Work in Progress: Survey-Based Insights into Engineering Student Design Tendencies

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Abstract

Understanding how students engage with design processes and problem-solving is a critical area of research in engineering design and education. Existing studies have explored cognitive tendencies, problem-solving strategies, and predictive modeling in educational contexts to enhance instructional methods. Prior research highlights the use of machine learning to predict student grades and learning styles, which can inform data-driven approaches to curriculum design. Building upon this work, the present study focuses on collecting survey data from students regarding their cognitive tendencies and prior experiences. This dataset provides a foundation for developing and validating predictive models that aim to capture how students' design approaches align with their responses and observed behaviors in structured design tasks. The study establishes a survey-based method for identifying design process tendencies. Data was collected from 220 engineering students enrolled in a sophomore-level, design-focused course. This work-in-progress (WIP) paper presents the survey results, discusses their implications, and outlines how they inform ongoing research. Future work will explore different types of predictive models including regression, classification, and hybrid approaches to compare predicted versus observed design behaviors and examine broader implications for engineering education and curriculum design.

Introduction

Understanding how students engage in the engineering design process is essential for advancing engineering education. Design-based problem solving requires students to think iteratively and creatively, skills that are central to professional engineering practice [1], [2]. However, engineering students differ widely in their cognitive tendencies, prior experiences, confidence levels, and problem-solving approaches. These differences present challenges for educators seeking to design instructional material that effectively supports student learning across diverse populations [3].

Despite significant progress in engineering education research, the relationship between students' cognitive and learning tendencies and their observed behaviors during structured design tasks is not well understood. While many studies have explored cognitive experiences during design-centered tasks using pre- and post-surveys [4], existing studies focus either on self-reported characteristics or on design outcomes, without explicitly linking these factors to students' design approach [5]. Addressing this gap is critical for developing instructional strategies that are both adaptive to student needs and based on empirical evidence.

This work introduces a survey-based framework for identifying engineering students' design approach tendencies. The framework establishes a foundation for future predictive modeling of student design behaviors and supports the development of data-driven approaches to curriculum design. As a work-in-progress (WIP) study, this paper presents initial survey results collected from undergraduate engineering students enrolled in a sophomore-level design-focused course. In addition to the survey focusing on students' cognitive and learning tendencies, a follow-up survey targeting student perspectives on the design process will be used to model the relationship between student attributes and their design approach.

Background

Engineering design is a cornerstone of engineering practice and education, representing a systematic and iterative process used to address open-ended, complex problems [2], [6]. Beyond defining the professional identity of engineers, design education plays a critical role in preparing students to address societal and technological challenges. Researchers and practitioners agree on the importance of design thinking, as evidenced by the wide range of design process frameworks that have been proposed. Traditional approaches often emphasize linear, phase-gated models in which designers progress sequentially through predefined stages [7]. In contrast, complex and ill-structured problems frequently favor iterative or spiral design frameworks, where designers revisit earlier stages to refine requirements, concepts, and solutions [1], [2].

Prior research consistently distinguishes novice and expert design behaviors [8]. Novice engineering students often adopt linear strategies, progressing step-by-step with limited iteration or backtracking. Their design activity tends to emphasize early problem scoping or solution generation, with little time spent on evaluating other solutions or refining decisions as constraints and requirements change [9]. Expert designers, by contrast, exhibit highly iterative behaviors, frequently revisiting problem definitions, constraints, and solution concepts as new information emerges [10].

In addition to increased iteration, expert designers demonstrate greater flexibility in navigating between design activities, moving fluidly among analysis, synthesis, and evaluation rather than a fixed sequence [11]. They are more likely to consider alternatives, engage in deeper modeling, and advance towards later stages of the design process, such as decision-making and communication [12]. These behaviors reflect a more sophisticated understanding of design as an exploration and opportunistic process, particularly when addressing ill-structured problems with competing objectives and incomplete information [12].

Individual differences further shape students' design behaviors. Cognitive style influences whether students favor structured, analytical approaches or more fluid, intuitive exploration of design spaces [13]. Confidence also plays a significant role: students with higher confidence are generally more willing to take risks, explore alternative solutions, and engage in iterative refinement, whereas students with lower confidence may rely more heavily on procedural or linear design strategies [14]. Prior experience with open-ended problem solving similarly affects students' willingness to iterate and experiment.

