

Identifying design process patterns: a sequential analysis study of design thinking

Euisuk Sung¹ · Todd R. Kelley¹

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Abstract Design is a key element of both the teaching and learning of engineering and technology. However, the process of engineering design has yielded limited research results. This study explored the iterative design process by searching for sequential design thinking patterns. The researchers collected nine concurrent think-aloud protocols from fourth-grade elementary students. The study identified that idea generation plays a central role in design that features the dominant use of time. In addition, the researchers revealed significant pathways in design thinking and built a design pattern model. The results will not only help engineering and technology educators the understanding of design behavior, but also support the harmonious matching of learning and teaching styles in engineering and technology education.

Keywords Design process · Design iteration · Design pattern · Protocol analysis · Design cognition

Introduction

Design is a key element of teaching and learning engineering and technology. Dym et al. (2005) noted that design has the unique feature of engineering, which involves a complex cognitive process. Katehi et al. (2009) emphasized design activities in engineering: “engineering is the process of designing the human-made world” (p. 27). Cross (2000) stated, “Everything around us that is not a simple untouched piece of nature has been designed by someone” (p. 3). The study of technology places a considerable emphasis on design. The publication for K-12 technology education standards, *Standards for Technological Literacy (STL)* (ITEEA 2000/2002/2007) explicitly underlines the core concepts of design, and the term *design* appears in 11 of the 20 standards. For example, standards 8–10 describe the

✉ Euisuk Sung
sunge@purdue.edu

¹ Department of Technology Leadership, and Innovation, Purdue University, 155S Grant Street Young Rm 345, West Lafayette, IN 47906, USA

importance of *design* in technology education. The three standards endorsed the attributes of design, the relationship between technology and engineering design, and the role of engineering activities in technological problem-solving. In addition, the Next Generation Science Standards (2013) posit engineering design as a central approach to learning science. The science standards attribute engineering design with a similar importance to scientific inquiry. NGSS claims that K-12 students should have the opportunity to practice the design approach, via authentic experiences to apply scientific knowledge into real-world problem-solving.

Research has been conducted to find design process models for the engineering design problem-solving (Atman et al. 2007; Hill 1998; Jin and Chusilp 2006), and there has been long debate upon design processes. In the late 1950s to the early 1980s, many researchers attempted to define design process models in terms of the design science approach which viewed design problems are logical, systematic, and rational (Bousbaci 2008). Simon (1973), for example, insisted that all design problems can be well-defined because he believed that designers were capable of solving problems by transforming an ill-defined problem into a stable and well-organized system. The underlying assumption of Simon's argument was that a skilled designer can fully identify the structure of the given problem even if the design problem is poorly structured. Therefore, many models of design process were illustrated in descriptive or prescriptive approach to identify the best practice of design processes (Cross 2008). However, the design science approach did not provide a rich explanation of the actual engineering design processes, which often feature complex, muddy, and murky characteristics. Moreover, Dorst (2006) argued about the issue of design process in terms of the designer, stating "the course of the problem-solving process and the very structure of the ill-structured problem are determined by the possibilities for action that the problem solver considers" (p. 8). In the discussion of the design problem, Dorst highlighted the role of the problem solver, who uses his or her unique way of problem-solving. These styles vary based on prior knowledge, experience, and problem-solving preferences.

Despite the acknowledged importance of design in engineering, a few evidence-based studies have focused on the process of engineering design. Atman and Bursic (1998) conducted a verbal protocol study to assess engineering students' design processes in performing an open-ended design task. Their study showed that the verbal protocol analysis can successfully identify processes of engineering design, which can be used to detect good or poor processes of engineering students by comparing the quality of the final design. Mosborg et al. (2005) studied whether the block diagram design processes shown in engineering textbooks are relevant to the practice of engineering practitioners. The study showed that only a few engineering practitioners agreed the design process model from an engineering textbook and provided alternative types of diagrams varied by their expertise and types of engineering tasks. Mosborg et al. concluded that there is no single correct procedural pathway that designers must follow step by step in a serial manner. Jin and Chusilp (2006) also studied how designers follow iterative processes in various engineering conditions. They stated that design is an iterative process of human cognition operated within the designers' mind. Jin and Chusilp's study confirmed that design activities involve procedural patterns of cognitive repetition that vary by problem type and constraints. Furthermore, Lawson (1979) conducted a comparative experiment to investigate the differences in the design behaviors of scientists and designers. The results of the experiment suggested that designers tended to use solution-focused approaches, while scientists emphasized problem-focused approaches. As shown in the prior research studies, the process of design varies according to the types of problems and the designer's level of expertise. These

findings reaffirm the NGSS framework (NRC 2012) comparison of science practices and engineering practices that feature scientists seeking to discover and understand phenomenon and engineers seeking to create solutions to problems (NRC 2012; Kolodner 2002). Crismond and Adams (2012) also argued whether strategic models of the design process are effective. The argument concluded that beginning designers tend to treat design as an end product or stage, while informed designers view design activities as a managed, iterative process.

When teaching and practicing engineering design, people use various design process models. These models were developed through a certain depth of abstraction of complex design process activities (Hubka 1982). Each design process model has unique features, including its history, paradigm, design genre, and philosophy. However, a common driver of developing design process models is the behavioral pattern of design activity (Clarkson and Eckert 2004). Therefore, this study explored the iterative procedural patterns of design thinking in young science students' engineering design problem-solving. Identifying iterative patterns of design thinking will provide a fundamental understanding of how people solve design problems. As STEM educators seek to employ engineering design as an approach to improve STEM learning, specifically science learning (NGSS Lead States 2013), it is extremely important to understand how young learners navigate through the design process and patterns in thinking that are displayed. To investigate the design thinking patterns, the researchers proposed two research questions:

Research Questions:

1. Which cognitive activities did fourth grade elementary students display when solving an engineering design task?
2. What are the common problem-solving patterns of fourth grade elementary science students' engineering design problem-solving?

