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Examining temporal dynamics of self-regulated learning behaviors in STEM learning: A network approach

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ABSTRACT

From a network perspective, self-regulated learning (SRL) can be conceptualized as networks of mutually interacting self-regulatory learning behaviors. Nevertheless, the research on how SRL behaviors dynamically interact over time in a network architecture is still in its infancy, especially in the context of STEM (sciences, technology, engineering, and math) learning. In the present paper, we used a multilevel vector autoregression (VAR) model to examine the temporal dynamics of SRL behaviors as 101 students designed green buildings in Energy3D, a simulation-based computer-aided design (CAD) environment. We examined how different performance groups (i.e., unsuccessful, success-oriented, and mastery-oriented groups) differed in SRL competency, actual SRL behaviors, and SRL networks. We found that the three groups had no significant difference in their perceived SRL competency; however, they differed in SRL behaviors of evaluation. Both the mastery-oriented and success-oriented groups performed more evaluation behaviors than the unsuccessful group. Moreover, the mastery-oriented group showed stronger interaction between SRL behaviors than the success-oriented group and the unsuccessful group. The SRL networks of the three groups shared some similarities, but they were different from each other in general. This study has significant theoretical and methodological implications for the advancement of research in SRL dynamics.

1. Introduction

Self-regulated learning (SRL) theory conceptualizes how learners engage in the processes of self-regulatory learning by coordinating their cognitive and metacognitive efforts towards the fulfillment of personal goals (Pintrich, 2000; Winne & Hadwin, 1998; Zimmerman, 2000). Perhaps one of the most dramatic advancements in SRL research is that the SRL process is increasingly examined as *events* that temporally unfold in real time during learning and problem-solving rather than *personal traits or aptitudes* (Azevedo, 2014; Sonnenberg & Bannert, 2019; Winne, 2019). SRL behaviors interact with each other over time, making up the internal dynamics and by that, the very nature of the learning process (Bringmann et al., 2016; Engelmann & Bannert, 2019). As a consequence, a range of

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methods has been introduced in the SRL research for detecting, tracking, collecting, and analyzing SRL data as events (Azevedo, 2014). In particular, the analytical techniques such as process pattern mining and state transition analysis that take the sequential and temporal structure of SRL behaviors into account, has gained growing attention from researchers (Bannert, Reimann, & Sonnenberg, 2014; Paans, Molenaar, Segers, & Verhoeven, 2019). As pointed out by Azevedo (2014), the cutting-edge analytical methods related to the examination of sequential and temporal characteristics of SRL have the potential to augment our understanding of the nature of SRL.

Of particular interest of this paper is to examine the temporal dynamics of students' SRL behaviors in STEM (sciences, technology, engineering, and math) learning. STEM tasks are often designed to foster divergent thinking and learning with limited external direction by nature. Therefore, STEM tasks emphasize the autonomous role of learner in uniquely constructing meaning, determining learning paces, making decisions, and evaluating learning outcomes. That is where self-regulated learning occurs, and new knowledge about SRL dynamics forms. Moreover, experienced teachers in STEM domains are increasingly emphasizing the cultivation of SRL skills among students rather than the technical side of STEM tasks (Barak, 2012). Thus, it is crucial to develop an understanding of the quality delivery of STEM education through the lens of SRL theories. Although there has been some progress towards answering this call, it remains unclear how students regulate their learning in solving STEM tasks and what kind of interactions between SRL behaviors lead to successful performance (Nelson, Shell, Husman, Fishman, & Soh, 2015; Zollman, 2012). In this study, we use a network approach to model the temporal dynamics of SRL behaviors in students' STEM learning. From a network perspective, SRL is considered to be a network of mutually interacting learning behaviors which leads to a new way of thinking about the SRL process. A network approach not only captures the sequential patterns of SRL behaviors but also reveals their bidirectional relationships: (1) the extent to which two SRL behaviors interact with each other and whether or not the interaction between the two behaviors is significant, and (2) whether the two behaviors stimulate or inhibit one another. By focusing on the interaction between students' self-regulatory learning behaviors, the network approach naturally captures the fact that SRL behaviors co-evolve dynamically (Bringmann et al., 2013): if an individual conducts a specific behavior (e.g., setting goals), that behavior can stimulate the occurrence of other behaviors as well (e.g., planning strategies to achieve goals). Therefore, instructors can provide timely interventions before undesirable behaviors occur, taking advantage of the network approach. Moreover, examining the temporal dynamics of SRL behaviors of different performance groups sheds light on the optimal trajectory to succeed in learning or problem-solving. Our study is one of the first to examine the interaction patterns of SRL behaviors in STEM learning using a network approach. In addition to adding to the theoretical discussions of the SRL process, this study provides the SRL field with unique methodological insights that can inform future studies and analytical practices.

2. Theoretical background

2.1. *Self-regulated learning*

Self-regulated learning (SRL) refers to an active, iterative process through which learners purposefully pursue pre-determined goals by controlling, monitoring, and regulating their cognitive/metacognitive processes and learning behaviors (Pintrich, 2000; Winne & Hadwin, 1998; Zimmerman, 2000). Researchers have reached a consensus that SRL is critical to students' performance in various domains and learning contexts (Lajoie et al., 2015, 2019; Li & Zheng, 2018; Sonnenberg & Bannert, 2019; Winne, 2019). In this study, we used Zimmerman's (2000) three-phase model of SRL because it provides a solid theoretical foundation for the analysis of students' problem-solving behaviors as they engage with STEM tasks. Specifically, the model proposes that learning consists of three cyclical phases: forethought, performance, and self-reflection. In the forethought phase, students seek to understand task environments, features, and requirements, e.g., what a specific engineering design task is asking them to do. Based on their perceptions of the task, students identify available resources, set individualized goals, and build plans to achieve their goals. In the performance phase, students take actions to fulfill their predetermined goals during which they consciously control and monitor their problem-solving processes. The last phase, self-reflection, involves students evaluating their performance and determining how to modify their plans, and the use of learning strategies for achieving better performance. In this study, we also referred to Winne and Hadwin's (1998) information-processing model of SRL, where SRL is describe as events embedded in a long series of transition states unfolding over time. We assume that the three phases of the SRL model are also recursive and weakly sequenced, which means that the output of

