Journal of Science Education and Technology
https://doi.org/10.1007/s10956-021-09906-3

Reciprocal Relations Between Students' Evaluation, Reformulation Behaviors, and Engineering Design Performance Over Time

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Accepted: 1 February 2021

Abstract

Understanding the design process may reveal when and where resources should be focused and how engineers can better use tools, methods, and techniques to enhance the quality of designs and creative performance. The literature suggests the importance of iterative evaluation and reformulation in the engineering design process. The current study collected 111 high school students' logs of designing an energy-saving house in Energy3D, a computer-aided design environment. Using a cross-lag model, we investigated the reciprocal relationship between students' evaluation and reformulation behaviors and how these behaviors influence students' design performance at the early, middle, and final design stages. The results suggest that there is a positive predictive relationship between students' evaluation and reformulation process; reformulation positively predicts design performance and mediates the relationship between evaluation and design performance across time. These results provide empirical evidence of the importance of iterative evaluation and reformulation in the design process and implications for teachers and system designers to support students' design.

Keywords Engineering learning · Design iteration · Evaluation · Reformulation · Temporal relationship · Learning analytics

Introduction

There is an increasing interest in K-12 engineering education given a concern that insufficient numbers of students, especially women and minorities, are attracted to post-secondary engineering programs (Custer et al., 2010). Engineering education provides an authentic problem-solving context for science and mathematics (Custer et al., 2010). Infusing engineering design projects in K-12 can enhance students' engineering design self-efficacy and understanding of design processes as well as attract students to engineering careers (Apedoe et al., 2008; Zhou et al., 2017). The purpose of engineering education is to cultivate graduate engineers who can think and work in a design mode (Dym et al., 2005). However, design thinking and skills are complex to learn and teach. Middle school instructors are concerned about how to scaffold students' hands-on experiences and modeling practices during engineering design yet encourage creativity (Bamberger & Cahill, 2013). Project-based learning (PBL), which enables learners to learn design by actively participating in and experiencing design, has become a popular pedagogical and practical method in engineering education (Dym et al., 2005). Students are even able to transfer what they have learned during PBL, such as reasoning about uncertainty, conducting experiments, and making estimations, to a new context (Bransford et al., 1999). Therefore, engaging students in real or simulated design experiments where they can conduct design projects

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Published online: 11 February 2021

and practice subject-matter conceptual knowledge, design concepts, theories, and strategies, has the potential to enhance students' design ability and skills.

Engineering design is an iterative process in which students go back and forth between analyzing the design problems and constraints, formulating designs, evaluating whether their design meets the constraints, and reformulating designs based on evaluation (Dym et al., 2005). Understanding the design process can reveal when and where resources should be focused and how engineers can better use tools, methods, and techniques to enhance the quality of designs and creative performance (Howard et al., 2008). Furthermore, understanding the design process and its routines may help teachers to guide their students to productive designs and solutions to issues emerging in the design process (Wong & Siu, 2012). Of all the design phases, evaluation and reformulation iterations indicate students' effort of moving towards the design goals by constantly evaluating whether their designs meet the requirements and constraints, conceptualizing reasons, and making relevant refinements using science domain knowledge and design knowledge (Zheng et al., 2020). Empirically modeling how students' evaluation and reformulation behaviors interplay with each other over time and how the design behaviors influence students' design performance is critical to the study of the engineering design process. Such a study will provide implications regarding how systems should be designed to support students to regulate their design process and how teachers can guide their students' design.

In this study, with the support of the Energy3D platform (see Fig. 2; Xie et al., 2018) and its embedded analytical tools, we were able to capture student design behaviors when constructing an energy-saving house. Using a cross-lag panel model (CLPM), we analyzed how 106 grade 9 participants continuously engaged in the evaluation and reformulation of their work with the affordances of the analytical tools and how this process affected their design performance. This study uncovers the reciprocal temporal relationship between evaluation, reformulation behaviors, and design performance and provides empirical evidence of the importance of iterative evaluation and reformulation in the design process.

The Significance of Evaluation and Reformulation Behaviors

Design is central to engineering activities (Simon, 1996). Engineering design is increasingly recognized as a systematic process in which professionals or engineering students attempt to solve a problem or meet user needs under a set of constraints by engaging in loops of analysis, generation, and evaluation (Dym et al., 2005; Wong & Siu, 2012). Although the design processes specified in different design models are various, these models share some common elements: problem analysis or scoping, generating design ideas, realizing ideas/implementation, and evaluating (Howard et al., 2008; Sheppard, 2003). Berland et al. (2014) summarized four characteristics of the engineering design process: defining the problem, generating and selecting between multiple possible solutions, modeling and analysis, and iteration. Similarly, Cross (2000, p. 34) noted that design models have a structure of "analysis-synthesis-evaluation." Using design-based research and conducting an extensive literature review, document content analysis, and consultations with experts, Moore et al. (2014) developed a framework for K-12 quality engineering education. The key factors of quality engineering education include problem and background, planning and implementation, testing, and evaluation (Moore et al., 2014). Taking successfully designing an energy-saving house as an example, students may need to systematically identify or analyze the design goals, the constraints, and the involved variables and their relationships. Then they may generate possible design ideas individually or in groups, for example, the house style, the orientation of the house, and the angles of solar panels. Promising ideas with a higher potential to meet the design goals may be selected for prototyping and implementation. The implementation process can take place physically or in simulated design environments. Simulated design environments usually make it easier to evaluate whether a design meets the design requirements with embedded analytical tools and may promote students' inquiry and reasoning abilities as they can provide immediate feedback (Develaki, 2019).