Design nature and design process models

The process of design thinking is surely not deterministic. In a long argument on the design problem, Simon (1973) argued that designers have difficulties with defining problems because of the designers' limited abilities. An underlying assumption of Simon's idea was that any design problem can be proposed with a well-defined criteria and constraints through a mechanical process. In other words, he believed that an experienced or well-trained designer could transform an ill-defined problem into a well-defined problem. However, Dorst (2006) suggested an alternative explanation for the design problem issue with three key arguments:

1. The "design problem" is not knowable at any specific point in the design process.
2. The "design problem" is hard to identify because it evolves in the design process.
3. The connotations of the very concepts that are used to describe a "design problem" are shifting as a part of the design effort (p. 16).

In fact, the deterministic nature of a design problem is closely related to the nature of design. Koen (2003) addressed four characteristics of engineering problems: *change*, *best*,

resources, and *uncertainty*. In terms of the *change* feature, Koen highlighted the fact that engineering problems never remain invariably, but rather are continually changed by various design activities as well as the surrounding conditions of the problem. Koen noted “Engineers cause change” (p. 11). Bucciarelli (2003) also noted that design is dynamic: “Designing, like language, is a social process” (p. 9). Bucciarelli referenced different design process models and noted that traditional design process models are described as an optimizing algorithm, where a designer inputs X into a model and receives Y as an output. However, Bucciarelli pointed that these design process models overlook two important aspects of design: its social nature and the people who are engaged in the design. Indeed, designers autonomously undertake the whole design process; therefore, the design processes inevitably vary by problem-solving style, problem type, and designer expertise.

Patterns rather than design process models

In the publication, *Design Expertise*, Lawson and Dorst (2009) introduced multiple views of design, and one approach is design as problem-solving. They pointed out that most design process models used for design education are based on a view of design as a problem-solving process. In fact, most design process models have similar problem-solving phases, such as identifying problems, analyzing data, generating ideas, creating a solution, and testing. It is true that these design process models provide novice designers with a straightforward guide to defining clear, stable, and comparable design ideas. Lawson and Dorst, however, warned of the danger of oversimplifying the complex structure of design processes, which leads designers to be incapable of handling the murky aspects of design problems.

A promising strategy to overcome the nebulous nature of the design process is to adopt patterns of design activity instead of the procedural approach (Clarkson and Eckert 2004). Clarkson and Eckert stated, “similarities (of various design process models) can be recognized as patterns of designing, describing elements of process behavior” (p. 18). The underlying assumption of the design pattern strategy is that design behaviors necessarily consist of numerous sets of repeated behaviors. In general, the term *pattern* represents a group of common elements of discernible observations in a predictable manner. For example, for a small engineering problem, a problem solver might begin with the specific problematic issues. In a large entrepreneurial project, the problem solver might start by searching market and customer needs or reviewing prior product feedbacks. Admittedly, the pattern approach requires enough data sources to detect repeatable common design process behaviors.

Patterns are widely used in various fields of science, mathematics, arts, and engineering. For instance, computer science often uses patterns to find sustainable solutions for software design. In visual art, designers use shapes and patterns in painting, drawing, ceramic tiling, or textiles to create the form of the artwork. Likewise, patterns in the study of engineering and technology education inform the engineering design process itself. Consequently, patterns of design process can help students to cope with the complex nature of design problems by conceptualizing successful pathways to problem-solving.

Methods

Context of the study

This study was conducted in the context of a National Science Foundation funded Math Science Targeted Partnership (MSP) project entitled Science Learning through Engineering Design (SLED, <https://stemedhub.org/>) of project website. The SLED team partnered with four school corporations located in the north-central Midwest. The overarching goal of the project was to improve the efficiency of science learning in grades 3–6 elementary students through an engineering-design approach. The SLED researchers primarily adopted an engineering design approach (Lewis 2006) and design-based science learning pedagogy (Fortus et al. 2004) to scientific inquiry (National Research Council 2012). The SLED team purposely integrated engineering and other STEM-related content to provide students with a strong understanding of the STEM pipeline. The SLED project team developed engineering design lessons aligned to Indiana Academic Science Standards (IDOE 2010). The lessons were delivered during a two-week teacher professional development, and then the participant teachers implemented the SLED lessons in their classroom. When delivering the lesson to the teachers, the project team asked them to use guiding questions for each design stage rather than sharing the SLED design process model with their students (see Fig. 1).

The researchers used a design task, titled Doggie Door Alarm, to capture the participants’ problem-solving behavior. The SLED research team developed the design task collaboratively based on Cross (2004). The approach included a goal, constraints, and design criteria to gauge the final design solution. As shown in Fig. 2, the design task was developed to measure the transfer of knowledge acquired from the SLED lesson; therefore, the design task applied the same science and engineering concepts into the