To capture these tendencies and preferences at scale, researchers have commonly used survey instruments as a means of collecting students' cognitive characteristics. Surveys enable a systematic method of measuring things such as cognitive style, confidence, motivation, and attitudes towards ambiguity, providing insight into how students might engage with an open-ended design problem [15]. When used with other data collection methods such as observational or performance-based data, surveys offer a practical approach for identifying patterns in how students approach design tasks, including preferences for a structured versus an exploratory approach. As a result, surveys have become a foundational tool in engineering design education research for examining design behavior within student populations [16]. Building on prior work that uses surveys to identify students' cognitive and affective tendencies, this study seeks to examine how these measured preferences correspond to students' approaches to the design process. Specifically, the following research questions guide this work:

RQ1: What aspects of student design approach can be predicted using artificial intelligence and machine learning (AI/ML) models based on their individual attributes?

RQ2: How well do current psychological constructs relevant to design process predict student design processes?

This paper does not yet present predictive model results; rather, it establishes the survey framework and reports initial descriptive findings that will support subsequent model development.

Methodology

This research leverages surveys to collect the data needed to examine the relationship between individual attributes and design approach. Student responses to survey items are coded into metrics, which will then be used to train predictive models capable of highlighting student design tendencies. Figure 1 shows the high-level steps of the study.

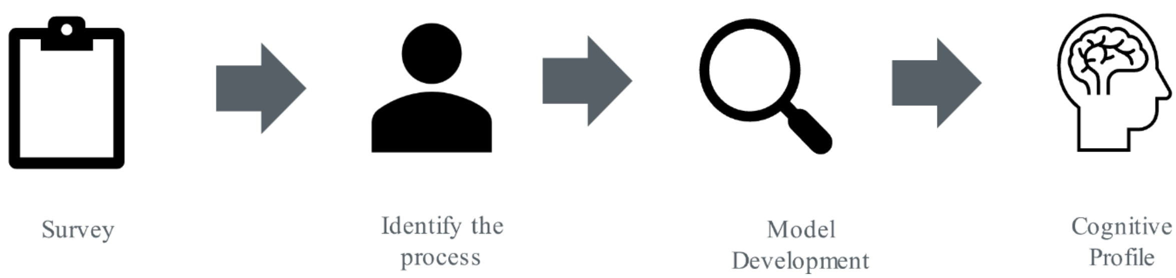

Figure 1: Visual representation of methods

Multiple survey instruments were employed to capture complementary dimensions of students' cognitive styles, learning preferences, affective states, and design identities. While no single instrument fully characterizes how students engage in design, together these measures provide a multidimensional representation of factors that influence students' navigation of the design process. This integrated approach enables more meaningful prediction and interpretation of observed design behaviors than reliance on any individual survey alone.

Participants in the study were undergraduate engineering students enrolled in a sophomore-level, design-focused course. Survey responses were analyzed to examine relationships among cognitive style, confidence, risk tolerance, and reported design tendencies. This initial analysis focuses on descriptive trends and patterns within the dataset, rather than predictive modeling.

Once data collection and preliminary analysis are completed, predictive and classification models will be developed to explore relationships between students' survey responses and reported design behaviors. Model development will be conducted using the MATLAB Machine Learning Toolbox. Multiple supervised learning approaches will be evaluated to assess the ability of survey-derived features to predict student groupings and behavioral outcomes observed during structured design tasks.

The focus of this WIP paper is the collection and analysis of the individual attributes data. This was done using a survey designed to characterize students' design tendencies, cognitive styles, confidence levels, and problem-solving approaches. The survey instrument incorporated several established measures. Table 1 presents the metrics and scoring ranges for each of the measures used in the survey. Each survey measure is then discussed in more detail.

