides preliminary evidence that dedicating structured class time for team-based problem-solving with instructor support was associated with meaningful improvements in PSSE across all measured dimensions, even as lecture time decreased. Together, these findings argue that the ability to solve realistic problems is a competency that must be explicitly scaffolded: sequenced carefully relative to content mastery, supported socially, and developed through deliberate exposure to representational ambiguity rather than left to emerge from solution practice alone.

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