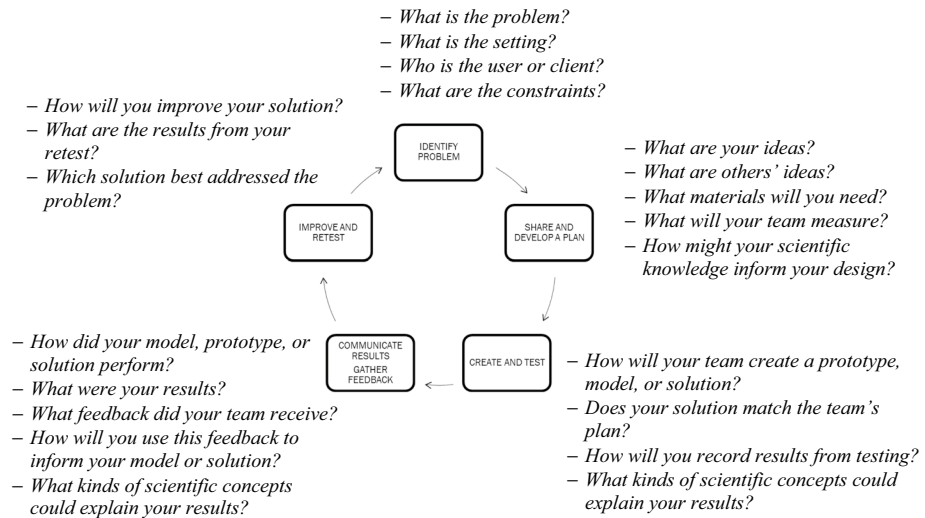


Fig. 1 ##PROJECT_NAME Design Process Model (From 2015 SLED Summer Professional Development Presentation, 2015 retrieved from <https://stemedhub.org/>)

Doggie Door Alarm

The Problem

Your grandma's dog Rex uses his doggie door often, and she wants to know when Rex is going outside. Grandma isn't always in the room when the door is used. She wants some kind of alarm signaling when the door is opened. You remember what you learned in the *Door Alarm* lesson, so you want to help design a doggie door alarm.

Criteria

- The door alarm should buzz when the door is opened.
- The door alarm should turn off after the door is closed.
- The alarm should sound even if the door is slightly opened.

Constraints

- Must use an alarm buzzer, a switch, wire, and batteries.
- Any other materials found in the typical classroom can be used.
- There is no lock on the door.
- The door only opens to the outside of the room.

Your Task

Describe how you would design a circuit to make a doggie door alarm that uses what you know about the design process in a fun and creative way.

Please describe aloud how you would start the design task - where would you begin?

What types of tests would you do to make sure that your circuit works?

Fig. 2 Design Task for Think-Aloud Session (Designed by Kelley and Kaluf 2013)

SLED lesson, but with a slightly different context. The science concepts embedded in the design task were electricity, power, and open- and closed-circuits.

Participants

In the data collection, a group of three students collaboratively solved a design task as a team. As Welch (1999) suggested, the SLED project collected data as a team to facilitate natural design conversation when students engaged in solving design problems. The researchers collected nine design sessions from nine classrooms; 27 students participated in the data collection. To recruit the participant students, the SLED researchers asked to classroom teachers to select three students based on selection-criteria (Ary et al. 2014): representative of regular classroom performance and agreeable to audio–video recording. The demographics of the participants in Table 1 shows that the participants were approximately balanced in gender ratio. The ethnicity ratios were representative of the school district demographics.

Table 1 Participant demographics

CTA session	Gender		Ethnicity					
	Male	Female	White	Black	Hispanic	Asian	Multi-racial	Other
1	2	1	1		1		1	
2	2	1	3					
3	1	2	1	1	1			
4	1	2	2			1		
5	1	2	2					1
6	2	1	1		1			1
7	1	2			1		2	
8	1	2	3					
9	1	2	2				1	
Total	12 (44%)	15 (56%)	15 (56%)	1 (3.5%)	4 (15%)	1 (%)	4 (15%)	2 (7%)

Data collection

To capture the cognitive thought processes used in design, the researchers adopted the concurrent think-aloud (CTA) technique (Atman and Bursic 1998; Ericsson and Simon 1993). The nine CTA sessions were collected from three elementary schools during the 2015–2016 academic year. Once the SLED teachers completed a SLED lesson, the SLED researchers contacted the teacher and arranged a schedule for the data collection. The CTA sessions were conducted in an empty classroom or hallway, which varied by school conditions. According to the Ericsson and Simon's guidelines (1993), the researchers provided the participant students with two instructions: (1) verbalize all thought processes related to design; and (2) utilize prior knowledge acquired from the SLED lesson. In addition, before starting the CTA session, the researchers collected Institutional Review Board (IRB) consent forms that described the possible benefits and harms from participating in the research study. Then, the researchers provided the triad with the design brief, pencils, and a piece of blank paper for sketching. During the data collection, the researchers avoided intervening in the participants' conversation as much as possible, and only guided the students to articulate their thinking. The entire CTA sessions were recorded via video/audio recorder (Table 2).

Data coding

The researchers analyzed the nine CTA sessions using the NVIVO software. The NVIVO software allowed the researchers to bypass the transcription process and directly segment and cod the data (Mentzer et al. 2015). To categorize the cognitive strategies that appeared in the CTA sessions, the researchers adopted Halfin's codes (1973). Halfin studied successful engineers, scientists, and technologists, and identified 17 commonly-used cognitive strategies. The 17 cognitive strategies were validated through a Delphi study survey of engineering and technology practitioners. Of the original 17 cognitive strategies, the researchers selected seven cognitive strategies that frequently appeared in the SLED CTA sessions. To obtain data coding reliability, two coders trained to use Halfin's code conducted the data analysis. A master coder analyzed all nine CTA sessions, and a second coded four randomly-selected sessions. The reliability test was conducted using intercoder agreement (Creswell 2013). The intercoder

Table 2 Halpin's (1973) seven cognitive strategies

Code	Cognitive strategy	Definition
DF	Defining problem(s)	The process of stating or defining a problem which will enhance the investigation leading to an optimal solution. It is transforming one state of affairs to another desired state
AN	Analyzing	The process of identifying, isolating, taking apart, breaking down, or performing similar actions for the purpose of setting forth or clarifying the basic components of a phenomenon, problem, opportunity, object, system, or point of view
PR	Predicting	The process of prophesying or foretelling something in advance, anticipating the future on the basis of special knowledge
QH	Questions/hypotheses	Questioning is the process of asking, interrogating, challenging, or seeking answers related to a phenomenon, problem, opportunity element, object, event, system, or point of view
DE	Designing	The process of conceiving, creating, inventing, contriving, or planning by which some practical ends may be effected, or proposing a goal to meet the societal needs, desires, problems, or opportunities to do things better
MA	Managing	The process of planning, organizing, directing, coordinating, and controlling the engineering design process
MO	Modeling	The process of producing or reducing an act, or condition to a generalized construct which may be presented graphically in the form of a sketch, diagram, or equation

agreement was 85.35%, which is higher than the recommended agreement rate (80%) in the social science (Miles and Huberman 1994).