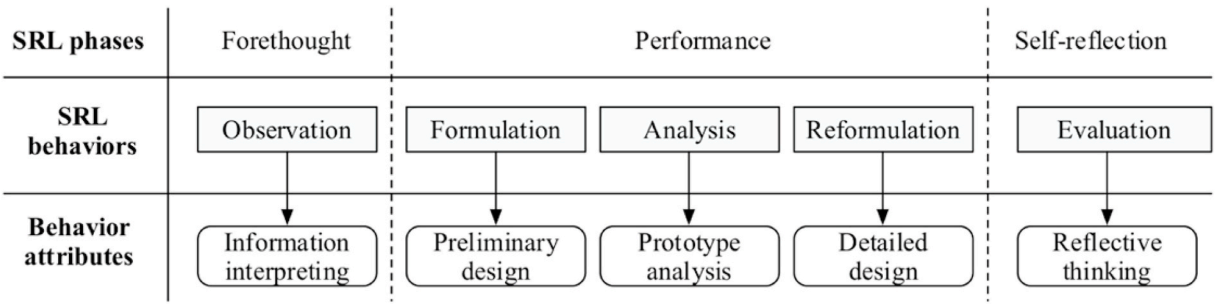

Fig. 1. The SRL model in engineering design.

earlier stages update conditions on which a student works during subsequent activities (Winne, 2019; Winne & Hadwin, 1998; Zimmerman, 2000). For instance, the output of self-monitoring in the performance phase provides the conditions that a student could reflect on his/her task progress and make fine-grained adaptations.

We adapted the three-phase model of SRL to explain students' learning for engineering design in a previous study (Li et al., 2020; Xing et al., 2019; Zheng et al., 2020). The model is shown in Fig. 1. Specifically, students develop an individualized understanding of the task in the forethought phase of SRL by familiarizing themselves with task environments and connecting environment-relevant information with specific task requirements. Learning behaviors that occur in this phase are referred to as observation behaviors in the context of engineering design. For example, students need to familiarize themselves with analysis functions if a task asks them to build a zero-energy building (a type of building that generates the same amount of energy as it consumes) in a computer-aided design environment. It is worth mentioning that observation behaviors are not necessarily regulatory activities, but they are considered as SRL behaviors, since self-regulated learners are aware of their observation-related behaviors and can make adaptations accordingly. In the performance phase, students generally conduct three types of behaviors (i.e., formulation, analysis, and reformulation) to accomplish the design goals depending on their perceptions of the task (Howard, Culley, & Dekoninck, 2008; Li et al., 2020; Zheng et al., 2020). It is noteworthy that the formulation, analysis, and reformulation behaviors contribute to the processes of preliminary design, prototype analysis, and detailed design, respectively. In particular, the formulation behaviors are to transform task requirements into design actions such as "add windows" or "add walls" in designing a zero-energy house. The analysis behaviors consist of the operations performed to analyze the features of a design artifact, and serve as an information function in that students become aware of the state and qualities of their design processes. For instance, students need to calculate the net annual energy of a house in the design process to check whether it is resource-efficient or not. Reformulation behaviors are triggered when students realize that the design state space needs to be revisited and changed to meet design specs. As an example, students may need to resize their house constantly if they notice that structure/function variables or ranges of values are not satisfactory. The self-reflection phase, typified by evaluation behaviors, involves students evaluating their design performance and determining how to improve their performance. In line with the theoretical contention that SRL phases are weakly sequenced (Winne, 2019), we hypothesize that SRL behaviors in engineering design occur in a specific order. If students are active self-regulated learners, their behaviors at an earlier stage (e.g., observation) should promote the behaviors later in the timeline of problem-solving (e.g., formulation) but not vice versa.

2.2. Research on the interplay of SRL behaviors

Researchers who consider SRL to be a dynamic interplay of various learning activities emphasize the importance of analyzing fine-grained traces of learning behaviors to understand performance differences of learners (Lajoie et al., 2015; Mudrick, Azevedo, & Taub, 2019; Sonnenberg & Bannert, 2019). Consequently, new analytical methods for capturing the evolving process of SRL are emerging and are increasingly being explored in various learning contexts (Azevedo, 2014). These techniques, such as process mining, sequential mining, state-transition analysis, co-occurrence analysis, and (Hidden) Markov Models, not only complement current stagnant methods and techniques (e.g., frequency analysis), but also have the potential to transform contemporary conceptions of SRL (Azevedo, 2014). For instance, Bannert et al. (2014) analyzed students' SRL processes in terms of a set of specific sequences of regulatory activities using the process mining (PM) algorithm of the Fuzzy Miner. In particular, the algorithm yields a transition diagram of learning activities when applied to event-based SRL data that is coded from verbal protocols. Mudrick et al. (2019) applied the sequential pattern mining algorithm to identify consecutive events that regularly occurred across participants. Specifically, the algorithm was applied to students' fixations on the AOIs (areas of interest) to understand their attention distribution patterns as students worked on multimedia science tests. It is worth mentioning that PM is different from sequential mining because the PM method assumes that the temporally-ordered event sequence is governed by one or more processes (i.e., process models), while sequential mining methods do not have such an assumption (Bannert et al., 2014). As another example, Lajoie et al. (2015) explored how co-regulatory episodes (e.g., changing the direction of previous activity) and self-regulatory metacognitive activities (e.g., planning and elaboration) co-occurred using co-occurrence analysis as students engaged in peer discussions in a synchronous computer-supported collaborative learning environment. Hidden Markov Models (HMM), a set of techniques to model temporal SRL data, are particularly useful in identifying frequently occurring sequence patterns when the states cannot be directly observed and can only be inferred from observable learning behaviors. For example, Jeong, Biswas, Johnson, and Howard (2010) derived an HMM regarding how students transitioned between different learning states (e.g., from initial state to assessment state and to wrap-up state) from their activity sequences. As pointed out by researchers, the novel analytical techniques that deal with sequentially and temporally unfolding data about SRL have forged new directions in the field (Azevedo, 2014; Kinnebrew, Loretz, & Biswas, 2013; Molenaar & Järvelä, 2014; Winne, 2019). Most importantly, the advancement of the analytical techniques provides new understandings of learning that traditional statistics cannot afford, such as: how students unfold the behavioral, cognitive, and metacognitive aspects of learning over time, and whether or not certain learning patterns are superior than others.

