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Comparing Optimization Practices Across Engineering Learning Contexts Using Process Data

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Abstract
Despite an increasing focus on integrating engineering design in K-12 settings, relatively few studies have investigated how to support students to engage in systematic processes to optimize the designs of their solutions. Emerging learning technologies such as computational models and simulations enable rapid feedback to learners about their design performance, as well as the ability to research how students may or may not be using systematic approaches to the optimization of their designs. This study explored how middle school, high school, and pre-service students optimized the design of a home for energy efficiency, size, and cost using facets of fluency, flexibility, closeness, and quality. Results demonstrated that students with successful designs tended to explore the solution space with designs that met the criteria, with relatively lower numbers of ideas and fewer tightly controlled tests. Optimization facets did not vary across different student levels, suggesting the need for more emphasis on supporting quantitative analysis and optimization facets for learners in engineering settings.

Keywords Optimization · Engineering design · Secondary education · Pre-service teachers · CAD simulation

Engineering in pre-college settings is gaining traction, with many states adopting the Next Generation Science Standards (NGSS, 2013) as well as offering standalone engineering curricula (e.g., Project Lead the Way, n.d.). Integrating engineering into pre-college settings enables more students to participate in the discipline, offering broader access to those who may not know about engineering as a field or career (e.g., Cunningham & Lachapelle, 2014; Moore et al., 2014a).

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Many efforts have characterized what should be included in K-12 engineering. For example, the Framework for P-12 Engineering Learning (Advancing Excellence in P12 Engineering Education & American Society for Engineering Education [ASEE], 2020) provides a three-dimensional taxonomy of engineering habits of mind, engineering knowledge, and engineering practice. Engineering habits of mind include traits such as optimism, creativity, persistence, and collaboration. Engineering knowledge consists of the mathematics, science, and technical expertise required to design solutions and complete engineering tasks. Engineering practice involves engineering design, material processing, professionalism, and quantitative analysis. As such, engineering design has been promoted as a context for science and math learning (English, 2016), as well as integrated STEM learning (Moore et al., 2014b; Purzer & Quintana-Cifuentes, 2019), in part because these projects can help students develop skills that transcend engineering design problems and have applicability across a wide set of problem-solving scenarios. Although a fair amount of research has focused on the engineering design in K-12 settings (e.g., Lammi et al., 2018; Purzer et al., 2014), relatively little has focused on the practice of quantitative analysis in pre-college engineering settings (e.g., Chao et al., 2017). In particular, few research studies investigate how pre-college students use systematic processes to optimize the designs of their solutions (Montgomery et al., 2020). Optimization relates more generally to solution refinement, improvement, and fine-tuning and not simply accepting a satisficing (Simon, 1996) or mediocre solution. Optimization is an important component of cost–benefit analysis or CBA (Karabiyik et al., 2022) which also has applicability across a broad range of problems that require tradeoffs between multiple, sometimes conflicting, criteria. Consequently, better understanding of how students engage in optimization addresses an important gap in how these engineering design practices develop, which has applicability to a wide variety of problem contexts.

Increasing use of computational models and simulations with engineering projects enables investigation of students' processes of analyzing quantitative information and how students may or may not be using systematic approaches to the optimization of their designs (Rahman et al., 2019). Computer-aided design (CAD) simulation environments can help students engage in systematic optimization and track learners' actions; however, little is known about what kinds of existing optimization facets learners may bring to pre-college settings, including teachers.

This study uses log file data of students working within Energy3D, a CAD simulation program specifically designed for learning in K-12 settings, to explore the kinds of optimization practices (operationalized below) that learners at various levels use during engineering design. This study compares groups of middle school students, high school students, and pre-service teachers engaging in the same energy-efficient home design challenge across three different contexts to explore how K-12 learners and pre-service teachers engage in optimization. In particular, we answer the following questions:

1. How do middle school students, high school students, and pre-service teachers optimize their designs within CAD simulation systems?
2. What kinds of optimization facets, or different optimization strategies, are used by successful designers?

Background

Optimization in Engineering Design

Optimization is central to engineering, yet it is characterized differently across different frameworks and national standards used in K-12 settings. For example, in the Informed Design Teaching and Learning Matrix (Crismond & Adams, 2012), optimization is implicitly included underneath the design strategy of conducting experiments, characterized as novice designers conducting few, confounded experiments and expert designers running controlled, "fair tests" to optimize their performance. In the NGSS, optimization is one of three central elements (ETS1.C: Optimizing the Design Solution) in the disciplinary core idea of engineering design, alongside defining and delimiting a problem, and developing possible solutions. The NGSS outlines a learning trajectory where optimization in K-12 settings consists of comparing different solutions. In grades 3–5, students start testing and evaluating different solutions to see which one best solves the problem. In grades 6–8, students are expected to be able to use "systematic methods to compare different solutions to see which best meets criteria and constraints" (pg. 4, 2013), and in grades 9–12, students are "expected to use mathematics and/or computer simulations to test solutions under different conditions, prioritize criteria, consider trade-offs, and assess social and environmental impacts" (pg. 5, 2013).

The Framework for P-12 Engineering Learning complements the NGSS and puts engineering learning squarely as the central focus, as opposed to a way to enhance science learning as put forth in the Framework for K-12 Science Learning (ASEE, 2020). Optimization within the Framework for P-12 Engineering Learning falls within quantitative analysis, which consists of designing and developing computational tools to address a task (computational thinking), choosing and using appropriate computational tools, collecting and analyzing data, and using system analytics to optimize performance. To some extent, optimization is also captured within engineering design practices, implicit behind information gathering, prototyping, and decision-making processes. Thus, although the NGSS makes optimization explicitly part of knowledge about engineering as a discipline, the ASEE framework treats optimization as a practice that complements engineering knowledge and habits of mind.