Sequential pattern analysis

Once the CTA session coding was complete, the researchers analyzed the sequential patterns of iterative design processes using the GSEQ 5.1 software. The GSEQ software was developed by Bakeman and Quera (2015) to analyze the sequential probability of continuous string data. The sequential analysis technique was developed in the 1970s to analyze the sequential patterns of behavioral events (Allison and Liker 1982; Bakeman and Gottman 1986; Bakeman and Quera 2011). Multiple studies from various research fields have adopted the sequential analysis technique to identify behavioral, psychological, or social patterns of sequential interactions (Bakeman and Brownlee 1980; Blount et al. 1989; Gottman et al. 1977; Jeong 2003; Justice et al. 2002).

In order to identify the common cognitive strategies from the coded CTA data, the researchers conducted descriptive analyses, including frequency, rate per 10 min, duration, and average. In addition, the researchers analyzed the sequential patterns of cognitive strategies using the two-event sequential analysis technique. The two-event sequential analysis seeks the probabilities of cognitive strategies from the coded CTA data. For example, the coded data generated a set of strings, such as “DF AN DE AN DE DF AN DE”. Then the two-event sequential analysis can be displayed through the transitional matrix shown in Table 3. In the table, codes in the Given rows represent the first event, and the Target columns are the second of the two sequential events.

The frequency of numbers in Table 3 is labeled as observed frequency (OF). Using the observed frequency values, the GSEQ software calculates the expected frequency (EF), which is the expected number of transition counts upon the observed frequency. The formula for the expected frequency is presented by Bakeman and Gottman (1986):

$$Expected\ Frequency\ (e_{rc}) = \frac{f(r) \times f(c)}{N - f(r)} \tag{1}$$

where $f(r)$ = sum of the counts in the r th column, Given code; $f(c)$ = sum of the counts in the c th column, Target code; N = sum of the total count.

Using the observed and expected frequencies, the probabilities of the two-sequential event can be calculated through the formula presented in Eq. (2).

$$Adjusted\ residual\ (Z\text{-score}) = \frac{x_{rc} - e_{rc}}{\sqrt{e_{rc} \left(1 - \frac{f(c)}{N}\right) \left(1 - \frac{f(r)}{N}\right)}} \tag{2}$$

where x_{rc} = observed frequency in the cell r th column and c th row.

Table 3 An example transitional matrix

	Target			Total
	DF	AN	DE	
<i>Given</i>				
DF	–	2	0	2
AN	0	–	3	3
DE	1	1	–	1
Total	1	3	3	7

In the two-event sequential analysis, the researchers pooled the nine sessions to test the statistical significance at the 0.05 level. Before analyzing the nine-pooled data, the researcher calculated the required sample size in terms of statistical significance. Bakeman and Gottman (1986) suggested that the transition events should be at least 30, and the total number of events should exceed four or five times of the number of coded cells. Because the sequential transitions do not allow for two consecutive events, such as designing to designing (DE → DE), the total number of cell size can be calculated by the formula $K \times (K - 1) \times 5$, where K is the number of the coding schemes. When using seven coding schemes, the total cell size is $7 \times (7 - 1) \times 5 = 210$. The researchers confirmed that the average number of transitions of a CTA session is over 30; therefore, the nine-pooled CTA sessions are sufficient to generate statistical significance ($30 \times 9 = 270 \geq 210$).

The statistical analyses were conducted by pooling data from the nine individual sessions. Bakeman and Quera (2011) warned that when pooling behavioral data of the human subject, researchers should avoid generalizing the sampled behavioral patterns for subjects. With careful consideration of this human-subject research, the researchers adopted the pooled sequential analysis to illustrate a general shape of the problem-solving pathways of cognitive strategies in an engineering design task.

Findings

Use of cognitive strategies

To investigate which cognitive strategies the participant students emphasized or overlooked in engineering design, the researchers summarized simple statistics based on the frequencies and durations shown in Table 4. Due to the time variations of the nine CTA sessions, the researchers created *relative frequency and duration* to show the standardized duration and frequency by 10-min segments. *Relative frequency* in Table 4 represents how many

Table 4 Summary Statistics for Nine CTA Sessions

Codes	Total		Relative frequency per 10-min ^a		Relative duration per 10-min ^b	
	Frequency	Duration (mm:ss.d)	Average	SD	Average (mm:ss.d)	SD (mm:ss.d)
AN	52	06:03.5	4.84	3.36	00:33.8	00:25.9
DE	231	36:05.8	21.49	6.83	03:21.5	01:13.9
DF	19	15:08.5	1.77	1.14	01:24.5	00:40.8
MA	44	02:29.3	4.09	2.27	00:13.9	00:10.3
MO	174	33:52.3	16.19	9.97	03:09.0	01:35.2
PR	62	07:44.2	5.77	4.95	00:43.2	00:34.2
QH	117	06:06.7	10.88	6.37	00:34.1	00:17.1
Totals	699	1:47:30.0	65.02	9.58	10:00.0	00:00.0

^aRelative frequency = Number of occurrences per 10-min (Freq × 600/Total duration)

^bRelative duration: Time duration per 10-min (Duration × 600/Total duration)

E.g. Relative frequency for AN per 10-min = $52 \times 600/6450 = 4.84$, 1:47:30 = 6450 s. Relative duration for AN per 10-min = $363.5 \times 600/6450 = 33.8$, 06:03.5 = 363.5 s

cognitive strategies occurred each 10-min, calculated through the formula, relative frequency = frequency × 600/Total duration. Likewise, the *relative duration* also denotes the relative duration for each 10-min period (relative duration = duration × 600/total duration).