Table 1: Summary of survey measures

Survey	Measure	Number of Items	Range
Risk-Propensity Scale (RPS) [17]	Risk Propensity (RPS)	7 (9-point scale)	-28 to 28
Concept Design Thinking Style Inventory (CD-TSI) [18]	Conditional	10 (5 items rank order)	10 to 50 (for each measure)
	Inquiring		
	Exploring		
	Independent		
	Creative		
Engineering Design Self Efficacy (EDSE) [19]	Self-Efficacy	9 (10 items Likert-scale)	0 to 100 (for each measure)
	Motivation		
	Success		
	Anxiety		
Cognitive Style Index (CSI) [21]	Intuitive	38 (3-point scale, True-False)	0 to 76
	Quasi-Intuitive		
	Adaptive		
	Quasi-Analytic		
	Analytic		
Kolb's Learning Style Inventory (KLS) [22]	Concrete Experience	10 (4 items rank order)	10 to 40 (for each measure).
	Reflective Observation		
	Abstract Conceptualization		
	Active Experimentation		
Preference for Design Approach Survey	Several different design processes	30 items	Variety of scores

The RPS captures how comfortable a person is with risk-taking in a variety of situations. The RPS consists of seven items, scored on a nine-point Likert scale. Others have used risk tolerance and other risk-taking constructs to evaluate and explain exploration, tolerance for ambiguity, unconventional ideas, and decision making within design research [23],[24].

The CD-TSI looks to capture how students prefer to think during design and helps bridge the gap between cognitive style and design thinking. The CD-TSI has ten questions, each with five options that are rank-ordered to determine a person's thinking style. CD-TSI was used in design teams during project-based learning to relate thinking styles to design outcomes [25]. Others also used a framework similar to show a relationship between students' cognitive development and preferred thinking style. Zhang showed that students operating at higher cognitive levels tend to employ more broad and flexible styles compared to students at lower cognitive levels, who exhibit a rule-based, direct approach [26].

The EDSE evaluates motivation, confidence, perceived success, and anxiety experienced while performing engineering design tasks. It has nine questions for each metric with participants scoring them from 0 to 100. The EDSE was validated to be used as a construct for novices and is robust to a variety of populations and educational contexts [27]. The framework was then expanded upon, showing that as students gain formal design experience, self-efficacy differentiates during the design process, allowing researchers to see where confidence develops or breaks down during design activities [28].

The CSI is used for capturing broader thinking tendencies and provides a cognitive profile that contextualizes design behavior. The CSI is 38 true-or-false questions to determine if the participants fit one of the five thinking styles provided in the survey. Prior work has shown that cognitive style influences how individuals frame problems, balance adaptive versus generative strategies, and engage in innovation-oriented tasks. Accordingly, CSI classifications were used in this study to interpret variation in design behaviors among participants with similar cognitive processing styles [31].

The KLS measures the preferred learning approach, where learning is viewed as a recurring problem-solving process. The learning styles introduced by this instrument are concrete experiences (CE), reflective observation (RO), abstract conceptualization (AC), and active experimentation (AE). The KLS is used to see how students may engage within the design process, such as where the students might start or which stages they emphasize. Felder and Brent used learning-style theory to analyze project-based and design-centric engineering courses [32]. Drawing on experiential learning theory, they show that design projects require students to cycle between analysis, experimentation, reflection, and iteration, thereby accommodating diverse learning preferences and promoting adaptive expertise rather than reinforcing fixed learning styles.

Because the survey instruments use different scoring ranges (see Table 1), all composite measures will be normalized prior to predictive modeling using z-score standardization. This transformation ensures comparability across constructs and prevents variables with larger numerical ranges from disproportionately influencing model training Standardization parameters will be computed using training data only to prevent data leakage during cross-validation.

To better outline how the different surveys map to the different aspects of cognition and behavior, Figure 2 shows a visual representation of the goals of each survey in the pursuit of creating a student design profile. Note that observed design behavior is not included in this paper; however, it is part of the larger research project.

As shown in Figure 2, the survey measures primarily address student cognitive preferences and affective states. One survey targeting design thinking style has been used, but student's design approach will be measured from an additional survey that was administered later in the semester. This survey was intended to capture students' evolving perspectives on design and problem-solving. This instrument included items asking students to rank different stages of the design process, reflect on their own design experiences, and express their views on design practices such as idea generation and prototyping. The purpose of this survey was to directly elicit students' self-described design and problem-solving approaches. The planned post-semester survey is found within the appendix of this paper. The intent of the survey is not to prescribe a normative design process, but to characterize variation in student design cognition.