Past research has also conceptualized optimization as akin to engineering experimentation (Crismond & Adams, 2012). Engineering experimentation is different from science experimentation (e.g., Schauble et al., 1991), in that experimentation practices in science often involve the testing of a specific hypothesis where learners can learn about a phenomenon or characterize devices or materials. Engineering experimentation, although highly related to scientific experimentation, may serve the different purpose of iteratively improving ideas or aspects of a design via feedback. While scientific experimentation may involve a process of convergent thinking in the knowledge domain with the goal of revealing a trend or pattern, engineering optimization may involve divergent processes in the concept domain with the goal of identifying disparate answers or multiple alternatives to a given problem (Dym et al., 2005). Specifically, in this kind of divergent thinking, one looks to find insight into ways that the solution may fail or test a wide range of inputs and processes to identify outputs and boundaries (Müller-Wienbergen et al., 2011, p. 716). While trying to optimize a solution, a person may try to test the boundaries of the solution space and then drill down along one criterion or variable to focus analysis. Students may use divergent approaches to test a wide range of solutions and solution spaces, then transition to a more convergent approach, testing a narrower band of solutions to maximize performance in one area (e.g., Montgomery et al., 2020). While more divergent behavior may help students identify the possibilities and limitations of the design space, convergent behaviors may help students to gain an understanding of how design decisions affect their test results (e.g., Zhang et al., 2020). Thus, optimization necessarily looks different than systematically controlling variables, with both divergent and convergent strategies occurring within the optimization processes (Goldschmidt, 2016).

Specifically, we expand upon optimization consisting of divergent and convergent thinking to encompass facets of *fluency*, *flexibility*, *closeness*, and *quality* (e.g., Shah et al., 2012). Fluency involves being able to generate many design solutions consistently. For example, students who are fluent can come up with multiple, distinct design solutions for a single problem, and divergent thinking involves testing many different designs. However, only measuring the amount or count of distinct ideas tested is not enough as students may generate and test superficial variants of one main design. Thus, *flexibility* is the ability to explore the design space in many directions or test a variety of different ideas. Similarly, convergent thinking while optimizing involves both *closeness* and *quality*. *Closeness* is the extent to which the designer conducts tests that are converging upon a single specific goal. This includes running experiments that control variables or conducting fair tests. However, students could optimize and run fair tests along a single design criterion and potentially ignore other project criteria. Thus, *quality* is the extent to which the tested solutions fit with the design goals.

Past research demonstrates that fluency is crucial to engineering design (Crismond & Adams, 2012; Daly et al., 2012; Purzer et al., 2015a, b; Shah et al., 2003) and optimization (Dym et al., 2014). This research has established that creating a larger set of design ideas can lead to stronger and more innovative solutions (Cross, 2011). Consequently, researchers have developed a wide variety of techniques for supporting fluency such as design heuristics (Daly et al., 2012), c-sketch (Shah et al., 2001), and morphological analysis (Allen, 1962). Studies also highlight difficulties faced in trying to generate multiple solutions to a problem. For example, novice designers often explore an idea in-depth without adequately exploring alternative ideas (Cross, 2004) or may generate "dead end" ideas that do not facilitate their ongoing design process (Svihla & Kachelmeier, 2020). However, providing support such as having students collaboratively build on their team members' ideas (Shah et al., 2001) or providing scaffolded expert strategies for idea exploration (Yilmaz et al., 2016) can help students become more fluent in their solution generation.

Research also demonstrates that flexibility is a key component of optimization. As several researchers have demonstrated, exploring the design space more thoroughly can lead to discovering more novel, creative, or better-performing design solutions (Akin, 1990; Murphy et al., 2017; Shah et al., 2003). Research also suggests that students have difficulty systematically exploring a solution space. For instance, when encountering a problem, students may fixate on a few well-established or familiar design ideas they have previously encountered (Sio et al., 2015; Viswanathan & Linsey, 2013).

Studies also investigate how students use fair tests and experimentation to converge upon specific criteria of a design project. For example, Vieira et al. (2016) characterized the experimental strategies of student designers and compared the experiments used (e.g., confounded or systematic experiments) to the performance of their final designs. Results reveal that students often faced challenges in systematically refining solutions, including not tightly controlling for variables or conducting too few experiments (e.g., Crismond & Adams, 2012).

Converging on a strong performing final design solution is dependent on the quality and scope of design solutions considered or tested (Austin-Breneman et al., 2012; Fu et al., 2010). For example, Toh and Miller (2015) found that engineering teams often selected design concepts on technical feasibility alone, but teams that considered other criteria developed more creative solutions. In another study, Fu et al. (2010) found that introducing a poor design example reduced team convergence and final design solution quality whereas introducing a strong design example led to greater final design solution quality.

Using Computational Tools to Enhance Optimization

Despite the importance of quantitative analysis and optimization in engineering, the way that engineering is implemented in pre-college settings often does not afford the ability for rich quantitative analysis. Many engineering projects involve students building physical prototypes of designs and running few tests with little quantitative feedback. Other approaches include technology-enhanced tools to help students collect and reflect upon design data (e.g., Chiu et al., 2013; Wendell et al., 2019) but do not provide tools to rapidly iterate and measure performance of different designs.