By employing elements of different design types in engineering design and cognitive psychology, Howard et al. (2008) linked different design operations with the nature of the activities in the design process. The design operations consist of formulation, synthesis, evaluation, documentation, and several reformulations. Formulation and reformulation correspond to generation in terms of their nature in the creative process, while synthesis and evaluation analogously correspond to evaluation. The evaluation usually involves subjective judgments and comparison of the current design or behaviors with expected ones and deciding on accepting or rejecting the design solution (Gero & Kannengiesser, 2004). If all design requirements are met, the design can be considered a success, but designers may still consider improving their designs based on the insights they gain during the design process. In contrast, if not all design requirements are met, designers may need to analyze possible reasons and think about how to reformulate the design. Addressing changes in the design state space is the reformulation process (Gero & Kannengiesser, 2004).

Evaluation and reformulation phases in which students analyze data and work towards solutions provide key opportunities for students to apply and update their engineering, math, and science domain knowledge (Galbraith, 2012). According to Kolb's Experiential Learning theory (1984), experience plays a central role in the learning process, and "knowledge is created through the transformation of experience" (Kolb, 1984, p. 38). The Experiential Learning theory suggests that in order to achieve new knowledge, skills, or attitudes, learners need to have the abilities to go through four modes: concrete experience (CE), reflective observation (RO), abstract conceptualization (AC), and active experimentation (AE) (Kolb, 1984). Taking the design task of the current study as an example, to meet the design requirements, students need to be able to involve themselves in concrete experiences—designing an energy-saving house in the Energy3D environment (CE). They need to observe their design from different perspectives (RO). This process can be facilitated by students' behaviors of evaluating their design using analysis tools embedded in the Energy3D. Through observation, comparison, and reflection, students may integrate new understandings into logically sound theories and update their engineering, math, and science domain knowledge (AC). This will help them to use new knowledge and theories to make decisions, reformulate their design, and solve problems (AE). Therefore, new knowledge is likely to be created between the evaluation and reformulation process as students find their initial design does not meet the requirements while the new design works better. This process is also likely to be accompanied by students' increased design performance.

In the field of engineering design, there is an understanding gap that needs to be addressed: how students' engineering design behaviors interact with their domain knowledge. This requires understanding the temporal design and learning process (Li et al., 2020; Reimann, 2009). While it is not easy to measure students' domain knowledge in the design process, computer-aided design environments enable real-time analysis of students' design performance (e.g., by analyzing students' design artifacts). A temporal analysis of students' evaluation behaviors, reformulation behaviors, and design performance sheds light on whether and when students update their science knowledge during their engineering design process, and how this influences students' design performance.

Analytical Tools to Support Evaluation and Reformulation Behaviors

Existing techniques of assessing engineering design, such as verbal protocol analysis, latent semantic analysis, and timeline analysis, have their limitations (Xie et al., 2014). First, it is usually time-consuming and intrusive to collect "thinking aloud" data for verbal protocol analysis (Atman & Bursic, 1998) and design documentation data for latent semantic analysis (Dong et al., 2003), which limits the scale of research. Timeline analysis regarding students' time allocation and transitions between different tasks does not always reveal students' design performance (Atman et al., 2007). Second, there may be a gap between students' descriptions of their design work and their actual design behaviors (Atman et al., 2008). Third, the data delay of analysis and the discrepancy between students' descriptions and design behaviors make it challenging to provide students with real-time feedback to support their engineering design.

Computers have shifted the ways of how engineering work is done in the past several decades (Madhavan & Lindsay, 2014) and made it possible to investigate students' design processes. The ability and skills to use computational tools and techniques to solve problems and develop design thinking are valued in industry professionals (ABET, 2013; ASEE, 2013). Computational tools enable learners' greater control over their learning and support the shifts from working with equipment to focusing on understanding the relationships between variables and outputs (Kollöffel & de Jong, 2013). Technology-based assessment makes real-time feedback and personalized support possible ([DOEd] 2010). Bywater et al. (2018) conducted an explanatory study to describe students' engineering design behaviors using machine learning and hidden Markov modeling techniques. Purzer et al. (2015) investigated the intertwining interactions between students' design behaviors and scientific explanations by coding and visualizing the design behaviors and reflection notes of two highly reflective high-school students. Purzer et al. (2015) found that the two students tended to connect with scientific concepts when they displayed trade-offs in design behaviors. Their results suggested that trades-offs, which require students to balance different and even incompatible features, opened up opportunities for systematic experimentation, scientific reasoning, metacognition, and decision making (Jonassen, 2012; Purzer et al., 2015).

The National Research Council (2014) argues for collecting data to inform assessment, adaptive instruction, and research on engineering learning. Applying analytical tools in technology-enhanced design environments can help designers to delve into their design performance in real-time through non-intrusive means (Neck et al., 1997) and reduces teachers' monitoring load. Energy3D (Xie et al., 2018) has integrated computer-based assessment and engineering design through logging computer-human interactions when solving design challenges. Furthermore, the computational simulators embedded in the Energy3D platform can provide various analyses such as energy analysis, cost analysis, and sensor analysis, which may help learners to compare specifications with required design constraints and provide evidence for their evaluation of designs. The embedded simulations, such as showing the shadow, showing heliodon, and animating sun, may help learners to understand design factors better, support students' evaluation, and may trigger reformulation behaviors (Xie et al., 2018).

Moreover, in Energy3D, the "what you see is what you get" (WYSIWYG) user interface design tends to facilitate adjusting design parameters and reformulating design solutions. The platform is easy to learn and allows users to build simple houses, complex buildings, and even power stations. The knowledge and thinking skills that students learn through Energy3D, like other CAD platforms, tend to be transferable to real-world situations. Furthermore, Energy3D enables learners to extend their learning into the real world by "printing-out" their design and assembling physical models (Xie et al., 2014).

Based on the interplay between evaluation and reformulation in the literature, this study proposed that the evaluation informs reformulation and reformulation triggers the next cycle of evaluation to confirm whether the evaluated issues are addressed. As a result, multiple iterations of evaluation and reformulation, if conducted appropriately and intentionally, would lead to improved design performance. Figure 1 shows a conceptual framework that characterizes the interactions between evaluation, reformulation, and design performance at the early (T1), middle (T2), and final stages (T3) of students' engineering design.