Recent attempts in advancing analytical methods have put emphasis on the temporal dependence of SRL behaviors in order to gather insights into SRL dynamics (Sonnenberg & Bannert, 2019; Winne, 2019). Temporal dependence refers to the degree to which current observations can be predicted by previous observation (Bringmann et al., 2017), for example, the degree to which a student's self-regulatory learning behavior at a given time is predictive of his/her behavior at subsequent time points. It is noteworthy that the temporal dependence of SRL behaviors is different from the concept of the sequential structure of learning behaviors. The analytical techniques that aim to reveal sequential and temporal patterns of SRL behaviors are exploratory in nature (Azevedo, 2014), whereas the techniques for analyzing temporal dependence of SRL behaviors attempt to uncover causal relationships between different behaviors. The network approach represents a good example of techniques assessing the temporal dependence of SRL behaviors. Instead

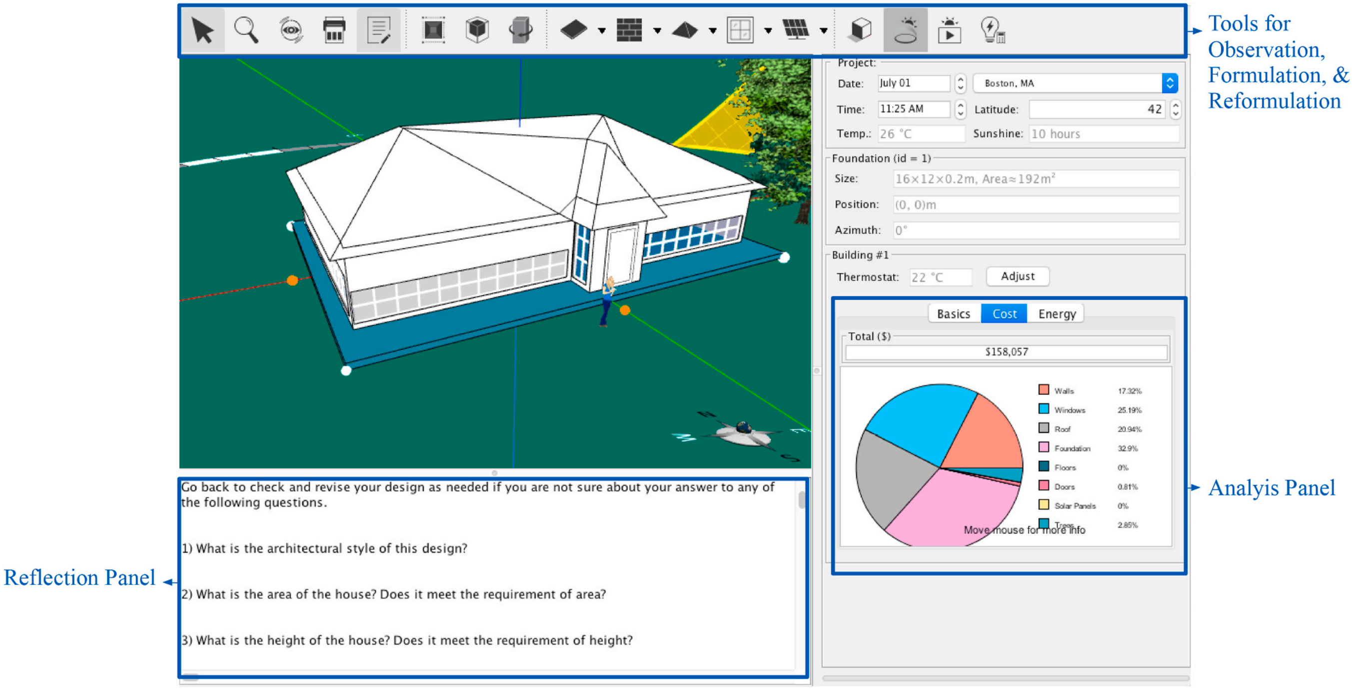

Fig. 2. Interface of Energy3D.

of merely describing the behavioral patterns, the network approach underscores how SRL behaviors interact with each other across time. A review of the literature suggests that network methodologies are currently being used in areas of clinical psychology, personality, and psychiatry (Bringmann et al., 2013; Cramer, Waldorp, Van Der Maas, & Borsboom, 2010). For instance, Bringmann et al. (2016) assessed temporal emotion dynamics and their relation to neuroticism from a network perspective. They created a population network (general patterns of edges connecting the emotion variables) and individual emotion networks to determine how different emotions augmented or blunted each other, and how the characteristics of the emotion networks (e.g., the density of the networks) associated with neuroticism. All in all, the network approach could enhance new understandings of student learning in STEM contexts by revealing not only the behavioral sequential patterns of students with various levels of performance but also the mechanisms about how the patterns are generated. To our knowledge, no research has used the network approach to model the interactions of SRL behaviors in STEM learning and engineering design in particular.

In the present study, we examine the temporal dynamics of SRL behaviors as students solve a STEM task related to engineering design while taking advantage of the network approach. We explore how SRL behaviors interact with each other over time and how these interactions may lead to performance differences. Moreover, we are interested in the explanatory power of SRL self-report surveys, actual SRL behaviors, and the SRL behavioral network in predicting learners' task performance. Self-report surveys are theorized under a view of metacognition that assumes learners can relatively accurately describe their learning experience and the characteristics of operations (e.g., frequency, intensity, and goal-orientation) applied to content (Winne, 2019). However, students tend to overestimate their use of study tactics in SRL due to recall mistakes and social desirability bias (Winne & Jamieson-Noel, 2002). Therefore, this study will inform future study designs and data collection practices in our efforts to compare the three measure approaches. Specifically, this study addresses the following two research questions:

(1) How do students' perceived SRL competency, SRL behaviors, and the interactions among SRL behaviors account for their performance?
(2) How do SRL behaviors dynamically interact with each other? Do students in different performance groups demonstrate different patterns of interactions among SRL behaviors?

3. Methods

3.1. Participants

A total of 111 ninth-grade students from a suburban high school located in the Northeastern United States volunteered and consented to participate in the study. This study was part of a larger project focusing on the modeling and simulation of engineering design in a computer-aided design (CAD) environment, Energy3D (Xie et al., 2018). Before the study, we received research ethics approval from the institutional review board. We also obtained an informed consent form from each student. In particular, students were enrolled in the physical science honors course, which was taught by a male teacher with over 17 years of experience in teaching physical sciences and five years' experience in mentoring engineering design projects. According to the information provided by the

Fig. 3. Colonial-style house.

school, the racial/ethnic demographics of the participants are as follows: 76.7% of students are White, 4.6% are Hispanic, 4.2% are African American, 3.4% are multi-race, 0.2% are Native American, and 0.2% are Native Hawaiian/Pacific Islander. Ten students did not complete the task in the current study, leaving a sample of 101.