The use of simulations in conjunction with computer-aided design (CAD) systems enables practicing engineers to develop and test solutions. CAD simulation systems have affordances to encourage optimization (Lee, 1999). For example, with CAD simulation systems, students can conduct rapid testing of their designs and get immediate feedback as to whether the system will meet the criteria (Seah & Magana, 2019; Vieira et al., 2016). CAD simulation systems can also encourage evidence-based revisions of designs by recording information about trials and helping students see patterns among tests and design criteria (McElhaney & Linn, 2011). In addition, the CAD simulation systems have affordances for studying learning by recording students' actions within the environment to investigate what kinds of optimization practices students may more easily use during design (Phadnis et al., 2021).

Research highlights how CAD simulation systems have unique affordances to help learners engage in optimization and measure fluency, flexibility, closeness, and quality. For example, many studies have used Energy3D, a CAD tool that was specifically designed for learning environments (Magana & de Jong, 2018; Purzer et al., 2015a, b). In Energy3D, students can create homes, buildings, and other structures and get immediate data about the building cost and daily and annual energy usage using real weather data and building material specifications and performance. CAD tools like Energy3D can measure fluency by capturing the number of different designs that students test (e.g., Chao et al., 2017). To measure flexibility, CAD systems can capture how much of the solution space that students test with different designs (e.g., Magana et al., 2021). To measure closeness, CAD systems can assess the degree to which students' tests are aligned to common design criteria. CAD tools enable the measurement of quality by capturing the extent to which students' tested designs meet various design criteria (e.g., Goldstein et al., 2015, 2018).

While CAD simulation systems have been primarily used for engaging learners in engineering design practices or related aspects of optimization, the use of computer simulations to investigate learners' optimization practices is relatively rare (e.g., Montgomery et al., 2020). Typically, simulations have been used to increase learners' understanding of targeted mathematics or science concepts (e.g., Magana & de Jong, 2018; Molina-Toro et al., 2019; Wieman et al., 2008). For example, Hutchins et al. (2020) discuss the C2STEM environment as a way for students to engage in computational modeling in high school physics classrooms. Hutchins et al. found that students made learning gains from pretest to posttest assessments in kinematics and computational thinking concepts and used logs from the environment as case studies into problem solving and debugging strategies. Other studies have used log data from simulations to understand what features support student learning of science (e.g., McBride et al., 2016), or to investigate experimentation strategies (Vieira et al., 2016; Magana et al., 2021; McElhaney & Linn, 2011). Some studies have used simulation systems to understand trade-off analysis (e.g., Purzer et al., 2015a, b). This paper seeks to build upon these efforts to use log data of students' design actions within CAD simulation systems to characterize learners' optimization facets of flexibility, fluency, closeness, and quality.

Thus, this study focuses on how middle school, high school, and pre-service teachers work to optimize their designs within Energy3D and to the extent to which different optimization facets are related to successful designs. We also articulate any differences among middle school, high school, and pre-service teacher learners' optimization facets. Given there is no existing learning progression for optimization but a trajectory outlined by the NGSS and ASEE, we look to identify what kinds of optimization facets various levels of students use when engaging in a design challenge to inform the field about what kinds of optimization facets students may be capable of with computational tools. In addition, we build upon research that operationalizes optimization (e.g., Montgomery et al., 2020) and specifically investigate relationships between optimization facets and final design performance.

Methods

Curricular Context

The curricular context of this study was a design challenge for students to design a home that aims for zero net energy usage over a year in three different classroom settings. Students used Energy3D to design a house from scratch that meets various cost, area, and height specifications while using less energy to heat and cool the house than would be captured by solar panels (Table 1). Students learned and applied passive heat strategies such as the placement of deciduous trees or awnings to reduce energy consumption (Fig. 1). In general, the challenge is designed for a duration of around four to five 50-min class periods.

Participants and Contexts

Middle School Students Seventy-one middle school students in 20 small groups from four Earth science classes taught by the same teacher participated in this study. The school was located in a mid-Atlantic state that had recently revised science K-12 standards of learning to include engineering. The classes that were used in this study mirrored the population of the school, where students were classified as 5% Asian, 35% Black, 16% Hispanic, 36% White, 7% multiple races or other, 15% students with disabilities, 50% receiving free or reduced lunch, and 14% emerging bilinguals.

Table 1 Design criteria and constraints for the three classroom settings

Case	Cost ($)	Area (m^2)	Height (m)	Energy consumption (kWh)
Middle school students	150,000	100–200	>6	≤ 0
High school students	150,000	100–200	>6	≤ 0
Pre-service teachers	120,000	150–200	>6	≤ 0