Regarding students' evaluation and reformulation behaviors during a design task, we proposed the following hypotheses:

H1: The frequency of students' evaluation and reformulation behaviors at a stage positively predicts their subsequent frequency of evaluation and reformulation behaviors, respectively.

H1a: The frequency of students' evaluation behaviors at T1 positively predicts their frequency of evaluation behaviors at T2.

H1b: The frequency of students' evaluation behaviors at T2 positively predicts their frequency of evaluation behaviors at T3.

H1c: The frequency of students' reformulation behaviors at T1 positively predicts their frequency of reformulation behaviors at T2.

H1d: The frequency of students' reformulation behaviors at T2 positively predicts their frequency of reformulation behaviors at T3.

H2: Students' evaluation behaviors positively predict their subsequent reformulation behaviors.

H2a: The frequency of students' evaluation behaviors at T1 positively predicts their frequency of reformulation behaviors at T2.

H2b: The frequency of students' evaluation behaviors at T2 positively predicts their frequency of reformulation behaviors at T3.

H3: In turn, students' reformulation behaviors positively predict their subsequent evaluation behaviors.

H3a: The frequency of students' reformulation behaviors at T1 positively predicts their frequency of evaluation behaviors at T2.

H3b: The frequency of students' reformulation behaviors at T2 positively predicts their frequency of evaluation behaviors at T3.

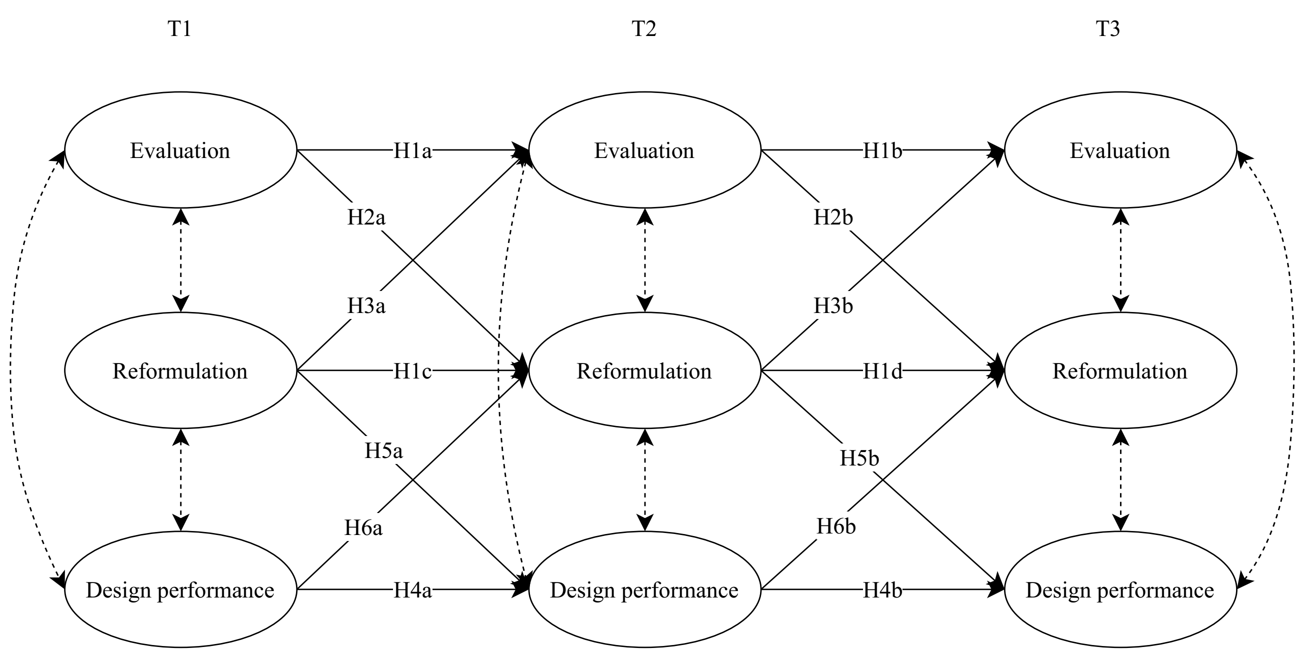

Fig. 1 The hypothesized reciprocal relationship between evaluation, reformulation, and design performance

Design Iterations and Design Performance

The design process is iterative in which designers cognitively engage in continuous evaluation and reformulation until achieving expected goals. Iteration is essential to the success of design due to the complexity of design—new information, constraints, and ideas uncovered during design processes (Dym et al., 2005). Iteration promotes innovation and design success (Atman et al., 2005). By reviewing 40 journal articles of empirical studies focusing on design processes, Mehalik and Schunn (2007) found that using interactive design methodology, exploring problem representations, and searching for alternative solutions were the most significant elements of good design. Factors such as self-monitoring activities, the intent of seeking better design, and awareness of iterative design strategies may trigger design iterations (Adams, 2001). Contrary to iteration, fixation refers to processes in which designers do not alter their design to meet design requirements. Fixation is often associated with negative design results as it limits creativity and the possibility of “thinking out of the box” (Perttula & Sipila, 2007).

Being unaware of the importance of prior design, having conscious blocks to change, and resistance to new ideas are possible reasons for fixation (Youmans & Arciszewski, 2014). Instructors need to be cautious to avoid conveying a notion that design is a linear process that consists of steps. In contrast, the importance of design context, systems thinking, and working with the ambiguities of ill-defined problems in a complex problem space should be emphasized (e.g., Adams et al., 2003; Daly et al., 2012; Lande & Leifer, 2010).