3.2. Learning environment and task

Energy3D is a simulation-based CAD platform for engineering design, supporting science and engineering education and training from middle schools to graduate schools (Xie et al., 2018). Specifically, Energy3D supports the design, construction, and analysis of green buildings that are environmentally responsible and energy-efficient with 3D modeling tools (see Fig. 2). The tools enable users to sketch a realistic-looking house structure in a short time and provide them the real-time information on the cost and the energy performance of a house. In Energy3D, students begin a task by first exploring available functions of the platform (i.e., observation), such as rotating the building, zooming in and out for different views, and showing shadow, axes, or heliodon. In an effort to approach the task, students construct a house (i.e., formulation) by adding walls, windows, doors, roofs, solar panels, etc. To meet design specs, students are required to conduct a series of analyses, for instance, calculating the annual energy usage for heating and cooling. Based on their analysis results, students decide how to revise their design to improve the energy efficiency of the house, i.e., the reformulation process. They may resize the house, adjust the height for selected wall, add more trees, or change the color for the whole building. Moreover, the embedded prompts require students to reflect on their design performance throughout the design process. It is noteworthy that each step of students' operational behaviors is automatically recorded in the system log files.

In this study, the students' task was to design a Colonial-style house (see Fig. 3). In particular, a Colonial-style house should meet the following requirements: the house needs to demonstrate curb appeal; the ratio of the total area of windows to the floor area must be between 0.05 and 0.15; the roof overhang must be less than 50 cm wide; the area of the house needs to be between 120 and 160 m^2, and the height needs to be between 8 and 10 m; tree trunks must be at least 2 m away from the walls of the house. In addition, the budget for the house should be within $200,000. Most importantly, the house should generate renewable energy to achieve sustainable development throughout a calendar year.

Regarding the procedures, students were asked to complete a pre-test concerning their prior science knowledge on designing green buildings before attempting to solve the task. A researcher-guided practice was then provided to help students familiarize themselves with the Energy3D platform, and afterward, a two-page print-out of instructional materials was handed out to each student. The handout illustrated a typical design process, listed specific design requirements, and provided some important notes, e.g., the height of a house can be adjusted as a whole. After confirming that students had no concerns and questions about the task, they were asked to accomplish the design task independently. Specifically, students finished the task in a science course during regular school hours. Once the students finished the task, they received another questionnaire asking them to report their perceived SRL competency.

3.3. Measurements

Prior Science Knowledge. Students' science knowledge about the construction of green buildings was measured with an 18-question test. In particular, the test questions were drawn from green building science textbooks (Hens, 2016; Montoya, 2010), and they covered the following domains of scientific knowledge: sun path and insolation, spatial and geometric, and heat transfer and representations. To ensure that the questions were valid and appropriate, the test was reviewed by a panel of high school science teachers, green building science experts, engineering design professors, and learning scientists. The internal consistency has been confirmed in our previous work with a Cronbach's alpha value of 0.82.

Perceived SRL Competency. An eight-item questionnaire adapted from the Motivated Strategies for Learning Questionnaire (MSLQ) (Pintrich, Smith, Garcia, & Mckeachie, 1993) was tailored to assess students' perceived SRL competency in the context of engineering design. A sample item was "I ask myself questions to make sure I understand the energy analysis results I get for my building". The items were presented using a 5-point Likert scale where 1 means 'strongly disagree', 3 stands for 'neutral', and 5 indicates 'strongly agree'. The Cronbach's coefficient of the questionnaire was analyzed to test its internal consistency and yielded a value of 0.73.

SRL Behaviors. Based on the aforementioned model of engineering design and our previous work (Li et al., 2020; Xing et al., 2019; Zheng et al., 2020), we identified five types of SRL behaviors, i.e., Observation, Formulation, Reformulation, Analysis, and Evaluation, from the logged files of the Energy3D platform. The sample activities for each type of SRL behavior are shown in Table 1. It is worth mentioning that we took the context-dependent nature of SRL into consideration when clustering engineering design activities into SRL behaviors. For instance, the activity of making notes was considered as an evaluation behavior in our context but it does not necessary to be an evaluation behavior in other contexts. In addition, we referred to the listed behaviors as SRL behaviors since they fit

Table 1
Sample activities for each type of SRL behaviors.

SRL behaviors	Sample activities
Observation	Rotate building; Show shadow, axes, and heliodon.
Formulation	Add walls, windows, floors, doors, roofs, solar panels, and trees.
Analysis	Compute solar energy, net energy, and the total cost of the design; Animate sun; Generate energy graphs
Reformulation	Edit walls, windows, and roofs; Change background albedo; Change U-factor for selected part; Resize building
Evaluation	Make notes; Make subjective and structural reflection

in well with the three-phase model of SRL proposed by Zimmerman (2000). We recognized that students are active learners who can purposefully control, monitor, and regulate their learning processes. By labelling the behaviors as SRL behaviors, we also took on an information-processing perspective that the output of earlier behaviors updates the condition of subsequent behaviors (Winne, 2019). For example, the behaviors of adding walls or windows provide the condition that whether or not a learner could compute the total cost of the design.

3.4. Performance

Students' performance was indicated by the net annual energy of the Colonial-style house built in the task. In particular, the net annual energy of a house equals the total amount of energy a house consumes over a year minus the total amount of energy it produces. A negative value indicates that a house produces sufficient energy to support its sustainable development throughout a calendar year, suggesting that students meet the design requirement. The lower the net annual energy value, the more energy-efficient the house. It is noteworthy that students were required to report each version of their design, describe the changes they made, and record the net energy usage. We also took this information into consideration when evaluating students' performance. Specifically, we identified three groups of students. The first group consisted of 32 students who failed to design an energy-plus house. We labeled this group as the unsuccessful group. The second group involved 43 students who ended their design processes as soon as a negative value was obtained in terms of net annual energy. They reached the preliminary goal of the design. We labeled this group as the success-oriented group. Students in the last group made adaptations even though a negative value was obtained. They pursued excellence in their performance with continuing design adaptations. There were 26 students in this group, which we labeled as the mastery-oriented group.

3.5. Analysis

To address our first research question, multivariate analysis of covariance was conducted to assess group differences in students' perceived SRL competency, SRL behaviors (i.e., observation, formulation, analysis, reformulation, and evaluation), and the interactions among SRL behaviors (i.e., the density of SRL network which will be explained below), controlling for students' prior science knowledge.