The summary data presented in Fig. 3 indicates that the participants frequently used *Designing* (DE, f = 231), *Modeling* (MO, f = 174), and *Questioning* (QH, f = 117) strategies

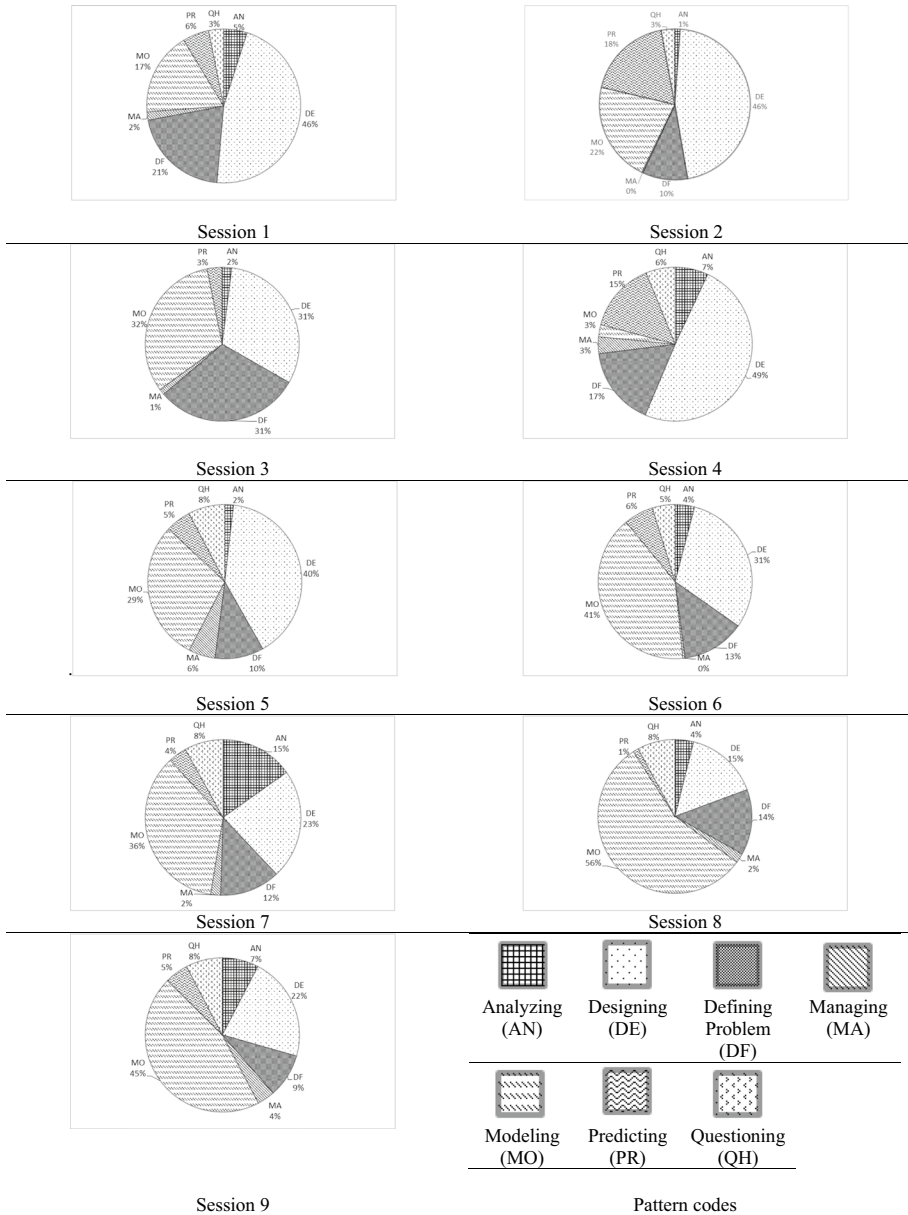


Fig. 3 Mean time percentages of cognitive strategies for nine CTA sessions

during their design problem solving. On the other hand, *Defining problem* (DF, $f=19$), *Managing* (MA, $f=44$), *Analyzing* (AN, $f=52$), and *Predicting* (PR, $f=62$) were less frequently utilized. The relative durations show that participants spent an average of 3:21.5 s on *Designing*, 3:09.0 s on *Modeling*, 0:13.9 s on *Managing*, 0:34.1 s on *Questioning*, and 0:43.2 s on *Predicting* per 10-min period. The researchers confirmed that the participant students hugely emphasized *designing* and *modeling* cognitive strategies, and less often referenced *defining*, *analyzing*, *questioning*, and *predicting* strategies.

Common patterns in the use of cognitive strategies

Bakeman and Gottman (1986) suggested that in order to run sequential pattern analysis, the sum of a sequential event must have at least 30 event counts. However, the number of *Defining Problem* frequency counts in Table 4 does not meet the criteria for sequential analysis (DF, $f=19 < 30$). Therefore, upon a careful review of the Halfin's coding schemes, the researchers collapsed *Defining Problem* (DF) and *Analyzing* (AN) into a new category. The description of *Analyzing* in Halfin's code was the process of identifying, isolating, taking apart, or breaking down the given problem. Therefore, the researchers framed the merged category as a problem-space that includes searching for the features of the problem space, identifying criteria and constraints, exploring the investigated areas of problem, and framing a problematic design situation (Cross 2004; Dorst and Cross 2001; Goel and Pirolli 1992; Yilmaz and Daly 2016).