Technologies provide the potential to examine whether students engage in iterative design processes or fixed design processes. Zhang et al. (2018) adopted the frequency of using energy analysis tools, the solar performance of students’ final designs, and the difference of solar performance between initial and final design as indicators of whether students were involved in design iterations or became fixated. Results demonstrated the effectiveness of using computational analysis to investigate the complex design process and indicated that half of the participants became fixation designers at the end of the project (Zhang et al., 2018). They also advocated support for students to perform iterative designs; otherwise, they may become frustrated and fixated (Zhang et al., 2018). However, this study only considered the initial and final solar performance of each student’s design. It is still not clear when students evaluated and reformulated their design and how these design behaviors contributed to the change of their design.

As previously discussed, we hypothesize iterative evaluation and reformulation contribute to better design performance. However, students’ evaluation behaviors may only influence their design performance through reformulation behaviors, and there may not be any direct prediction relationships between evaluation and design performance. In contrast, better design performance reduces the need for reformulation. Students’ design performance during a stage should positively predict their subsequent design performance. Specifically, we hypothesize the following:

H4: Students’ design performance at a stage positively predicts their subsequent design performance.

H4a: Students’ design performance at T1 positively predicts their design performance at T2.

H4b: Students’ design performance at T2 positively predicts their design performance at T3.

H5: The frequency of students’ reformulation behaviors positively predicts their design performance.

H5a: The frequency of students’ reformulation behaviors at T1 positively predicts their design performance at T2.

H5b: The frequency of students’ reformulation behaviors at T2 positively predicts their design performance at T3.

H6: Design performance negatively predicts the frequency of reformulation behaviors.

H6a: Students’ design performance at T1 negatively predicts their reformulation behaviors at T2.

H6b: Students’ design performance at T2 negatively predicts their reformulation behaviors at T3.

Methodology

Participants and Context

The participants in this study were 111 9th grade students from a suburban high school in the northeastern USA. Table 1 shows the demographic information of the students registered in the school. The reason for studying middle students’ engineering design behaviors and performance is to contribute to our

Table 1 Demographic information of the participating school

Demographic categories	Sub-categories	Percentage
Gender	Female	53%
	Male	47%
Expected future pathways	4-year colleges	87%
	2-year college	8%
	Work or are unsure	5%
Ethnicity	White	76.7%
	Hispanic	4.6%
	African American	4.2%
	Multi-race	3.4%
	Native American	0.2%
	Native Hawaiian/Pacific Islander	0.2%

understanding of how to scaffold the hands-on experiences and modeling practices of middle students, which may enhance the possibility for students to choose STEM programs in post-secondary education. Three students' files were incomplete, and two students' performance was much lower than others (e.g., the design performance of E06 is about 13 times worse than others). After eliminating these students, the remaining sample was 106 students. All students enrolled in five class sections of honors physical science taught by the same teacher. This teacher had over 17 years of experience teaching physical science and five years of experience mentoring engineering design projects.

In this research, participants were required to design a Cape Cod-style energy-saving house whose solar panels could generate enough electricity to offset the consumption of energy throughout an entire year. The living space was required to fall on a scale of 100 to 150 square meters, height was to range between seven to nine meters, and the cost for materials was not to exceed $200,000. In addition, the task required participants to take other aspects of building a house into account, like window-to-floor area ratio, the distance between tree trunks and house, and the width of the roof. Participants completed the task within 1–2 class periods. Such a design task in a CAD environment responds to the advocates of engaging K-12 students in the practices of science to build their proficiency and appreciation for science in school (National Research Council, 2012).

Minimal explicit guidance was given to the students by the teacher and researchers. Before designing the house, the students were given two-page printed instructions that include design requirements, design instructions, and important notes, and an engineering design cycle to guide students' design (see the supplemental materials). Before constructing a house in Energy3D, the students were asked to understand the design requirements first and were encouraged to discuss their ideas with their classmates.

Data Collection and Behavior Measures

The dataset of this study was mainly the design behaviors of students designing a Cape Cod-style energy-saving house in Energy3D. Energy3D (see Fig. 2) is a 3D CAD environment that enables users to design and construct buildings with provided elements such as floors, walls, and solar panels. Users can evaluate buildings with embedded analysis, such as cost analysis and energy analysis, to assess whether design constraints were satisfied. Moreover, individual experimentation results, electronic notes, and design artifacts are recorded in Energy3D.

The version of Energy3D adopted in this study was capable of recording 95 distinct design behaviors in the log files. Based on the Data Schema of Energy3D and the similarity and roles of the design behaviors during the