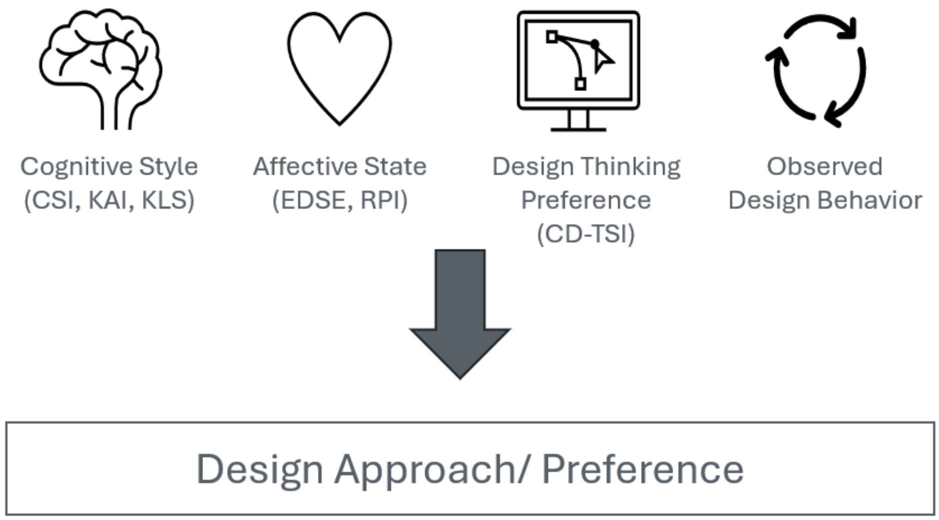

Figure 2: Mapping survey measures to cognitive, affective, and behavioral dimensions of student design preference

In contrast, the initial survey was intended to characterize students' cognitive and affective profiles, allowing underlying tendencies and preferences to be identified. While these profiles provide important context for understanding how students may engage in design activities, they do not fully capture how students conceptualize or articulate their design processes. The second survey addresses this limitation by offering insight into how students perceive and describe their thinking during design tasks, providing a more complete representation of students' design cognition. Together, these instruments span cognitive (CSI), affective (EDSE, RPS), and behavioral preference (CD-TSI, KLS) domains, enabling a structured mapping from underlying traits to observable design tendencies.

After collecting and analyzing responses from the post semester survey, both input measures (cognitive, affective, design thinking) and output measures (reported design approach) will be available for use in developing predictive models. Planned models include linear regression for continuous design tendency scores and classification models (e.g., SVM, decision trees) for grouped design approach categories. Feature selection methods such as Spearman correlation, F-tests, and MRMR will be used to identify the most predictive survey constructs. These models will allow for the examination of potential threshold effects or non-linear relationships among constructs that may not be adequately captured using strict linear methods.

Results

Student responses to the survey measures were reviewed for completeness and duplication. Once the data collected were cleaned and organized, metrics for each measure were computed. Summary statistics are presented in this section. It should be noted aggregated scale scores from the survey were treated as interval-level measures for the purpose of descriptive statistics. This is because several of the survey instruments employ Likert-type or other ordinal response formats. This approach is consistent with common practice in engineering education and psychological research when multiple ordered response categories are combined into composite scores. Although ordinal in origin, these aggregated measures approximate continuous distributions, particularly when based on multi-item scales.

Results from the Risk Propensity Scale, presented in Figure 3, show that Q1 has the lowest central tendency, with several high outliers. From there, there is an increase in central tendency. Q5 has the highest mean and median values. For Q6 and Q7, the central tendency drops and eventually drops back towards the middle.