To answer the second question, we examined the interaction between SRL activities using a network approach. A network has nodes and edges, and edges connect any two nodes. In a directed network, all the edges have a direction with a value indicating the strength of the connection between two nodes. The value of an edge, also known as weight, can be positive or negative. In our case, an SRL network for each participant has five nodes representing five SRL behaviors, i.e., Observation (OB), Formulation (FO), Analysis (AN), Reformulation (RE), and Evaluation (EV). The weight of an edge connecting two behaviors can be positive or negative, indicating one behavior stimulates or inhibits the other behavior. Specifically, the directed weighted edges between SRL nodes are obtained by the multilevel VAR (vector autoregressive) model (Bringmann et al., 2016).

The multilevel VAR model is a combination of multilevel modeling and the VAR model, while a VAR model can be considered to be a regression model in which multiple variables at time point *t* are regressed to a lagged (measured at a previous time point, *t-1*) version of those same variables (Bringmann et al., 2013). By combining multilevel modeling and a VAR model, the multilevel VAR model enables temporal dynamics to be modeled at both individual and group levels. To build an SRL network for each participant, we segmented each student's design process into ten equal time periods. We calculated the frequencies of the five types of SRL behaviors for each time period. Those data served as the basis for our network analysis. To be specific, for each participant *p*, the frequency *Y* of current SRL behavior *i* at time *t*, can be predicted by all of the participant's former behaviors at time *t-1*, represented by the following equations:

$$\begin{aligned} Y_{pit} = a_{0pi} + w_{1pi}{*}Observation_{p,\,t-1} + \ w_{2pi}{*}Formulation_{p,t-1} + \ w_{3pi}{*}Analysis_{p,t-1} \\ + w_{4pi}{*}Reformulation_{p,\,t-1} + \ w_{5pi}{*}Evaluation_{p,t-1} + \varepsilon_{pit} \end{aligned} \tag{1}$$

, where $i \in \{Observation, Formulation, Analysis, Reformulation, Evaluation\}$, $p \in \{1, 2, \ldots, 102\}$, $t \in \{1, 2, \ldots, 10\}$, $Y \in \boldsymbol{N}$, ε is the white noise process. There are five different SRL behaviors; therefore, the multilevel VAR model will generate five equations for each participant. To generalize (1), we get:

$$\mathbf{y}(\mathrm{t}) = \boldsymbol{a} + \boldsymbol{w}_1 * Observation(t-1) + \boldsymbol{w}_2 * Formulation(t-1) + \boldsymbol{w}_3 * Analysis(t-1) + \boldsymbol{w}_4 * Reformulation(t-1) + \boldsymbol{w}_5 * Evaluation(t-1) + \boldsymbol{\varepsilon} \tag{2}$$

, where $\mathbf{y}$ is a matrix of all Y_{pit}, and so forth. As an example, $\boldsymbol{w}_1$ is the coefficient matrix of all five SRL behaviors in predicting the frequency of *Observation* in the next time period. From a network perspective, $\boldsymbol{w}_1$ is a set of weight values whose edges start from the nodes of *OB*, *FO*, *AN*, *RE*, *EV*, and point to the node *OB*. With the coefficient matrices from equation (2), we build an individual network for each participant. Moreover, the density was computed for each individual SRL network by averaging over the absolute values of the edges (the slopes) in the network, following the practice in Bringmann et al.'s (2016) research.

It is noteworthy that the coefficient matrix of equation (2) can be decomposed as:

$$\boldsymbol{w} = \boldsymbol{\beta} + \boldsymbol{b} \tag{3}$$

, where β is the matrix of the fixed effects indicating how one behavior during a previous time period can be used to predict itself or another behavior in the following time window for all participants. b refers to the random-effects matrix, which indicates the deviation for each value. With β, we can build an overall SRL network to examine general interaction patterns between SRL behaviors. In addition, we built three separate SRL networks for the three performance groups, i.e., the unsuccessful, success-oriented, and mastery-oriented groups, in order to compare differences in their interaction patterns of SRL behaviors.

Regarding the analyses, it is important to mention that a key assumption of data stationarity should be met to use the multilevel VAR model, which means that data properties such as mean, variance, and covariance do not change over time. We performed the Augmented Dickey-Fuller (ADF) test with the Python 3 *statsmodels* module to check this assumption. The results suggested all the p-values for the five types of SRL behaviors were significant, indicating that our data did not violate the stationarity assumption.

4. Results

(1) How do students' perceived SRL competency, SRL behaviors, and the interactions among SRL behaviors account for their performance?

The results of multivariate analysis of covariance showed that there was a statistically significant difference between the three groups (i.e., unsuccessful group, success-oriented group, and mastery-oriented group) on the dependent variables after controlling for students' prior science knowledge, $F(2, 97) = 1.894$, $p = .029$, Wilks' $\Lambda = 0.762$, partial $\eta^2 = 0.127$. A follow-up univariate analysis of covariance, as shown in Table 2, indicated that the three groups had no significant difference in their perceived SRL competency. There were also no significant differences in students' SRL behaviors except the Evaluation behavior. In particular, both the mastery-oriented group ($M = 316.08$) and the success-oriented group ($M = 252.47$) conducted significantly more evaluation behaviors than the unsuccessful group ($M = 150.63$), $F(2, 97) = 4.449$, $p = .014$, partial $\eta^2 = 0.084$. It is noteworthy that the effect size value ($0.084 >$ medium effect size of 0.059) suggested a moderate to high significance (Cohen, 1988; Richardson, 2011). Furthermore, the three groups differed significantly in SRL network density, $F(2, 97) = 3.636$, $p = .030$, partial $\eta^2 = 0.070$. Specifically, students in the mastery-oriented group ($M = 18.31$) demonstrated stronger interactions among SRL behaviors than those in the success-oriented group ($M = 13.19$) and the unsuccessful group ($M = 13.94$).

(2) How do SRL behaviors dynamically interact with each other? Do students in different performance groups demonstrate different patterns of interactions among SRL behaviors?

Fig. 4 shows the general interaction patterns between the SRL behaviors (i.e., overall network in the top left corner) and the SRL network for each of the three groups. From Table 3 and Fig. 4, a few insights on the dynamical network structure between the five SRL behaviors can be derived. First, consistent with a dynamic view of the SRL process, the SRL behaviors form a cluster representing self-perpetuating cycles in which learning behaviors interact. Moreover, the figure shows that SRL behaviors can either augment or blunt each other. Augmenting refers to one SRL behavior stimulating another behavior, whereas blunting refers to one SRL behavior

Table 2
Univariate tests of the Dependent Variables for the Three Groups.