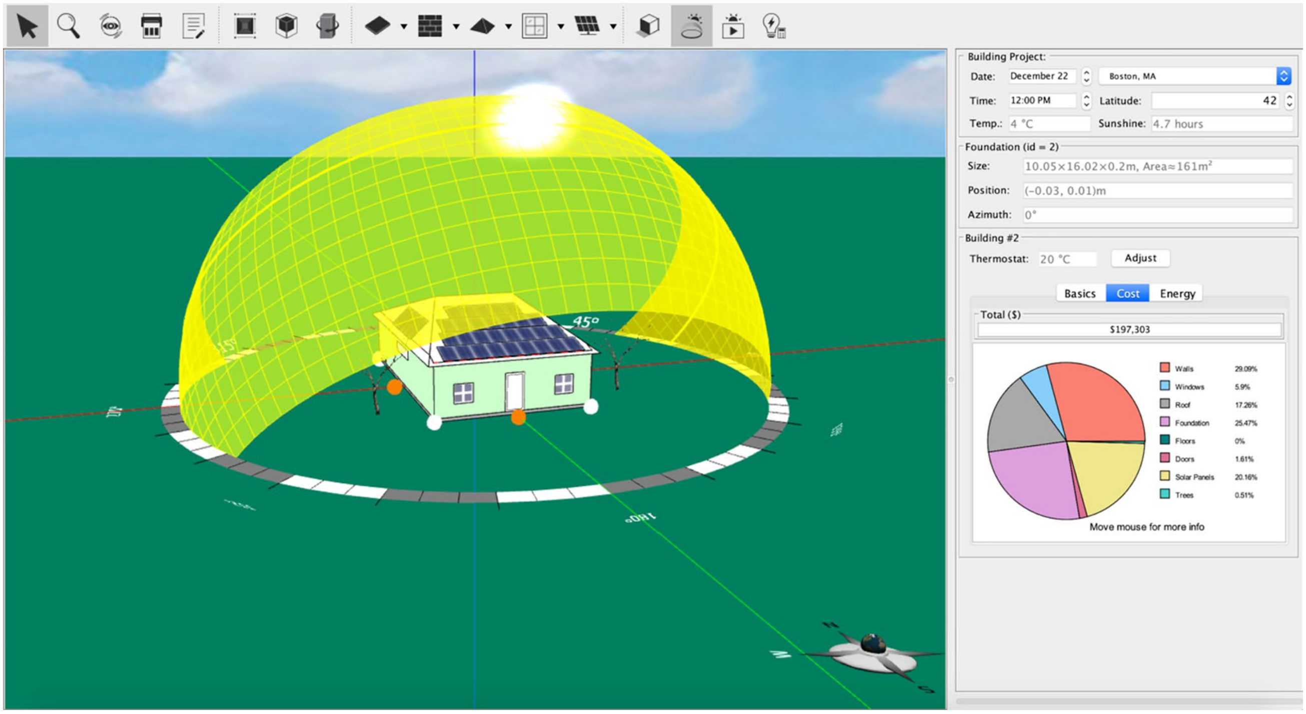

Fig. 1 Screenshot of the Energy3D graphical user interface. Students can construct the house on the section to the left using the tool bar on the top of the screen by adding solar walls, windows, roofs, solar panels, and trees, for example. Simulation functionality enables students to see the solar path throughout the day. On the right-hand side, students can change the date, time, and location of the home and immediately see changes in solar path as well as performance feedback such as the cost of the building and energy usage across days or years

The Earth science class aimed to help students learn about Earth's structure, composition, and processes including weather and climate, as well as utilization of Earth's resources. Students engaged in the net-zero home challenge as an introduction to the unit on the utilization of Earth's resources, with the goal of learning about Earth science concepts in the context of the home design. Students largely participated in small groups of 2–3 to complete the project, with some groups of 1 or 4 due to attendance or computer availability.

High School Students Thirty high school students in 14 groups of two to three students from two environmental science classes taught by the same teacher participated in this study. The school was also located in the same mid-Atlantic state as the middle school students. The classes reflected the population of the school, with students classified as 6% Asian, 29% Black, 12% Hispanic, 46% White, 7% multiple races or other, 14% students with disabilities, 39% receiving free or reduced lunch, and 12% emerging bilinguals.

The environmental science classes aimed to help students understand environmental concepts and be able to examine solutions to environmental problems. Students engaged in the net-zero energy project in their classes over five block classes, each 90 min. Students largely participated in pairs to complete the project, with some exceptions for absences.

Pre-service Teachers Forty-three pre-service teachers in 23 small groups from a physics for elementary education course in a large midwestern university participated in the study. The pre-service teachers reflected the university population, which was classified as 8.5% Asian, 2.9% Black or African American, 5.2% Hispanic or Latino/a/x, 64% White, 13.7% non-resident alien, 0.1% American Indian or Alaska Native, 0.1% Native Hawaiian or other Pacific Islanders, and 5.5% with ethnicity unknown.

The class focused on helping pre-service elementary teachers understand physical science concepts as well as practices of science and engineering design. The course aimed to help students develop practices and concepts as defined by the NRC Science Education standards (National Research Council, 2012) and Project 2061 Benchmarks (American Association for the Advancement of Science, 1994). The net-zero home challenge was used to help introduce and apply physical science concepts such as energy transfer. Pre-service teachers mostly worked through the project in pairs, with some individuals working alone.

Data Sources

Data sources included the log files of students working through the Energy3D CAD simulation environment. Log files included specific Energy3D replays of students' design processes that automatically saved every few seconds and when students tested a specific design. Students could add a roof, add windows, change the size of the house, and then decide to test their solution by simulating the energy performance of the house over a year. We used this simulation data as the primary data source for our study. Every time a student tested their design for energy performance, cost, size, or height, the log files contained the cost, size, height, and energy performance of the tested design. We used this data set to investigate students' optimization facets. Any sequential and identical tests were counted as one test since nothing about their design was changed from one test to another. The final designs were collected from the logs as the final saved state of the students' files, which researchers checked with what students turned in as their final design to their teacher to ensure that this was the final design.

All projects were implemented with students in small groups of 2–4 each, and only one log was created for each small group. We excluded log files from students who were absent and did not complete the project, with less than six tests. This resulted in 57 logs, with 20 from middle school, 14 from high school, and 23 pre-service teachers. All analyses of log files and project performance use the small group files.