To investigate the common cognitive patterns in participants' design strategies, the researchers conducted a two-sequential pattern analysis using GSEQ 5.1 software. The researchers pooled the nine CTA sessions, which resulted in observed frequencies shown in Table 5. The Given columns represent the first codes, and the Target columns are the later codes from the two-sequential patterns. For example, 14 frequencies across Given DE and Target MA represent that in the nine CTA sessions, the number of transitions from DE to MA occurred 14 times.

To identify the significant patterns in two-event transitions, the researchers generated the expected frequencies in Table 6 using GSEQ 5.1 software (see Eq. 1).

In addition, using Eq. (2), the GSEQ software calculated the z-scores and probabilities for two-event sequential transitions from the nine-pooled CTA sessions.

Table 5 Observed frequencies for nine pooled CTA sessions

Observed Frequency	Target						Total
	Designing	Managing	Modeling	Predicting	Questioning	Defining and analyzing	
<i>Given</i>							
Designing		14	48	33	36	16	147
Managing	12		15	1	8	2	38
Modeling	25	9		13	48	11	106
Predicting	39	2	3		5	3	52
Questioning	52	10	28	3		14	107
Defining and analyzing	25	5	13	2	10		55
Total	153	40	107	52	107	46	505

Table 6 Expected frequencies for nine pooled CTA sessions

Expected frequency	Target					
	Designing	Managing	Modeling	Predicting	Questioning	Defining and analyzing
<i>Given</i>						
Designing		14.95	47.11	19.97	47.23	17.74
Managing	14.62		8.34	3.54	8.36	3.14
Modeling	47.98	8.69		11.60	27.43	10.31
Predicting	20.49	3.71	11.69		11.72	4.40
Questioning	48.46	8.77	27.64	11.73		10.41
Defining and analyzing	21.44	3.88	12.23	5.18	12.26	

Table 7 shows the results of the two-event transition sequential analysis. The statistical probabilities shown in Table 7 were calculated as two-sided P values. A right-tailed significance at 0.05, for example, implies that the probability of the two-sequential event occurring is more than 95%. The statistics identified the right-tailed significant patterns as *Designing* → *Predicting* ($p < 0.001$, $z = 3.66$), *Managing* → *Modeling* ($p = 0.007$, $z = 2.7$), *Modeling* → *Questioning* ($p < 0.001$, $z = 4.98$), and *Predicting* → *Designing* ($p < 0.001$, $z = 5.17$). The results show a bi-directional iteration between *Designing* and *Predicting*. The description of the *Predicting* strategy was “The process of prophesying or foretelling something in advance, anticipating the future on the basis of special knowledge”, which is a unique feature of engineering design that predicts the possible consequence of the ideas. This result suggests that there is no cognitive border between predicting and generating ideas; rather, participants used the two strategies simultaneously during their design problem-solving. Meanwhile, the data illustrates that *Modeling*, which is largely represented by sketching behaviors, led to uses of the *Questioning* strategy. Table 5 shows that 48 of 107 *Questioning* instances directly followed after *Modeling* strategies. This finding confirmed that the modeling behavior is a mixture of mental and physical reactions that represent an internal idea in an external, drawn form (Goldschmidt 1991; Tversky and Suwa 2009; van der Lugt 2005). Moreover, the use of drawing, or sketching facilitates creative design inquiry by igniting designers’ cognitive linkages between the external representation and internal mental image.

To visualize the right-tailed significant patterns, the researchers drew the pattern diagrams in Fig. 4. The diagrams illustrate that the significant pathways have higher than a 95% statistical probability.

Meanwhile, the transition diagrams in Fig. 5 show that there exist negative transitions at the 0.05 significance level. These negative significances imply that the transitions happened less than 5% of possibilities. As Fig. 5 illustrated, the probability of the transition from *Modeling* to *Designing* is less than 0.001 ($z = -4.47$); only 25 instances of *Designing* strategy ($f = 147$) occurred after *Modeling* ($f = 106$). Likewise, the transition from *Designing* to *Questioning* ($p = 0.029$, $z = -2.19$), *Predicting* to *Modeling* ($p = 0.003$, $z = -3.02$), *Predicting* to *Questioning* ($p = 0.02$, $z = -2.33$), and *Questioning* to *Predicting* ($p = 0.002$, $z = -3.03$) have negative significances. These negative patterns indicate that the directional pathways between the two strategies have a weak mental relationship during students’ design problem-solving process.

Table 7 Z-scores and statistical probabilities for nine pooled CTA sessions

<i>p</i> value (z score)	Target					
	Designing	Managing	Modeling	Predicting	Questioning	Defining and analyzing
<i>Given</i>						
Designing		0.764 (-0.3)	0.865 (0.17)	<0.001* (3.66)	0.029** (-2.19)	0.603 (-0.52)
Managing	0.395 (-0.85)		0.007* (2.7)	0.139 (-1.48)	0.881 (-0.15)	0.484 (-0.7)
Modeling	<0.001** (-4.47)	0.897 (0.13)		0.624 (0.49)	<0.001* (4.98)	0.795 (0.26)
Predicting	<0.001* (5.17)	0.327 (-0.98)	0.003** (-3.02)		0.020** (-2.33)	0.459 (-0.74)
Questioning	0.490 (0.69)	0.624 (0.49)	0.928 (0.09)	0.002** (-3.03)		0.190 (1.31)
Defining and analyzing	0.332 (0.97)	0.529 (0.63)	0.795 (0.26)	0.119 (-1.56)	0.441 (-0.77)	