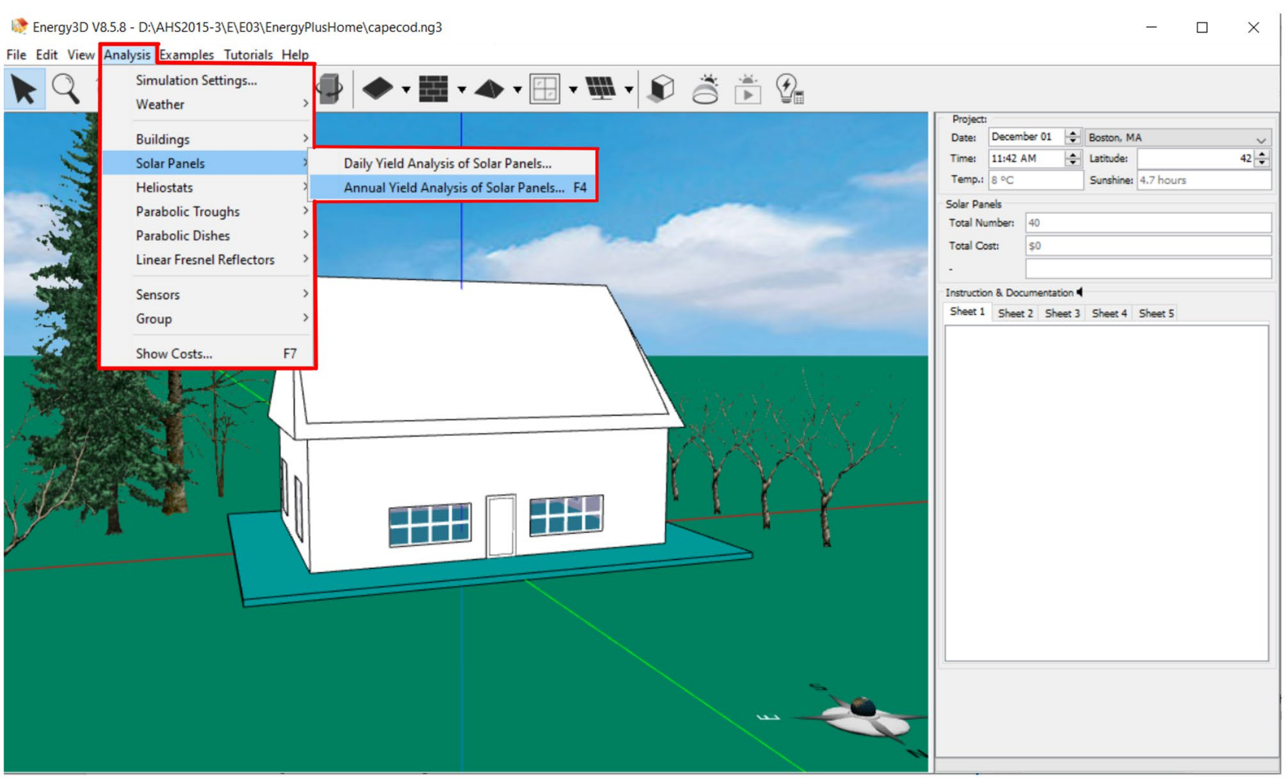

Fig. 2 The interface of Energy3D

design processes, two researchers discussed all the design behaviors, reached an agreement, and categorized them into six major design categories. The six major design categories are building, observation of surroundings, changing an environment parameter, reflection, evaluation, and reformulation. The building category consists of 41 raw behaviors such as adding or removing foundation, door, window, floor, solar panels, people, and trees. The observation of surroundings category includes five behaviors: camera, spin view, top view, showing annotation, and showing axes. The changing environment parameter category consists of five raw behaviors, which are about changing city, date, latitude, time, and inside temperature, respectively. The reflection category only includes the behavior of taking electronic notes. The evaluation and reformulation categories consist of nice and 34 raw design behaviors, respectively. Their detailed raw behaviors are shown in Table 2.

Given the importance of evaluation and reformulation to the updates of students' domain knowledge, in this study, we only focused on the evaluation and reformulation stages and their relevant behaviors. Specifically, in each stage, we used the sum frequency of corresponding behaviors to represent students' levels of evaluation and reformulation when they conducted the design.

Data Analyses

To examine the temporal relationship between evaluation, reformulation, and design performance, we divided students' design process into three stages: the early stage (T1), middle stage (T2), and final stage (T3). The students were given 90 min to build a Cape Cod-style energy-saving house. For each individual, we segmented the time that they spent on the task into three average stages. Each stage consisted of about 30 min. This segment enabled us to investigate design iterations. At each stage, we used the net energy, the difference between solar energy output, and the consumption of energy of the building of a whole year (10^3 kw·h) to represent the level of students' design performance. Net energy equal to or greater than 0 suggests good design performance; otherwise, the design does not meet the design requirements.

CLPM and random intercept cross-lagged panel model (RI-CLPM) have attracted much attention in fields such as sociology, economics, and psychology in the past several decades (Oud, 2007). They are considered ideal models for examining the temporal relationships between multiple variables because they take various sources of error, such as the stability of the variables, cross-sectional associations, and prior associations into account at the same time (Jaya et al., 2018). The RI-CLPM requires a much larger sample size to increase its power and efficiency because of the high uncertainty (random intercepts and covariances). For example, Masselink et al. (2018) found even a sample of 1,500 to 2,000 could only get a small significant effect within a three-wave study using the RI-CLPM. Therefore, we selected CLPM in this study. Before conducting CLPM analysis, descriptive analysis and bivariate correlation of all variables were conducted in this study. The Skew-Kurt test result suggests that students' design performance at T3 in this study was non-normally distributed; therefore, we conducted the subsequent analysis using the Robust Maximum Likelihood (MLR) estimator with robust standard errors, which was robust to non-normality (Muthén & Muthén, 1998).

Table 2 Coding scheme of evaluation and reformulation behaviors

Process	Definition	Raw behaviors in the log
Evaluation	Using the analysis tools embedded in the Energy3D to assess the current design artifacts	Show Shadow, Show Heliodon, Animate Sun, Cost, EnergyAngularAnalysis, EnergyAnnualAnalysis, Compute Energy, SolarEnergy, AnnualSensorData
Reformulation	Revising and refining the design artifacts by editing the design elements in the design state space	Edit Wall, Edit Foundation, Edit Floor, Edit HipRoof, Edit Door, Edit Window, Edit SolarPanel, Edit PyramidRoof, Edit CustomRoof, Edit Sensor, Texture Change, Color Change for Selected Part, Color Change for Whole Building, U-Factor Change for Whole Building, U-Factor Change for Selected Part, Efficiency Change for Selected Solar Panel, Efficiency Change for All Solar Panels of Selected Building, SHGC Change for All Windows of Selected Building, SHGC Change for Selected Window, Change Solar Heat Map Color Contrast, Convert to Gable, Move Oak, Move Dogwood, Move Building, Move Jack, Move Jill, Move Jose, Move Maple, Move Pine, Move Jane, Move Jeni, Move John, Resize Building, Rotate Building