Data Analysis

Optimization *Fluency* was calculated as the number of unique home designs that were tested (Table 2). For example, if students tested an initial design, changed the placement of solar panels, and tested the revised design, which would count as 2 unique designs. To calculate *flexibility*, we considered each of the four criteria (cost, size, height, and energy performance) in turn and divided the standard deviation for the specific student's design tests by the standard deviation for the design tests of all students across all three cases. These standardized standard deviations for each criterion were then combined by calculating the Euclidean norm so that flexibility represents the number of standard deviations that the student explored across the solution space. Specifically, flexibility was calculated as:

$$\text{Flexibility} = \left[\sum_i \left(\frac{\sigma_{i,student}}{\sigma_{i,all\ students}}\right)^2\right]^{\frac{1}{2}} \text{ where } i \text{ represents the four variables}$$

$$= \text{typical number of standard deviations a student's designs explored}$$

For *closeness*, we used the four criteria of cost, size, height, and energy performance as the dimensions of the solution space and created standardized vectors specified as starting from one test and ending at the next test (e.g., Zhang et al., 2020). By measuring the angle between subsequent vectors, we counted the number of angles that were either between 0 and 45 degrees (i.e., return to earlier design) or between 135 and 180 degrees (i.e., continue in the same direction). We then divided by the total number of unique home designs (or fluency number) for each group for the fraction of overall tests that were close to the previous test. For *quality*, we took the average of the number of criteria met by the specific test. For example, a test of a design that met the energy, area, and height design but not the cost would score a 3 out of 4. Finally, to see if there were any differences among the optimization facets of the three populations, we conducted a one-way ANOVA to see if there were any differences among groups for optimization facets.

Design Performance As shown in Table 1, middle school, high school, and pre-service teachers each had slightly different design criteria. We used each implementation's criteria to normalize each group's final design performance across contexts. Thus, normalized size was computed by dividing the size of the individual group's final design by the largest constraint size (200 m^3), normalized cost was calculated by dividing the final design cost by the cost limit

Table 2 Definitions, metrics, and measures for fluency, flexibility, closeness, and quality facets of optimization

Facet	Definition	Metric	SmartCAD measure
Divergent			
Fluency	Ability to generate many solutions consistently	Quantity of ideas generated	Number of unique designs tested (not the same house multiple times or multiple tests on the same design)
Flexibility	Ability to explore design space in many directions	Variety of ideas generated	Number of standard deviations across the four criteria that the solution vectors explored
Convergent			
Closeness	Extent to which designer optimizes for specific goals	Coherence of tests with one another	Fraction of tests with angles of standardized vectors that are either between 0 and 45° (i.e., return to earlier design) or between 135 and 180° (i.e., continue in same direction)
Quality	Ability to consider technical, manufacturing, and economic feasibility	Closeness of fit with design goals; tech and economic feasibility	Average number of tests that met design criteria, with every test scoring 0–4 depending on how many criteria they meet

Table 3 Means and standard deviations of fluency, flexibility, closeness, quality, and final performance scores by participant context

Context	*n*	Fluency	Flexibility	Closeness	**Quality	**Final Performance
Middle School	20	16.55 (9.13)	1.55 (1.58)	0.64 (0.22)	2.33 (0.55)	0.46 (0.12)
High School	14	21.93 (8.93)	0.83 (0.43)	0.64 (0.14)	2.23 (0.36)	0.30 (0.12)
Pre-service	23	20.22 (10.9)	1.05 (0.62)	0.64 (0.14)	1.98 (0.39)	0.31 (0.11)
Overall	57	19.18 (9.82)	1.17 (1.04)	0.64 (0.17)	2.13 (0.51)	0.36 (0.14)

**Significant differences were found for quality and final performance among groups

($150 K for middle and high school, $120 K for pre-service teachers), and normalized net energy was computed by the final design net energy over a year divided by the most negative net energy produced by the same group of students (e.g., within middle school students, high school students, pre-service teachers). The total design performance was computed by averaging the three design scores, given that participants were not told that one criterion was more important than the others. Designs that did not meet constraints were assigned a value of zero, including a positive net energy value (zero to negative net annual energy was the goal for the energy-efficient house).

We split students into two groups based on their design performance scores. We used a 50th percentile split for high/low performers. We ran independent samples *t* tests to compare the means of final performance and the four facets of optimization to examine if there were any significant differences among the optimization facets used by students of different design performance levels.

Results

RQ1: How Do Middle School Students, High School Students, and Pre-service Teachers Work to Optimize Their Designs Within CAD Simulation Systems?

In general, the number of tests increased with the age of students (middle school students M (SD) = 30.8 (23.1); high school students M (SD) = 48.8 (16.1); pre-service teachers M (SD) = 52.0 (35.3). Table 3 shows the means and standard deviations of each facet of optimization broken down by participant group. High school and pre-service teachers tended to have higher scores for fluency, translating into more unique designs tested than the middle school students, but this trend was not significant ($F = 1.378$; $p = 0.26$). Middle school students tended to score more highly in flexibility, indicating a more comprehensive range of solution diversity tested, with pre-service teachers and high school students scoring relatively lower in flexibility, but this was also not significant ($F = 2.25$; $p = 0.11$). Middle and high school students and pre-service teachers had very similar closeness scores with no significant differences ($F < 0.01$, $p = 0.998$). However, middle schoolers had higher quality of tests, with relatively more of their tested solutions meeting design criteria than either high school or pre-service teachers, and this trend was significant ($F = 3.42$, $p = 0.04$). Additionally, middle school students significantly outperformed both high school students and pre-service teachers on their final design performance ($F = 12.86$, $p < 0.001$).

An example of high fluency is Eugene and Meri, a pre-service teacher group. Figure 2 represents a particular section of designs that the group tested, from first building the walls, windows, and doors, and checking the cost (1) and (2), to then adding a roof (3 and 4), removing the roof (5), and testing a different kind of roof (6 and 7). They then went back to the original roof (8), added solar panels (9), added more solar panels (10), trees (11), and then removed trees (12). The variety of different ideas that they tested resulted in a high fluency score.