	Group	Mean	SD	F	Sig.	η_p^2
Perceived SRL competency	1	3.56	.70	.616	.542	.013
	2	3.40	.76			
	3	3.56	.85			
Observation	1	1024.22	881.46	.004	.996	.000
	2	1020.49	664.26			
	3	1027.73	625.88			
Formulation	1	127.47	89.81	.957	.388	.019
	2	127.60	86.70			
	3	103.12	59.45			
Analysis	1	88.00	85.48	.247	.782	.005
	2	97.93	96.00			
	3	100.15	84.68			
Reformulation	1	313.78	289.83	.610	.545	.012
	2	329.63	260.94			
	3	268.54	144.03			
Evaluation	1	150.63	207.80	4.449	.014[a]	.084
	2	252.47	191.22		Group 2 > 1[a]	
	3	316.08	252.31		Group 3 > 1[a]	
The density of SRL Network	1	13.94	6.85	3.636	.030[a]	.070
	2	13.19	5.88		Group 3 > 1[a]	
	3	18.31	12.20		Group 3 > 2[a]	

Note.
Group 1 = unsuccessful group, Group 2 = success-oriented group, Group 3 = mastery-oriented group. η_p^2 refers to partial eta squared which is a measure of effect size. The range of perceived SRL competence is from 1 to 5, the density of SRL network was calculated as the mean of the absolute values of the edges (the slopes) in the network, and the other items were compared in terms of the average number of behaviors.

[a] $p < .05$

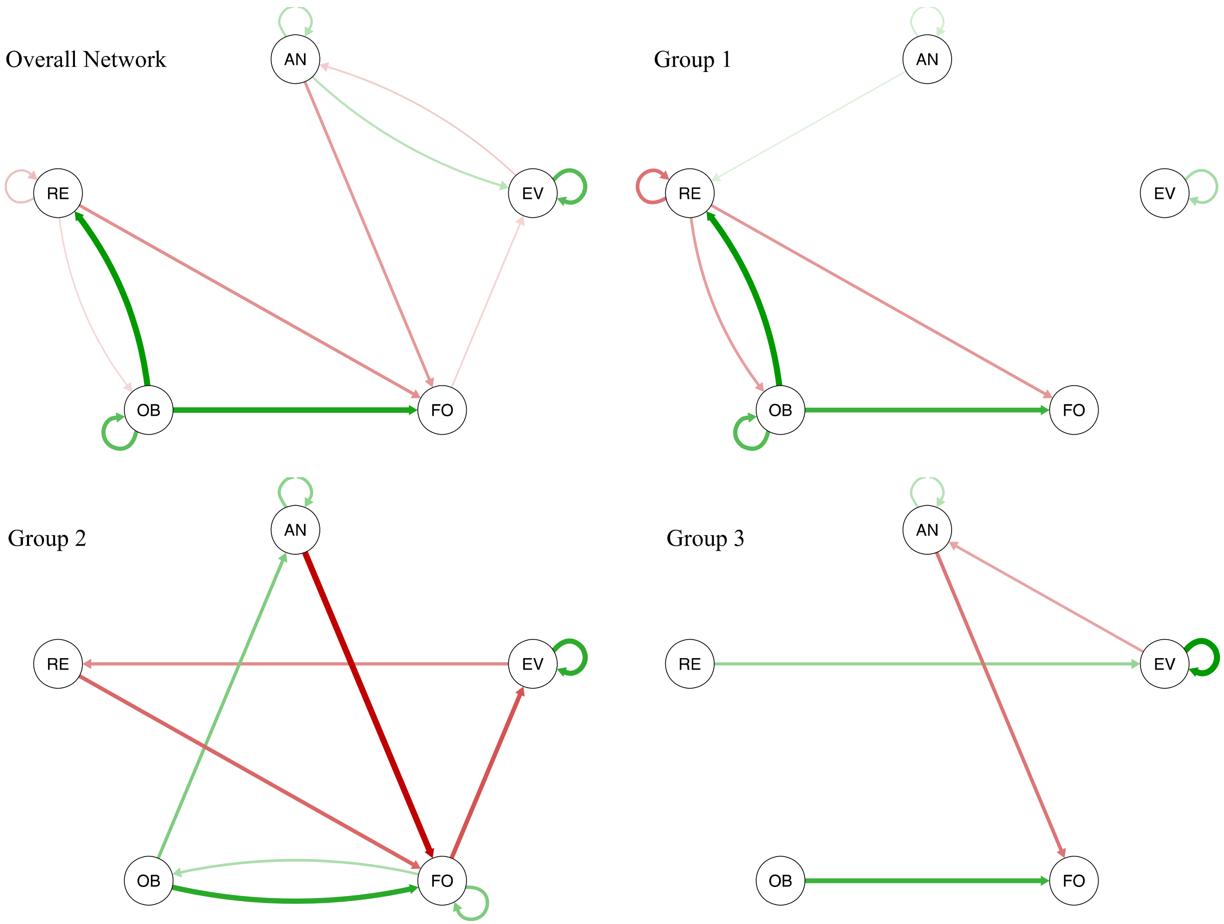

Fig. 4. The overall SRL behavior network and the networks for each group. Only edges that surpass the significance threshold (i.e., p = .05) are shown. Note: OB = Observation, FO = Formulation, AN = Analysis, RE = Reformulation, EV = Evaluation. The red arrows are the negative (i.e., inhibitory) edges, and the green arrows are the positive (i.e., excitatory) edges. The thickness of the arrows indicates the strength of the edges. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

inhibiting a subsequent one (Bringmann et al., 2013). It is worth mentioning that the only edges that were significant ($p < .05$) are shown in Table 3 and Fig. 4. In particular, the green arrows in Fig. 4 are the positive (i.e., excitatory) edges, and the red arrows are the negative (i.e., inhibitory) edges. For example, in general when a student performs an observation behavior, she or he is more likely to conduct a formulation behavior at the next moment. Students are less likely to perform a formulation behavior as a next step if they are engaging in analysis behaviors. Furthermore, the results show that students in different performance groups share some similarities in the interaction patterns among SRL behaviors. In particular, observation behaviors significantly stimulate formulation behaviors for the three groups. The networks of all three groups have self-loops for the analysis and the evaluation behaviors. However, the networks of the three groups are different from each other in general.