*Right-tailed significant at 0.05 level

**Left-tailed significant at 0.05 level

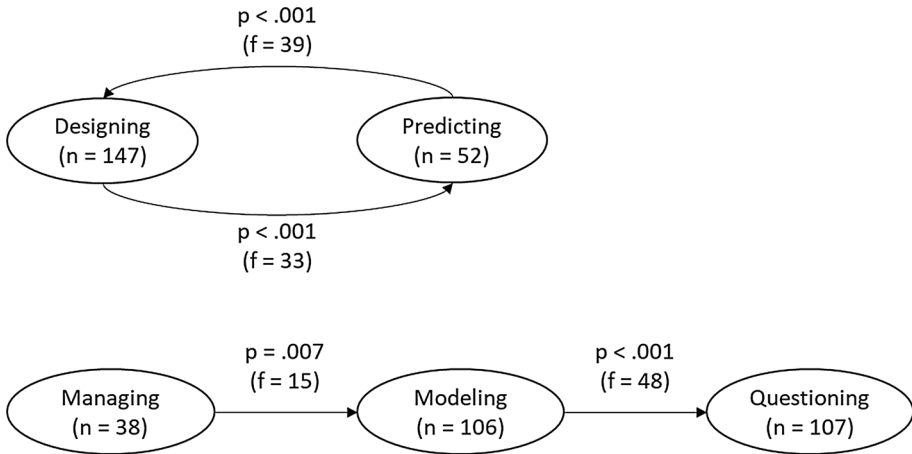


Fig. 4 Right-tailed significant patterns at the 0.05 level. Note *n* frequency of a single event; *f* frequency of transition

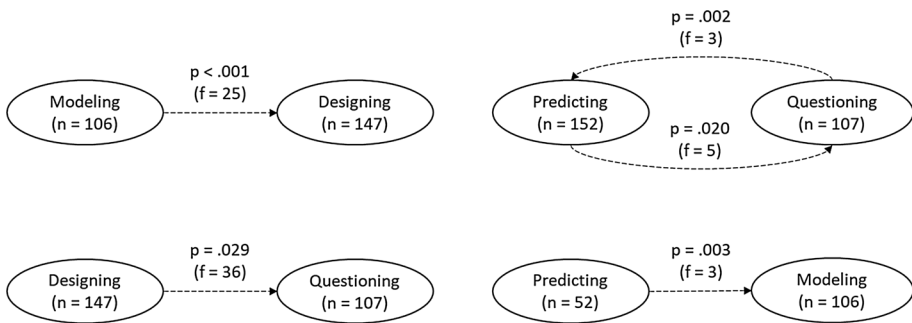


Fig. 5 Left-tailed significant patterns at the 0.05 level

One interesting finding from the negative pattern was an insignificant probability from *Modeling* to *Designing*. The interesting aspect of this pattern is that there exists a strong positive pathway in its opposite, *Designing* to *Modeling*. To further explore the *Modeling* to *Designing* pathway, the researchers sought alternative pathways from the entire transitional probabilities in Table 7. The alternative pathways shown in Fig. 6 indicate that *Questioning*, *Designing and Analyzing*, and *Predicting* strategies proxy the pattern of *Modeling* to *Designing* strategies.

Problem solving pathways

In order to further illustrate the problem-solving pathways of design thinking patterns, the researchers demonstrated the problem-solving pathway diagram shown in Fig. 7.

The problem-solving pathway diagram was illustrated in Table 7 using right-tailed events only (positive z-scores). The statistical description of the right-tailed probabilities is that the two-sequential events with positive z-scores occurred more than 50%. The pathway

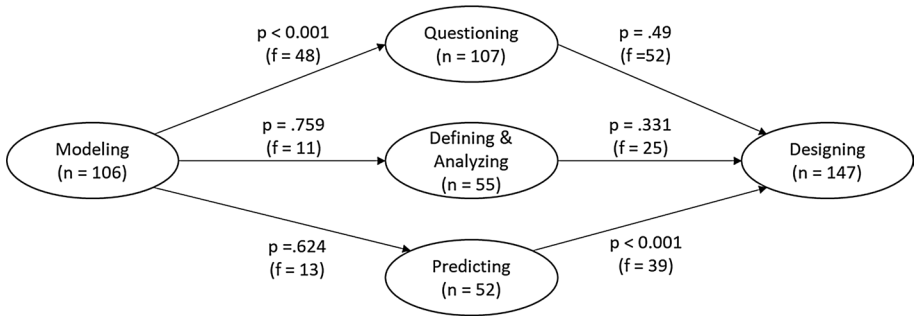


Fig. 6 Alternative transitional routes from modeling-to-designing strategy

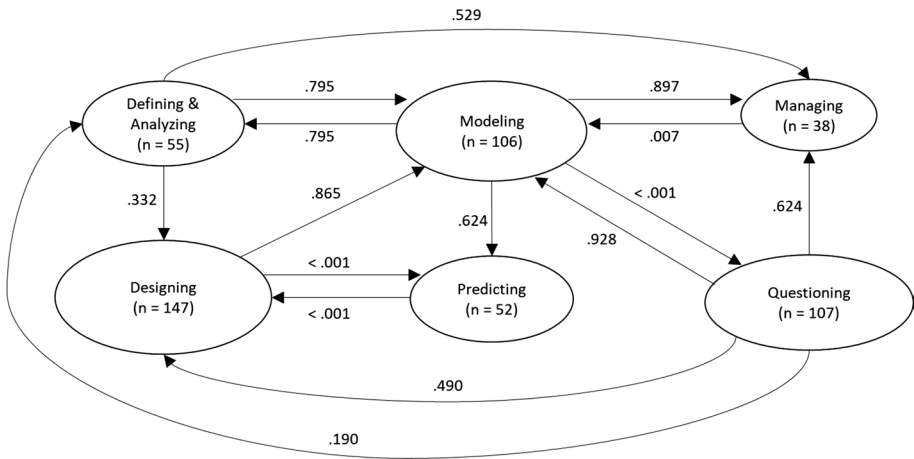


Fig. 7 A problem-solving pathway model using right-tailed probabilities of two-event sequences (positive z-scores). *Note* The numbers on the arrow lines are the p values of the transition from one to another. For example, the line from defining and analyzing to managing with 0.529 implies that the possibility of the transition from defining and analyzing to managing is 47.19% ($1 - p$ value) of the entire transitions from the state of defining and analyzing