Table 3 Descriptive statistics of all variables

	Mean			Std. deviation			Skewness			Kurtosis		
	T1	T2	T3	T1	T2	T3	T1	T2	T3	T1	T2	T3
Evaluation	26.92	39.31	26.92	23.58	37.75	26.55	1.34	1.56	1.86	2.10	2.15	4.22
Reformulation	69.14	61.44	48.14	47.01	52.11	41.78	1.09	1.23	1.23	1.51	0.87	1.29
Design performance	−22.00	−8.45	−2.24	18.76	13.76	7.46	−0.56	−1.85	−2.79	−0.70	2.78	9.57

T1 first 30 min, *T2* second 30 min, final 30 min

To assess how well the CLPM fits the data, we conducted a chi-square test and followed these criteria: non-normal fit index (NNFI/TLI), comparative fit index (CFI), and root-mean-square error of approximation (RMSEA). A chi-square test with a χ^2/df value smaller than 2 or 3 would indicate a good model fit (Hu & Bentler, 1999). A model with NNFI/TLI and CFI values above 0.90 and RMSEA value less than 0.08 is considered acceptable (Schermellehengel et al., 2003). Furthermore, we referred to the modification indexes (MIs; Sörbom, 1989) when building our model. The modification index indicates the minimum amount that the chi-square statistics will decrease after freeing or adding a certain parameter.

Results

Descriptive Statistics

Before conducting CLPM analyses, descriptive statistics and bivariate correlation analyses of evaluation, reformulation, and design performance at T1, T2, and T3 were conducted. Table 3 presents the result of descriptive statistics. On average, T2 has the highest frequency of evaluation behaviors, while T1 and T3 have a similar level of evaluation behaviors. This result suggests that the participants were more likely to evaluate their design using embedded analysis tools at the middle stage of their design process rather than at the beginning and final stages. The frequency of the reformation behaviors tends to decrease over time, suggesting the participants tended to edit their design more at the beginning. This may be because they might have reformulated and refined their designed buildings to certain levels, and thus, fewer editing behaviors are needed. This increasing design performance over the three stages provides evidence to this explanation. Another possible reason is that they evaluated and thought more at the T2 and T3 stages before reformulating their designs.

Table 4 shows the bivariate correlation matrix of all variables at different stages. There are positive correlations between students' evaluation at different stages, suggesting the consistency of students' evaluation behaviors across their design duration. Similarly, students' reformulation behaviors positively correlate with each other across the stages, indicating the students who frequently reformulated their design at one stage also tended to do so at the other two stages. At each stage (i.e., T1, T2, and T3) evaluation and reformulation are significantly correlated with each other (all *ps* < 0.01), suggesting the reciprocal relationships between students' evaluation and reformulation behaviors across time stages.

Design performance at T1 is negatively correlated with evaluation and reformulation at T3. This result suggests that the students who performed well at the early stage were less likely to evaluate and formulate their design at the final

Table 4 Bivariate correlation matrix of all model variables

	Eval T1	Eval T2	Eval T3	Rfml T1	Rfml T2	Rfml T3	Perf T1	Perf T2	Perf T3
Eval T1	1								
Eval T2	0.724**	1							
Eval T3	0.627**	0.777**	1						
Rfml T1	0.380**	0.512**	0.414**	1					
Rfml T2	0.411**	0.603**	0.465**	0.669**	1				
Rfml T3	0.496**	0.515**	0.565**	0.435**	0.409**	1			
Perf T1	−0.115	−0.142	−0.238*	−0.164	−0.115	−0.228*	1		
Perf T2	0.175	0.056	−0.036	0.198**	0.066	−0.004	0.642**	1	
Perf T3	0.146	0.048	0.030	0.184**	0.167**	0.027	0.521**	0.642**	1

Eval evaluation, *Rfml* reformulation, *Perf* design performance

**$p < 0.01$; *$p < 0.05$

stage. Reformulation at T1 is positively correlated with design performance at T2. Similarly, students' reformulation behaviors at T1 and T2 both positively predict their design performance at T3 (all *ps* < 0.01). These results indicate that reformulation behaviors played positive roles during the design process and contributed to students' design performance. Finally, there are positive correlations among students' design performance across the three stages (all *ps* < 0.01), suggesting the consistency of students' design performance during their engineering design.

Cross-Lag Model

A CLPM conducted on evaluation, reformulation, and design performance resulted in an acceptable model fit χ^2 (13) = 20.682 ($p > 0.05$), CFI = 0.977, NNLI/TLI = 0.941, RMSEA = 0.075, SRMR = 0.051. In this study, the highest MI is 5.31, which is smaller than the conservative criterion of 6.635 (Jung & Yoon, 2016) or 8.0 proposed by Feldt et. al. (2004) in a cross-lagged structural equation model study. The small MIs indicate the parameters and relationships displayed in our final model are ideal. As shown in Fig. 3, there were several significant pathways among the variables during T1 and T3. First, the frequency of students' evaluation behaviors positively predict their subsequent frequency of evaluation behaviors (H1a accepted: $\beta = 0.635$, se = 0.079, $p < 0.001$; H1b accepted: $\beta = 0.791$, se = 0.084, $p < 0.001$). Students' reformulation behaviors at T1 positively predicts their reformulation behaviors at T2 (H1c accepted: $\beta = 0.589$, se = 0.085, $p < 0.001$), while there is not a significant prediction relationship from students' reformulation behaviors at T2 to those at T3 (H1d rejected: $\beta = 0.158$, se = 0.115, $p > 0.05$). Moreover, students' evaluation behaviors at T1 positively predict their reformulation behaviors at T2 (H2a accepted: $\beta = 0.209$, se = 0.085, $p < 0.05$), and their evaluation behaviors at T2 positively predict reformulation behaviors at T3 (H2b accepted: $\beta = 0.423$, se = 0.109, $p < 0.001$). Reformulation at T1 can positively predict evaluation at T2 (H3a accepted: 0.272, se = 0.084, $p < 0.01$), while the prediction effect of reformulation from T2 to T3 is non-significant (H3b rejected: $\beta = -0.011$, se = 0.103, $p > 0.05$).