With regard to the network of group 1 (i.e., the unsuccessful group at the top right of Fig. 4), it has a unique self-loop for the SRL behaviors of observation, indicating that students tended to perform such behaviors repetitively in the design process. Compared with the networks of the other two groups, the network of group 1 also has a unique self-loop for reformulation behavior. Specifically, the current reformulation behavior negatively predicts future behaviors of reformulation. Moreover, the network shows that both observation and analysis behaviors positively predict reformulation behaviors, which is different from those of the other two groups. In addition, there are no significant interactions between the evaluation behavior and any other SRL behaviors for this group of students. The evaluation behavior is isolated in the network.

Regarding the success-oriented group, the network (bottom left corner of Fig. 4) reveals that the observation behavior positively predicts the analysis behavior. In addition, there is a positive interaction between the observation and the formulation behaviors, showing that students conducted these two types of behaviors alternately for a relatively long time. Additionally, the network of this group differs from the other two groups in that the formulation behavior negatively predicts the evaluation behavior, while the evaluation behavior negatively predicts the reformulation behavior.

For the mastery-oriented group, the network (bottom right corner of Fig. 4) demonstrates a clear and meaningful interaction pattern among SRL behaviors. In particular, the reformulation behavior significantly stimulates the evaluation behavior. Moreover, the evaluation behavior negatively predicts the analysis behavior, and the latter negatively predicts the formulation behavior.

5. Discussion

The results demonstrated that the three groups (i.e., unsuccessful, success-oriented, and mastery-oriented groups) had no significant difference in their perceived SRL competency; however, they differed in SRL behaviors of evaluation. These results inform future research in that perceived SRL competency does not equate to actual SRL behaviors. Perceived SRL competency is one's subjective judgment of his/her self-regulatory skills. Students may over- or under-estimate their SRL competency in solving complex problems.

Table 3
The temporal connections between SRL behaviors of the three groups.

Group	SRL Behavior	Temporal Effect	*S.E.*	*p*
Group 1	Analysis → Analysis	.186	.066	.005[b]
	Analysis → Reformulation	.134	.062	.031[a]
	Evaluation → Evaluation	.351	.074	.000[c]
	Observation → Formulation	.752	.112	.000[c]
	Observation → Observation	.654	.081	.000[c]
	Observation → Reformulation	.982	.090	.000[c]
	Reformulation → Formulation	-.402	.104	.000[c]
	Reformulation → Observation	-.375	.075	.000[c]
	Reformulation → Reformulation	-.543	.084	.000[c]
Group 2	Analysis → Analysis	.124	.052	.017[a]
	Analysis → Formulation	-.277	.075	.000[c]
	Evaluation → Evaluation	.228	.079	.004[b]
	Evaluation → Reformulation	-.128	.054	.018[a]
	Formulation → Evaluation	-.186	.073	.011[a]
	Formulation → Formulation	.140	.065	.030[a]
	Formulation → Observation	.093	.047	.050
	Observation → Analysis	.139	.063	.027[a]
	Observation → Formulation	.233	.092	.011[a]
	Reformulation → Formulation	-.165	.080	.038[a]
Group 3	Analysis → Analysis	.132	.067	.050
	Analysis → Formulation	-.246	.101	.015[a]
	Evaluation → Analysis	-.164	.064	.011[a]
	Evaluation → Evaluation	.453	.098	.000[c]
	Observation → Formulation	.346	.136	.011[a]
	Reformulation → Evaluation	.191	.093	.040[a]

Note.
S.E. = Standard Error. Group 1 = unsuccessful group, Group 2 = success-oriented group, Group 3 = mastery-oriented group.
[a] $p < .05$.
[b] $p < .01$.
[c] $p < .001$.

This result is partially in line with the research of Winne and Jamieson-Noel (2002), who examined the calibration of self-reports about study tactics and its relations to task performance. They found that students were positively biased about (overestimated) their use of study tactics in SRL, although the self-report unequivocally represented students' perceptions about how they studied. Our study added more evidence about the superiority of trace data to self-reports when exploring SRL processes, considering that calibration bias and inaccuracy in self-reports may result in misinterpretations about what students actually did when they solved a task. In an effort to examine group differences in SRL behaviors recorded in log files, we found that students in different groups varied in their evaluation behaviors. Specifically, both the mastery-oriented group and the success-oriented group performed significantly more evaluation behaviors than the unsuccessful group. Evaluation, in our research context, refers to comparing self-monitored information with design specs, whereby self-feedback is generated to guide future actions such as reformulation and reanalysis. Consistent with theoretical claims and an abundance of empirical evidence, the evaluation behavior is proven to be a crucial element of SRL that leads to performance differences ((Sonnenberg & Bannert, 2019; Xing et al., 2019; Zimmerman, 2000).

A key finding of this research is that the density of an SRL network (how strongly the network of SRL behaviors is interconnected; Newman, Barabási, & Watts, 2006) was found to play a significant role in predicting students' performance. Specifically, students in the mastery-oriented group showed stronger interactions among SRL behaviors than those either in the success-oriented group or the unsuccessful group. This result indicated that the decision-making process of the mastery-oriented group was based on the information they gathered to a greater extent than the other two groups. In general, students' choices of current behaviors were affected more by their previous behaviors, while their current behaviors had a greater influence on their subsequent behaviors for the mastery-oriented group when compared to the other groups. A further explanation is that students in the mastery-oriented group thought about their actions deliberately in a rational, evidence-based manner instead of performing behaviors randomly when solving problems. One implication of this finding is that future educational researchers should take the intensity of the interactions among SRL behaviors into consideration. Only when accounting for how strongly the SRL behaviors are interconnected can the students' decision-making processes and academic functioning be fully and accurately understood. This study also informs the educational practice in terms of intelligent learning diagnosis and instructional scaffolding, considering that the behaviors of mastery-oriented group are more predictable than the other two groups.

As another noteworthy contribution, our findings provide insight into the temporal dynamics of SRL behaviors and how these behaviors influence each other or themselves at a group level. In line with the SRL studies that consider the "fundamental unit" of SRL as an IF-THEN rule (Winne, 2019), we found that an operation (THEN) can be either applied or restrained when particular conditions (IFS) are presented. For instance, in general when a student performs an observation behavior, she or he is more likely to conduct a formulation behavior at subsequent time points. Students are less likely to perform a formulation behavior at the next moment if they are performing analysis behaviors. From a network perspective, SRL behaviors can either augment or blunt each other. In addition, we found that students in different performance groups shared some similarities in the interaction patterns among SRL behaviors. As an example, the SRL networks of the three groups all have self-loops for the analysis and evaluation behaviors. However, the networks of the three groups are generally different from each other. We discussed the differences in SRL networks of the three groups below to gather insights about performance differences.