diagram shows that participant students often began the design activity with defining and analyzing ($f=55$) the given problem statement. Then, they moved to designing solution ideas (*Defining and Analyzing* → *Designing*, $f=25$), modeling or sketching ideas (*Defining and Analyzing* → *Modeling*, $f=13$), or managing the team dialogue (*Defining and Analyzing* → *Managing*, $f=5$). When participants engaged in the *Designing* strategy ($f=147$), the most frequent cognitive strategy, they frequently proceeded to the *Modeling* strategy (*Designing* → *Modeling*, $f=48$), and *Predicting* (*Designing* → *Predicting*, $f=33$). These pathways illustrate that participants commonly used drawing or sketching to facilitate idea generation. Moreover, the bi-directional pathway between designing and predicting shows that predicting the consequence of the design ideas and generating design ideas involve a strong mental relationship.

The second most frequent strategy in the nine CTA sessions was the *Questioning* strategy ($f=107$). The transitions from *Questioning* provide a critical implication of how and

why participants maneuver strategy during the design process. After using the *Questioning* strategy, participants moved to *Designing* (*Questioning* → *Designing*, $f=52$), *Modeling* (*Questioning* → *Modeling*, $f=48$), *Defining and Analyzing* (*Questioning* → *Defining and Analyzing*, $f=14$), or *Managing* strategies (*Questioning* → *Managing*, $f=10$). The iterations surrounding the questioning strategies confirmed the role of doubt in design thinking, which energizes and enhances the quality of creative work by leveraging designing, modeling, and analyzing the problems (Locke et al. 2008). In addition, as the Next Generation Science Standards emphasized scientific inquiry (NGSS Lead States 2013), these results indicate that engineering and technology educators need to emphasize design inquiry ability when teaching design thinking (Dym et al. 2005).

Conclusions

The underlying idea of the study was to search for iterative design thinking patterns in young students' design problem-solving. The researchers expected that the investigation of young students' thinking patterns would provide a fundamental data point for understanding human cognition in terms of problem-solving. The first achievement of this study was the successful adoption of the sequential pattern analysis to detect patterns of students' problem-solving. The sequential pattern analysis was introduced in the early 1970s to identify patterns of behavioral interactions between mothers and infants (Gottman et al. 1977). The research method has been adopted in many studies to examine patterns of iterative behavior or cognitive events. The researchers confirmed that the use of sequential analysis successfully depicted the actual process of engineering design in young learners' problem-solving. As shown in Fig. 7, the results of two-event sequential analysis created a pathway model of cognitive strategy that illustrates the detailed iterations of design thinking.

Second, the researchers confirmed that the statistical analysis identified four significant two-event sequential patterns. The problem-solving patterns found in this study may be useful for engineering and technology teachers when instructing engineering design approach to students. For example, the iterative patterns between *Designing* and other cognitive strategies confirmed that when students generate ideas, designing is a central point of the entire process, often followed by drawing, predicting, or questioning. This pattern concurs with the idea that design is an ongoing process of developing and refining ideas (Dorst and Cross 2001). In addition, the iteration between *Designing* and *Predicting* illustrates that when young students were given an open-ended design problem, they tended to journey within the solution-space, often using the designing and predicting strategies ($t(\text{Designing} + \text{Predicting})=43:50.0$, 40.78% of the total duration). This result informs when instructing design lessons using engineering design approach, teachers might need to teach assessment technics such as *Decision Matrix* with ideation strategies (Kelley 2010). Moreover, the data provides evidence that the transition from *Modeling* to *Questioning* has a significant possibility at the 0.05 level. This result supports Goldschmidt's study (1991) that sketching is an important cognitive tool to externalize internal mental images. The use of the *Modeling* strategy has the same implications as Tversky (2003); sketching is a critical process of creative idea generation when designers make inferences from the *seeing that* objects of sketching.

Finally, the results of this study can contribute to improving the efficiency of teaching and learning by fitting teaching style and learning style. Felder and Silverman (1998) studied the relationship between learning and teaching styles in engineering education. They found that mismatched learning and teaching styles not only leads to poor student

performance, but also results in teacher frustration. Admittedly, like a human nature, multiple pathways of cognitive strategies exist to develop a successful design solution. Moreover, as Buchanan (1992) stated, a design problem has multiple solutions due to the indeterminacy of design problems, including clients, situations, criteria, constraints, resources, and even end users. The researchers believe that the accumulation of the strategic pattern data of design pathways will not only develop our understanding of design behavior, but also support the harmonious matching of learning and teaching styles in engineering and technology education.

Future works

Future work will include a comparative experiment between experts and novices to identify the effective design pathways of cognitive strategies. Atman et al. (2007) investigated how expert and novice designers use design strategies differently, and that expert designers tend to emphasize defining the problem and gathering information more than novice designers. The researchers believe that the comparative study will identify effective strategic patterns of the design process as well as better inform the greater engineering education community of effective design problem-solving strategies.

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