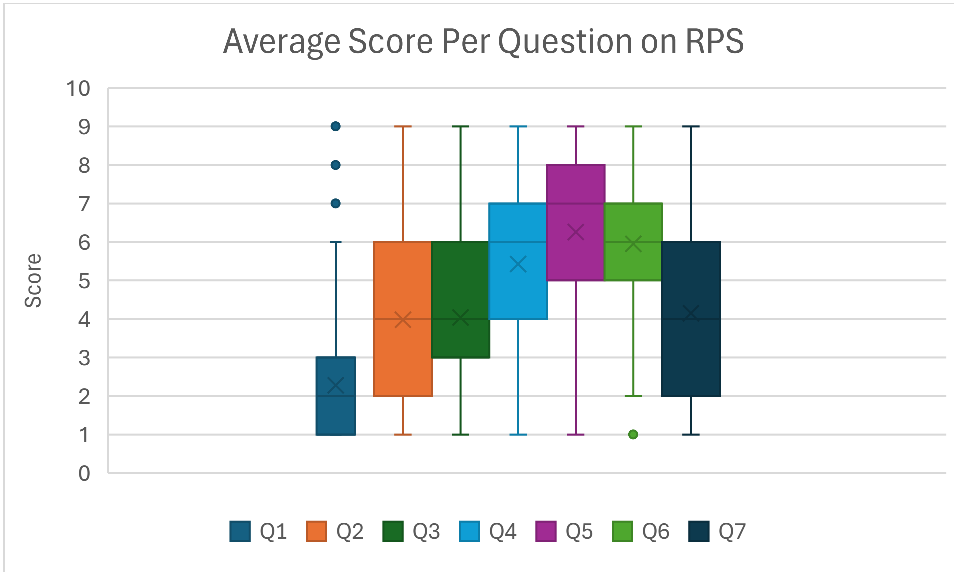

Figure 3: Results from RPS

Results from the Concept Design Thinking Style Inventory, shown in Figure 4, show that independent and creative styles have the highest central tendencies with few outliers. The conditional style contains the largest spread among categories while the exploring style contained the greatest number of outliers.

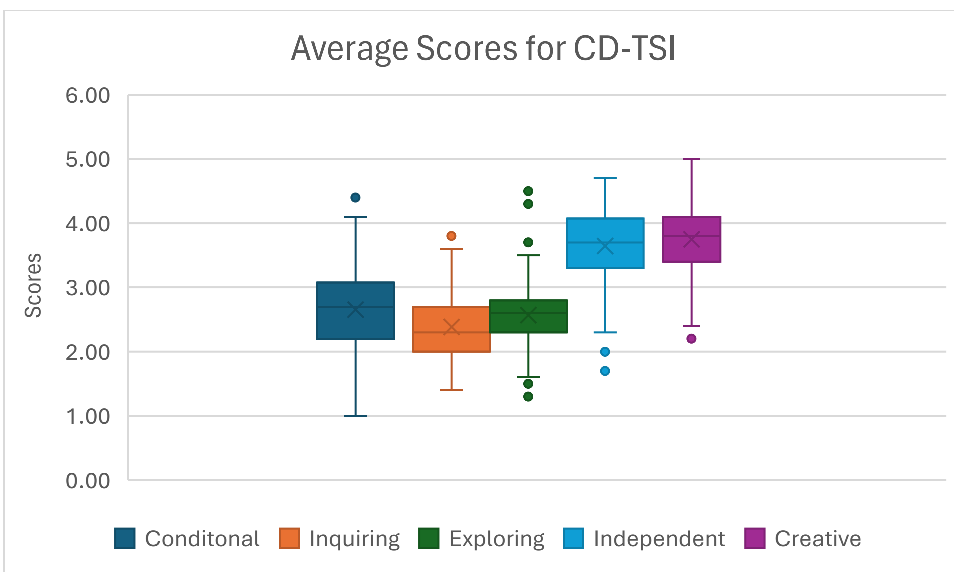

Figure 4: Results from CD-TSI

Results from the EDSE, shown in Figure 5, show motivation has the highest central tendencies, clustered around the mid-60s. Confidence and perceived success are also quite high, centered around the high 50s to low 60s. Anxiety is also lower on average compared to the first three. Anxiety also has the widest spread, spanning the full scale whereas motivation is the most tightly clustered.