With regard to students' design performance, as expected, significant autoregression was evidenced cross-time (H4a accepted: $\beta = 0.695$, se = 0.053, $p < 0.001$; H4b accepted: $\beta = 0.636$, se = 0.075, $p < 0.001$). Moreover, student design performance was positively predicted by their previous reformulation frequencies (H5a accepted: $\beta = 0.291$, se = 0.06, $p < 0.001$; H5b accepted: $\beta = 0.126$, se = 0.051, $p < 0.05$). However, their design performance does not predict their reformulation significantly (H6a rejected: $\beta = 0.004$, se = 0.072, $p > 0.05$; H6b rejected: $\beta = 0.002$, se = 0.058, $p > 0.05$).

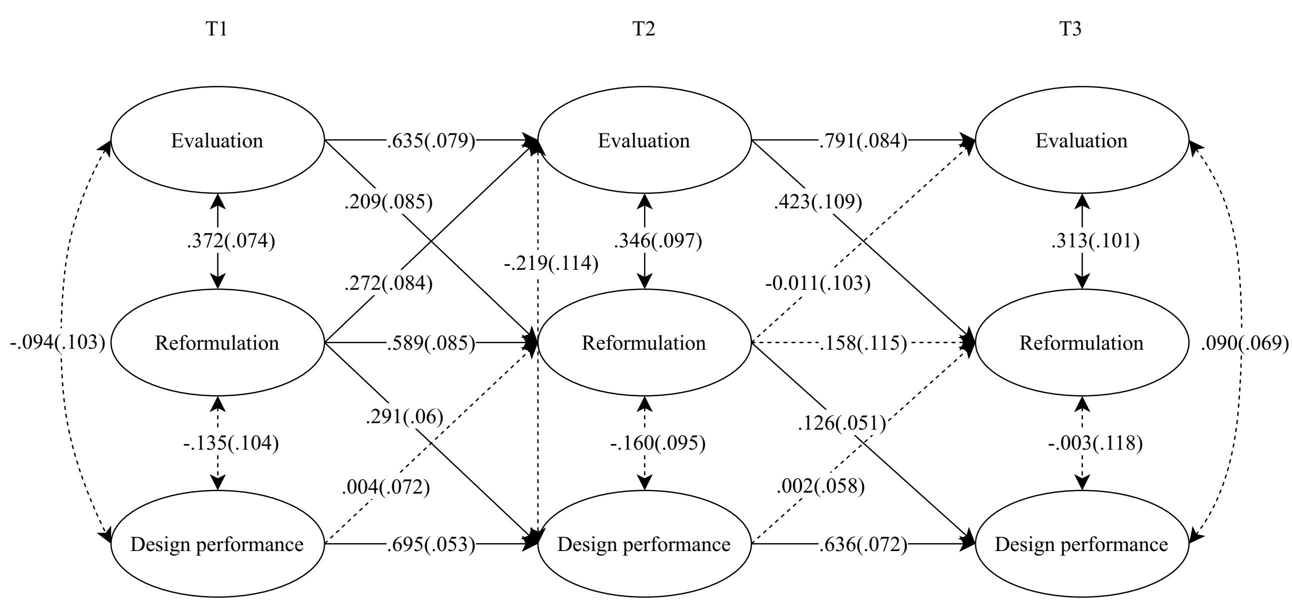

Fig. 3 Results of the cross-panel model with all standardized beta coefficients (standard error). Note. Dotted lines are non-significant pathways (*ps* > 0.05).

Discussions

The results show that the hypotheses H1a, H1b, and H1c were confirmed, while H1d was rejected. The results suggest that overall, the participants had consistent evaluation behaviors at different stages: the ones who engaged in evaluation more at the early stage also tended to evaluate more at the middle and final stages, and vice versa. The predictive relationship between the frequencies of reformulation behaviors at different stages was more complex: reformulation behaviors at the beginning stage predicted reformulation behaviors at the middle stage; however, reformulation behaviors of the middle stage did not predict those of the final stage. A possible explanation for this is that at the beginning and middle stages, the majority of the students were still involved in building and refining the houses and had consistent behaviors. While at the final stage, some students might have achieved their design goals and did not need to reformulate their design, which messes up the relationship between reformulation behaviors and design performance between subjects. Similarly, H4a and H4b were confirmed, suggesting that students' design performance at a stage can predict their design performance at subsequent stages.

The results of H1 provide implications to teachers and researchers that feedback can be provided very early as the students who do not have a good design start are not likely to figure out how to design by themselves. On the other hand, the students who design well at an early stage tend to perform well as time unfolds, and they may design better with support. The technology-based assessment offers advantages such as identifying productive pedagogical sequences and suggesting sequences that meet students' needs, adapting resources to support the identified personalized needs, and predicting students' future learning (Recker et al., 2016). This current research is an attempt to investigate how analyzing students' interaction with assessment tools and design processes may result in feedback tailored for greater design performance and learning outcomes (Cheville, 2012).

The results confirm that the frequency of students' evaluation behaviors at a stage positively predicts the frequency of their reformulation behaviors at subsequent stages (H2a and H2b are confirmed). Consistent with the literature (e.g., Atman et al., 2005; Gero & Kannengiesser, 2004; Howard et al., 2008), evaluation provides students a better understanding of whether their current design meets their design goals and informs them to make appropriate reformulations in order to approach their goals. Analytical tools that can support students' judgments during evaluation play an important role here. Tools can be designed to monitor students' design behaviors and provide prompts to support their design. For instance, for students who conduct continuous analysis but do not reformulate their design, knowledge about the relationship between variables may be provided to help users to make plans for how to reformulate their design. For students who do not evaluate their design at all or only partially assess some variables, feedback can be provided to remind the students that they may want to evaluate their design to check whether design requirements are met or additional variables are remaining to be considered.