An example of high closeness is in a high school example of Jayden and Keri changing the placement and number of solar panels (Fig. 3). In this chain of events, the group has three groups of five solar panels on the west, south, and east-facing roofs that they have tested (1). On the next test, they add an additional row of five panels to the south roof and two additional rows of panels on the east roof (2). After testing that larger configuration, they remove the two additional rows on the east roof and test again (3). After getting the results, they add an additional row to the east roof (4), test, and then try a single panel on the north-facing roof (5). On the next test, they move the single panel to the west-facing roof (6) and then decide to add a whole row to the west-facing roof (7). Jayden and Keri represent high closeness as they carefully added and subtracted solar panels between each test, not changing other variables such as the size of the house, placement of windows, or placement of trees as they work to meet the criteria of the challenge.

RQ2: What Kinds of Optimization Facets Are Used by Successful Designs?

When grouped by the final performance, the low-performing group consisted of three middle school student groups, 10 high school student groups, and 16 pre-service teacher groups, whereas the high-performing group consisted of

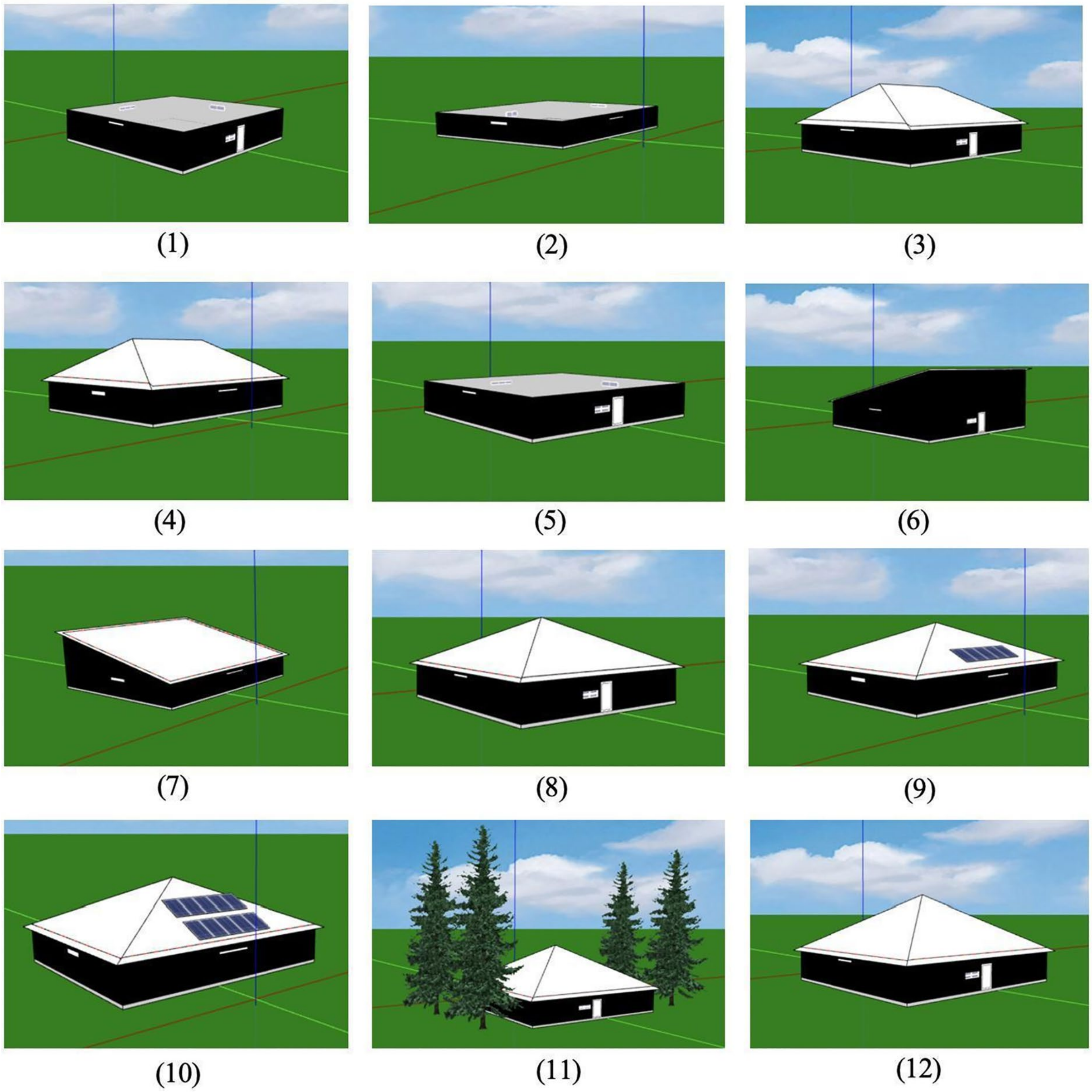

Fig. 2 An example of a student pair with a high fluency score. The student group builds walls, windows, doors, tests different kinds of roofs, adding solar panels and trees

17 middle school student groups, four high school student groups, and seven pre-service teacher groups.

Significant differences were found between student groups who had final performance scores above and below the mean (Table 4). Student groups who scored higher in final performance had higher scores in flexibility and quality, with lower scores in fluency and closeness. In contrast, student groups who scored lower in final design performance had higher scores in fluency and closeness, with lower scores in flexibility and quality. Significant differences between these student groups were found for fluency ($t(55) = 2.362$, $p = 0.022$) and quality ($t(55) = -3.172$, $p = 0.002$).