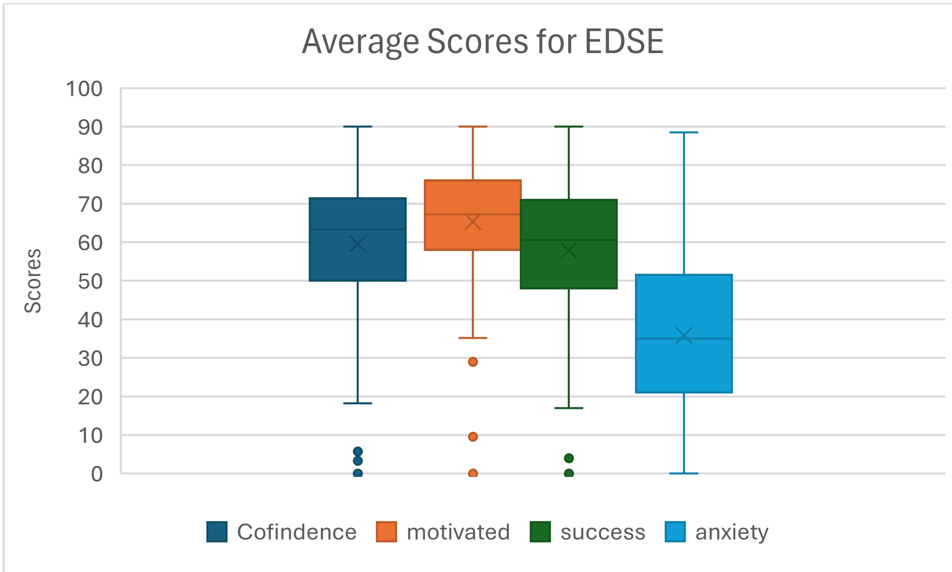

Figure 5: Results from EDSE

Kolb's Learning Style Inventory, shown in Figure 6, results showed that no one style dominated. Concrete Experience (CE), Reflective Observation (RO), Abstract Conceptualization (AC), all have similar medians. Active Experimentation (AE) stands out between the four with a slightly higher median and mean, hovering around the upper twenties.

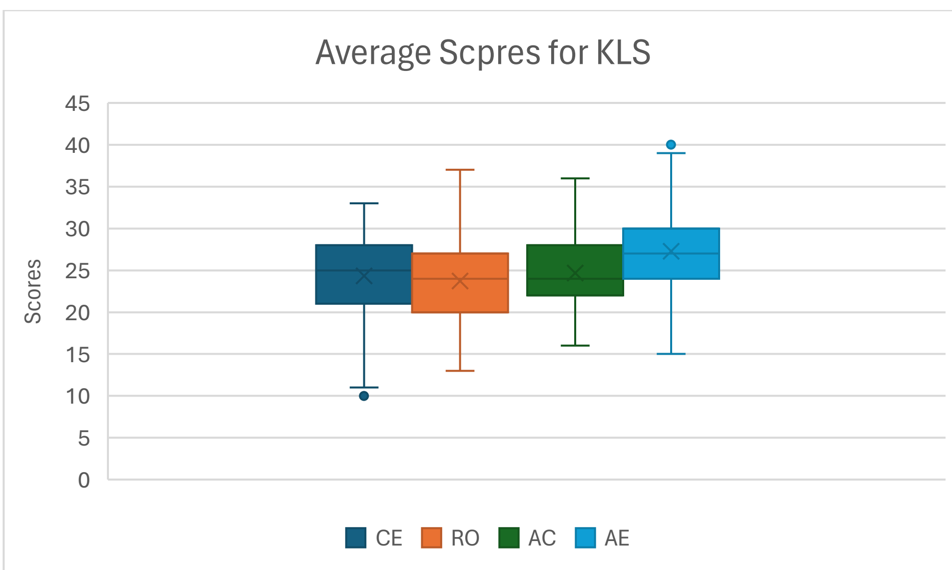

Figure 6: Results from KLS

Results from the CSI and the post-semester survey are not reported in this paper, as additional validation and analysis are required prior to interpretation. These analyses, along with further refinement of the predictive and classification models, are the subject of ongoing and future work.

It should be noted that outliers presented in box-and-whisker plots (see Figure 3 - Figure 6) were identified using the standard interquartile range (IQR) criterion ($x > 1.5 \times IQR$). No data points were removed from the dataset; outliers are displayed for transparency but retained in descriptive and future predictive analyses unless they are identified as data-entry errors.

Discussion

The results from the survey suggest that students tend to be more risk-taking, motivated, independent and creative. From the RPS, a mean risk tolerance score of 4.58 was found. This suggests that this population of students tends to take more risks and, within the context of design, may be more willing to iterate on a design without worrying about getting it right the first time [33]. From the CD-TSI, the students showed higher scores in the independent and creative sections. Scoring high on these dimensions tends to indicate that students prefer to work autonomously, value originality, and are more comfortable with ambiguity and open-ended problems. These students may spend more time in the idea generation and concept exploration stages and may propose unconventional concepts.