In turn, the frequency of reformulation at the beginning stage positively predicts the frequency of evaluation at the middle phase (H3a confirmed). During the design process, reformulation usually triggers another round of evaluation to check whether the new refinement works as expected. However, the frequency of reformulation at the middle stage does not predict the frequency of evaluation at the final phase (H3b rejected). A possible reason as to why H3b was rejected is that a group of students already achieved their design goals and thus did not need to evaluate again. The increase in students' average design performance during the middle stage supports this explanation. Furthermore, this explanation is also consistent with the fact that for this group of participants, 43 students ended their design as soon as they met the design requirements regarding net annual energy, while only 26 students continually improved their design (Li et al., 2020). As hypothesized, the frequency of students' reformulation behaviors at a stage positively predicts their design performance at subsequent stages (H5a, H5b confirmed). Reformulation informed by evaluation helps students better approach their design goals and achieve better design performance.

On the other hand, design performance does not predict reformulation at any time (H6a, H6b rejected). These results suggest that even students with similar design performance may continue their design in different paths. For example, some students might continually reformulate their design to improve, some might want to improve their design but did not know how to, while some might be satisfied with their design and did not engage in reformulation behaviors anymore. These results connect to the literature that different designers show various design behaviors, and some may engage in iterative design, while some may involve in fixed design. For instance, Zhang et al. (2018) suggested that at the end of the project, half of the participants became fixation designers, while others were still actively involved in iterative designs. Crismond and Adams (2012) found that informed designers tend to fully consider design constraints, conduct valid tests and experiments, evaluate in focused and analytical ways, balance trade-offs, and justify decisions; in contrast, design beginners usually focus attention on problematic areas, conduct confounding experiments, evaluate in unfocused and non-analytical ways, and do not successfully weigh options and trade-offs. Further research can be focused on why some students stop reformulating their design, especially the ones who have not achieved the desired design performance. Adaptive models should be developed to support students with different design pathways at different design stages.

Taking the three design stages into consideration, we can see that evaluation at the early stage positively predicts reformulation at the middle stage, and reformulation at the middle stage positively predicts design performance at the final stage. These results suggest a path of evaluation, reformulation, and better design performance. This result provides empirical evidence to the literature that emphasizes the importance of formulation, evaluation, and reformulation in quality engineering design (Howard et al., 2008). Furthermore, the result confirms the mediating role of reformulation, indicating that through the process of evaluation and reformulation, students improve their designs. Similarly, we found that reformulation at an early stage positively predicts evaluation at the middle stage which in turn positively predicts reformulation at the final stage, further suggesting the reciprocal relationship between evaluation and reformulation over time. These results are consistent with the literature that suggests informed designers use feedback and strategies to help them improve design ideas iteratively (Purzer et al., 2015). These results are also aligned with the Experiential Learning Theory (1984) which suggests that ideas are not fixed but can be formed and reformed through experience. New knowledge is achieved by integrating reflective observation into logically sound theories and solving problems using updated theories (1984). In the design task, students' evaluation behaviors provided opportunities for them to observe and reflect on their design, identify inconsistency between their design and requirements (indicators of their prior knowledge or solutions do not work), as well as increase their awareness and prompt them to update their knowledge and reformulate their design.

Conclusion, Limitations, and Future Directions

This study adopted a CLPM to investigate the temporal relationship between the evaluation, reformulation, and design performance of 106 high school students designing an energy-saving house. We found that during all stages (early, middle, and final), there is a positive reciprocal predictive relationship between evaluation and reformulation; reformulation positively predicts students' subsequent design performance and mediates the effects of evaluation on design performance. These findings imply the importance of engaging students in the four modes of experiential learning, especially supporting them to analyze and reflect on their design through feedback and analysis tools, as well as facilitate them to update their domain knowledge during the design process. Just being exposed to the design environment but without appropriate support, students are not likely to figure out how to design or learn by themselves.

This study has several limitations. First, in this study, we only examined 106 students' design behaviors within a complete 90-min engineering design task. Due to the nature of the design task and accessibility constraints, the participants were from a suburban high school in the northeastern USA, and the majority of the students in the participating school were reported to be White. In the future, efforts need to be made to diversify the population sampling and examine the design patterns of other student groups, especially the underrepresented students in the research of STEM fields. Further research is also needed to investigate the relationships between evaluation, reformulation, and design performance during longer engineering design activities or over multiple designs. Second, this study mainly focused on students' design behaviors generated by this design process. Students' prior subject-matter knowledge, engineering design knowledge may influence their design behaviors and pathways. Furthermore, the design process and conceptual knowledge may reciprocally support one another. Further studies on how to measure students' conceptual knowledge, and how their conceptual knowledge interacts with their design participation are needed. Another limitation of this study is that the students individually designed their energy green housing, although they discussed with peers during the problem and background understanding process. The processes of students scoping design problems and planning design were not captured by the Energy3D. Moore et al. (2014) advocated "teamwork" and "communication-related to engineering" as two key indicators of quality K-12 engineering education given the importance of collaboration and communication in multiple manners (e.g., verbal communication, symbolic representations, pictorial representations) to practicing engineers.

Acknowledgements The authors are indebted to Joyce Massicotte, Elena Sereiviene, Jie Chao, Xudong Huang, and Corey Schimpf for their assistance and suggestions.

Funding This work is supported by the National Science Foundation (NSF) of the USA under grant numbers 1503196 and 2105695.

Declarations

Disclaimer Any opinions, findings, and conclusions or recommendations expressed in this paper, however, are those of the authors and do not necessarily reflect the views of the NSF.

Ethical Statement The data set was collected with IRB approval from the fifth's author organization.

Consent Statement Consent forms were collected from all the participants of this study.

Conflict of Interest The authors declare that they have no conflict of interest.

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