Discussion and Implications

This study investigated how middle school, high school, and pre-service teachers optimized designs using a CAD simulation tool. Results demonstrate how measuring optimization facets of fluency, flexibility, closeness, and quality can provide insight into how students test and revise designs to optimize design performance. Findings have implications for researchers, educators, and curriculum developers to help conceptualize and promote optimization practices in science classroom contexts. Given the nuance in how students engaged in facets of optimization and how this relates

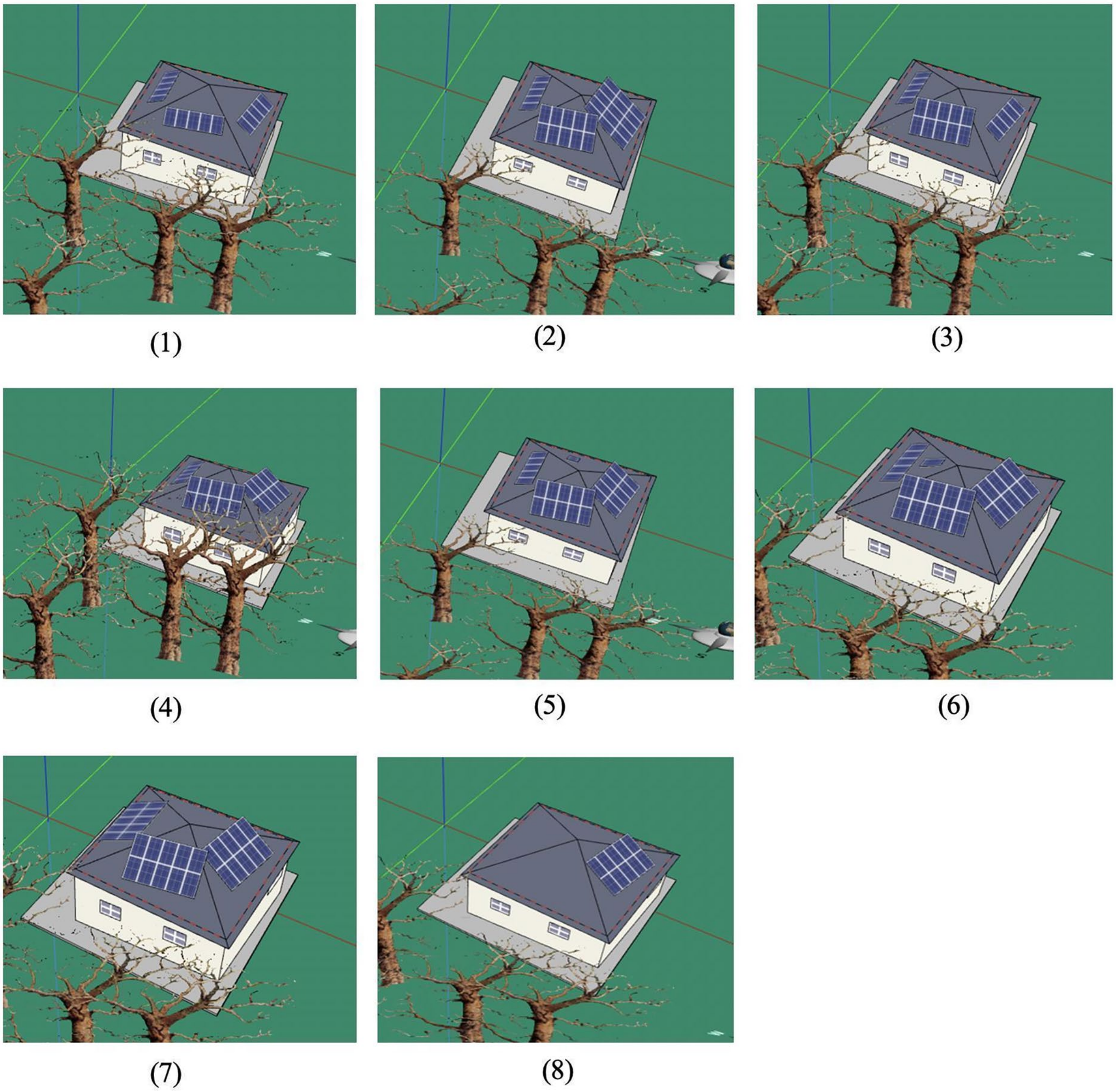

Fig. 3 An example of a student pair with a high closeness score. The student group carefully tests different numbers and configurations of solar panels and does not change the rest of the design (e.g., structure, placement of the house, or trees)

to their design outcomes, new questions are raised about how to best support optimization in engineering design and what may be fruitfully transferred from this learning to other problem contexts.

Findings revealed that students with more successful designs tended to have higher scores for flexibility and quality and lower scores for fluency and closeness. These results provide nuance on how to conceptualize, operationalize, and promote optimization with students. First, the results of higher flexibility scores with lower scores for fluency suggest that the extent to which a student explores the design space, as opposed to just the number of unique tests, can support more successful designs. Results align with other research emphasizing the importance of exploring the design space (Cross, 2011). Findings provide implications for supporting students with divergent operationalization approaches. Prior research to support divergence has often focused on the generation of ideas to combat idea fixation (Daly et al., 2012). Helping students come up with different designs may not be enough. Instead, instructional guidance may need to help promote and potentially center the systematic exploration of the design or solution space. Students may need explicit help to generate and test designs that push the boundaries along all design criteria.