The EDSE results indicate high levels of student motivation alongside moderate confidence and perceived success. However, anxiety exhibits substantial variability, suggesting that students' affective experiences during design activities differ widely even when motivation is high. It remains unclear whether these scores from the EDSE reflect calibrated confidence or early-stage overestimation of ability. Prior research on metacognitive development suggests that early learners may exhibit inflated self-assessment before exposure to complex design failure. Longitudinal comparison across academic levels will be necessary to contextualize these findings.

The KLS results indicate that learning style preferences are relatively evenly distributed across the four Kolb dimensions. While no single learning style dominates the cohort, Active Experimentation exhibits the highest mean and median scores. This suggests a modest tendency for students to prefer learning through action, testing, and iteration when engaging with design or problem-solving tasks. The slightly elevated Active Experimentation scores may reflect the hands-on, project-based nature of engineering coursework, where prototyping and iterative refinement are emphasized. However, the strong overlap among distributions indicates that students are not exclusively aligned with a single learning mode, reinforcing the view of design as a cyclical and non-linear process rather than a strictly sequential one.

Taken together, these results highlight the diversity of design-related cognitive attributes present even within a relatively homogeneous cohort of sophomore engineering students. While professional engineers may adapt their design strategies fluidly based on task context, novice engineers often require more structured guidance to effectively navigate open-ended problems. Understanding how students perceive and engage with different design approaches can help educators better tailor instructional content, particularly in first-year or cornerstone design courses. For example, students with higher confidence and risk tolerance may benefit from greater design freedom, while more adaptive or structured thinkers may benefit from scaffolding that gradually introduces iterative design practices. These findings underscore the importance of aligning instructional strategies with students' cognitive and experiential profiles rather than assuming a one-size-fits-all design pedagogy.

From an instructional perspective, this work does not assume that student design approaches should converge toward a single 'optimal' process. Rather, the intent is to understand and support the natural diversity in design tendencies, while enabling students to develop the ability to flexibly navigate between divergent and convergent phases of the design process.

Conclusion

This work-in-progress study introduces a multidimensional survey framework grounded in established psychological constructs to examine how engineering students' cognitive and affective profiles relate to their design process tendencies. Initial findings highlight meaningful variability within an otherwise relatively homogeneous cohort, underscoring the need for instructional approaches that move beyond a one-size-fits-all model of design pedagogy. Although predictive modeling and further analysis are still ongoing, the presented results provide empirical grounding for future efforts to link students' attributes to observable design behaviors. Ultimately, this research seeks to contribute to a data-informed understanding of how individual differences shape engagement in engineering design, with implications for adaptive curriculum development, intentional team composition, and the cultivation of reflective design expertise.

Future Work

Still ongoing is the analysis of responses to the CSI survey and the post-semester survey. Future analysis will incorporate Cronbach's alpha, correlation matrices, and potential exploratory factor modeling to investigate the interconnectivity between the constructs, reduce dimensional redundancy, and clarify how cognitive and affective variables influence design tendencies. Once these analyses are completed, the current MATLAB model can be further expanded upon. Some next steps could be the use of models such as neural networks, once a larger dataset becomes available. With sufficient longitudinal data, such models could capture time-series trends and reveal how students' design behaviors evolve across courses or academic years. Future integration of large language models or agent-based modeling could enable the generation of adaptive, student-specific design problems that evolve alongside learners' development.

Additionally, component, factor, or vector analyses could prove to be useful. To strengthen the survey instruments, this analysis could be employed to examine the structure and relationships among the chosen constructs. Component analysis could be used to identify dominant directions of variance across responses, revealing redundant dimensions and enabling dimensionality reduction without imposing assumptions. Factor analysis can be used to model latent constructs in the observed survey measures, allowing for validation of the survey scales aligned with their intended uses. Finally, vector analysis could be employed to represent the constructs as vectors within a multidimensional space, where the magnitudes reflect the relationships between the captured measures.

Predicted design tendencies could also support more effective team formation by aligning students with complementary approaches, confidence levels, or motivational profiles. These insights may enable instructors to form teams that are better balanced and more resilient during complex design projects. Finally, a deeper understanding of student design approaches could support personalized learning experiences.

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Appendix

The survey used to collect student perspectives on the design process and their approach to complex problem solving is presented here.

Preference for Design Approach Survey

Q1.1 Describe your approach to solving a complex problem.