Findings also highlight that students with higher final design performance had relatively lower scores for closeness

Table 4 Means, standard deviations, standard error, effect size, and *t* test statistics for optimization facets for students with low and high design performance

	Design performance	n	Mean	Std. dev	Std. error	Effect size *d*	*t*	*p* value
Fluency	Low	29	22.28	10.67	1.98	0.63	2.36	0.02
	High	28	16.32	8.20	1.55			
Flexibility	Low	29	1.06	0.69	0.13	0.23	0.83	0.41
	High	28	1.29	1.35	0.25			
Closeness	Low	29	0.66	0.14	0.03	0.26	0.97	0.34
	High	28	0.61	0.19	0.04			
Quality	Low	29	1.98	0.41	0.08	0.84	3.17	< 0.01
	High	28	2.35	0.46	0.09			
Design performance	Low	29	0.25	0.04	0.01	3.06	12.01	< 0.01
	High	28	0.48	0.10	0.02			

or tightly controlled tests. These results align with other research that demonstrates that quantitative analysis for engineering encompasses more than just controlling variables and that tightly adhering to procedures of controlling variables may be less likely to help students understand complex problems (McElhaney & Linn, 2011). Instead of focusing solely on controlled experiments, supporting convergent approaches may need to emphasize conducting fair tests of solutions that meet design criteria. For example, being able to run experiments that only change one variable at a time may not be ultimately that helpful to design performance. Students may need targeted help to engage in facets that help them understand and optimize the performance of their design within the entire solution space, not only the effects of two variables in isolation.

Results also demonstrated that middle school students significantly outperformed high schoolers and pre-service teachers on the final design performance of this energy-efficient home design task. More middle school student groups were able to successfully meet the design criteria on their final design than the high school or pre-service teachers. Moreover, middle school students had significantly more tests that satisfied the criteria than either the high school or the preservice teachers. The criteria for the middle and high school students were the same, but the pre-service teachers had a slightly lower cost criterion but similar size constraint. Findings reveal that middle school students are very capable of successfully using CAD simulation tools to engage in design practices. Findings also demonstrate the importance and potential of providing opportunities for middle school students to be able to design, test, receive feedback, and redesign solutions within CAD simulation tools to engage in sophisticated and authentic engineering practices.

However, findings also reveal that ultimately, there was little overall difference within the optimization facets of fluency, flexibility, and closeness among the middle school, high school, and pre-service teachers, with overall performance somewhat decreasing with older students. Results suggest that there may be little growth from middle school to undergraduate settings in these important convergent and divergent optimization facets (e.g., Dym et al., 2005; Shah et al., 2012). These findings may be due to the novel CAD simulation environment and if students were to work again with the same environment then perhaps they might exhibit different optimization facets. These specific findings may also be due to the lack of exposure or explicit instruction on different optimization facets. Findings underscore the need for further research into opportunities to strengthen students' engineering optimization.

This study highlights the implications of the added value of CAD simulation tools to help facilitate and research quantitative analysis. The affordances of the CAD simulation tool enabled students to get immediate, quantitative performance data, which offered multiple opportunities for students to revise and test their designs. Given the importance of quantitative analysis for engineering practice, and the relative dearth of CAD simulation tools in pre-college settings, the development of these kinds of technologies can be particularly beneficial to engage students in authentic engineering practices and for researchers to be able to capture and investigate these important processes.

Limitations

Limitations include the relatively small sample of student groups that were used in this analysis. We understand that this limits the power and generalizability of our analysis and does not account for teacher effects that could potentially have a large influence on design outcomes. Future research can investigate if these trends continue in different contexts with larger populations of students at various levels. Similarly, although these findings present insights into optimization facets at different levels, it does not explicitly connect these facets to other learning progressions or trajectories of student ideas at each of these stages (e.g., Magana, 2017). Future work can explore in more detail the kinds of sequences or progressions of different optimization facets at different levels.

Additionally, this paper explores a single design scenario of a net-zero energy home design across three different levels. Other scenarios and design challenges may elicit different kinds of optimization facets. Future research can also investigate optimization facets across different design scenarios to understand how different facets may or may not be elicited or supported across different design contexts.

This study used a performance metric that averaged the three design scores of size, cost, and net energy score. However, having different performance metrics that have different weights for the different criteria (e.g., placing more weight on the net energy score) may affect the different optimization facets elicited by students. Moreover, informal classroom observations revealed that different groups had a variety of approaches to the cost criteria, with some groups trying to keep the cost at the limit while finding ways to minimize net energy. Other groups tried to maximize the amount of money spent so they would not be wasting available money. Future research can investigate how students interpret and value different performance criteria and how that may affect the kinds of optimization facets used by students.

Conclusions

This study explored how middle school, high school, and pre-service students used optimization facets of fluency, flexibility, closeness, and quality during the design of a net-zero energy home. Results demonstrated that groups with successful designs tended to have higher flexibility and quality scores and lower fluency and closeness scores. Findings also illustrate the optimization facets did not vary across different student levels, suggesting the need for more emphasis on quantitative analysis and optimization in engineering learning settings.

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Declarations

Ethics Approval All procedures involving human participants in this study were in accordance with the ethical standards of the Institutional Review Boards of the universities. This study was approved by the Human Research Protection Program/Review Board for Social and Behavioral Sciences at the two universities.

Consent Statement Informed consent was obtained from all adult participants included in the study. The middle school and high school contexts were deemed as normal educational practice in educational settings by the Institutional Review Board. Informed notification of the study was given to parents/guardians of middle and high school students including study purposes, data gathered, processes to make the data confidential and secure, as well as contact information to withdraw from the study.

Conflict of Interest The authors declare no competing interests.

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