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Q1.2 What factors most influence your design decisions? (e.g., cost, aesthetics, performance)

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Q2.1 The next three questions present you with steps or phases of a design process. For each question, please rearrange the phases in the rank order that most resembles your approach to solving problems. Note that there is no "correct" sequence, rather you are asked to produce a sequence that you most resonate with.

Q2.2 Rank the order of the following items based on how you would complete them.

______ Problem Clarification (Understand and define the problem) (1)

______ Conceptual Design (Generate broad solution ideas) (2)

______ Embodiment Design (Choose and develop the best ideas) (3)

______ Detail Design (Finalize dimensions and specifications) (4)

______ Manufacturing (Build and produce ideas) (5)

Q2.3 Rank the order of the following items based on how you would complete them.

______ Site Analysis (Study location, environment, and constraints) (1)

______ Conceptual Design (Develop big picture ideas) (2)

______ Schematic Design (Create basic drawings and layouts) (3)

______ Design Development (Refine design and add details) (4)

______ Construction Documents (Prepare technical drawings) (5)

Q2.4 Rank the order of the following items based on how you would complete them.

______ User Stories (Describe features from a user's point of view) (1)

______ Sprint Planning (Decide what to build in the next cycle) (2)

______ Iterative Development (Build in small repeatable cycles) (3)

______ Testing (Check if the product works correctly) (4)

______ Deployment (Release product to users) (5)

Q3.1 For the following statements, select to level of agreement from “strongly disagree” to “strongly agree” within the context of solving complex problems.

	Strongly disagree (1)	Somewhat disagree (2)	Neither agree nor disagree (3)	Somewhat agree (4)	Strongly agree (5)
I believe it is important to understand the context of the problem. (1)	○	○	○	○	○
I believe it is important to identify all relevant stakeholders. (2)	○	○	○	○	○
I believe it is important to generate engineering requirements. (3)	○	○	○	○	○
I believe it is important to decompose the problem into smaller problems. (4)	○	○	○	○	○

I believe it is important to generate multiple ideas. (5)	○	○	○	○	○
I believe it is important to prototype and test ideas. (6)	○	○	○	○	○
I believe it is important to develop criteria to select the best idea. (7)	○	○	○	○	○
I believe it is important to design for manufacturing. (8)	○	○	○	○	○
I believe it is important to verify that the proposed solution will meet engineering requirements. (9)	○	○	○	○	○
I believe it is important to validate that the proposed solution will satisfy stakeholder needs. (10)	○	○	○	○	○

Q4.1 For the following questions, identify how likely you are to do something within the context of solving complex problems.

	Extremely unlikely (1)	Somewhat unlikely (2)	Neither likely nor unlikely (3)	Somewhat likely (4)	Extremely likely (5)
Do you finish a step first before moving	○	○	○	○	○

to the next one? (1)					
Do you come back to steps? (2)	○	○	○	○	○
Do you explore many options or ideas? (3)	○	○	○	○	○
Do you typically iterate on your design more than once? (4)	○	○	○	○	○

Q4.2 Which statement do you most agree with?

	Strongly disagree (1)	Somewhat disagree (2)	Neither agree nor disagree (3)	Somewhat agree (4)	Strongly agree (5)
Do you prefer a more structured approach for design? (1)	○	○	○	○	○
Do you think design is inherently a chaotic process? (2)	○	○	○	○	○

Q4.3 Have you ever gone back to the drawing board (restarted the idea generation process) after testing a design?

○ Yes (1)

○ Maybe (2)

○ No (3)

Q4.4a Please give an example of when you have had to go back to the drawing board or start over the idea generation process.

____

Q4.4b Please comment on why you might want to avoid going back to the drawing board or restarting the idea generation process.

Q5.1 Do you use any formal brainstorming methods?

- Yes (1)
- No (2)

Q5.2 Name one formal brainstorming method you have used.

Q5.3 Do you create prototypes before finalizing your design? If so, how?

Q5.4 Do you prefer low-fidelity (e.g., sketches, paper) or high-fidelity (e.g., CAD, simulation) prototypes first?

- ○ low fidelity only (1)
- ○ more low-fidelity than high-fidelity (2)
- ○ more high-fidelity than low-fidelity (3)
- ○ High-fidelity only (4)

Q5.5 Do you test your design physically or virtually before building the final design?

- ○ only physically (1)
- ○ more often physically than virtually (2)
- ○ more often virtually than physically (3)
- ○ only virtually (4)