The network of the unsuccessful group has a unique self-loop for the SRL behaviors of observation. It is highly possible that students in this group could not identify influential features of the task environment through self-observation, and thus they conducted the observation behaviors recurrently. In contrast with the other two groups, the unsuccessful group also has a unique self-loop for reformulation behaviors. Nevertheless, the current reformulation behaviors inhibited such types of behaviors for the next moment. In the context of engineering design, the presence of reformulation behaviors is supposed to be based on analysis results. Students in the unsuccessful group may be incapable of completing a comprehensive analysis of their design artifacts and therefore could not maintain a series of reformulation attempts to meet the design criteria. Moreover, one notable difference in SRL networks between the unsuccessful group and the other two groups is that the prior group showed no significant interactions between the evaluation behavior and any other SRL behaviors. Considering the key role of evaluation in SRL, perhaps this is the very reason that the unsuccessful group failed to achieve their goals.

With regard to the network of the success-oriented group, it is unique in that there is a positive interaction between the observation and the formulation behaviors. It seems that students in this group approached the task by observing and initiating design ideas alternately, whereas the other two groups began to construct their houses only when a complete and careful observation was made. This result helps us understand how different groups of students interpret and react to tasks, resulting in different problem-solving trajectories. In addition, the network of the success-oriented group shows a distinctive pattern of students' observation behavior (information collection and interpretation) stimulating their analysis behavior (prototype analysis). This result is beyond our expectations as observation behaviors are supposed to stimulate formulation behaviors, which then promote the behaviors of analysis from the perspectives of SRL theories and the engineering design circle (Xing et al., 2019; Zheng et al., 2020; Zimmerman, 2000). One possible reason is that students in this group hastened to accomplish the task, so that they checked the analysis functions even before constructing the house. Future research is needed to examine this pattern more explicitly. Moreover, the network differs from the other two groups in that formulation behaviors negatively predicted evaluation behaviors, while evaluation behaviors inhibited reformulation behaviors. Considering that this group was not intent on performance excellence, it might be the fact that they were reluctant to reformulate their design ideas as long as the task was addressed, regardless of the evaluation products. Qualitative studies and results are needed in the future to shed light on the explicit explanation of this phenomenon.

In terms of the mastery-oriented group, the network demonstrates a clear and meaningful interaction pattern among SRL behaviors. Specifically, reformulation behaviors stimulated evaluation behaviors, while evaluation behaviors inhibited analysis behaviors, and analysis behaviors inhibited formulation behaviors. Adding to a clear logic of engineering design, these patterns are in line with the theoretical claim that SRL behaviors at earlier stages update conditions on which a student works during subsequent activities (Winne & Hadwin, 1998). Despite the contention of educational psychologists that the three phases of SRL are weakly sequenced, the three phases do not necessarily unfold in linear order (Pintrich, 2000; Winne & Hadwin, 1998; Zimmerman, 2000), our results suggested further that SRL behaviors even in the same phase of SRL occur in sequence. Moreover, SRL behaviors restrain the occurrence of behaviors at earlier stages, indicating that students in this group perform quality SRL behaviors for each step of problem-solving so that they do not need to repeat previous behaviors.

This study has significant theoretical and methodological implications for the advancement of the research in SRL dynamics. The current SRL literature shows a clear lack of studies that have examined the temporal dynamics of SRL behaviors in detail and its relations to performance (Winne, 2019). Thus, there is a great need for rethinking study designs and analytical methods in this area of research to capture the dynamic effects of SRL behaviors. Our study enables a shift in the paradigm from static ways of conceptualizing SRL towards studying dynamic learning processes, which has the potential to develop a deep understanding of students' decision-making procedures and to improve learning outcomes accordingly. Furthermore, we combined the VAR model with a multilevel model, which allowed us to model the temporal dynamics of SRL behaviors not only within an individual, but also at the group level. To the best of our knowledge, the combination of both modeling approaches has not yet been applied to study students' SRL behaviors in STEM education and in the context of engineering design in particular. The network perspective provides a novel vision of the dynamic change processes of SRL that may open new and interesting scientific leads to come closer to the essence of students' learning and problem-solving.

6. Conclusion

In this study, the problem-solving process is understood as networks of interacting SRL behaviors. Therefore, we used a network approach and the multilevel-VAR model in particular to study the interaction between SRL behaviors, as 101 students designed green buildings in Energy3D, a simulation-based computer-aided design (CAD) environment. Specifically, we examined how different performance groups (i.e., unsuccessful, success-oriented, and mastery-oriented groups) differed in SRL competency, actual SRL behaviors, and SRL networks. We found that the three groups had no significant difference in their perceived SRL competency; however, they differed in SRL behaviors of evaluation. Both the mastery-oriented and success-oriented groups performed more evaluation behaviors than the unsuccessful group. Moreover, the mastery-oriented group showed stronger interaction between SRL behaviors (a denser SRL network) than the success-oriented group and the unsuccessful group. The SRL networks of the three groups shared some similarities, but they were different from each other in general. In addition to the theoretical contribution concerning studying SRL dynamics, this study introduced a novel methodology to model the temporal interaction between SRL behaviors.

Moreover, this study provides implications for practitioners who strive to help students be more academically successful. The visualization of the dynamic interaction between SRL behaviors provides an immediate intuitive understanding of the complex structure of SRL network, and allows instructors to visually pinpoint the differences in SRL processes among different performance groups. For one, instructors would be more confident to intervene if they find that some students conduct a certain behavior repeatedly. Our findings also highlight a potentially superior pathway for solving STEM tasks. In particular, students who demonstrate a clear and logical behavioral pattern in problem-solving are those who are more likely to succeed. Hence, instructors should increase students' cognitive and metacognitive awareness in terms of controlling and monitoring their learning behaviors. With regard to student assessment, our findings suggest that actual SRL behaviors and their temporal connections are more reliable than self-report surveys in predicting students' performance.

Although the present findings increase knowledge of the temporal dynamics of SRL behaviors, this study is not without limitations. Because the participants came from the same school in the Northeastern United States, we cannot make a conclusive argument that an SRL network is powerful enough to understand performance differences for students in different age groups and from different institutions. Another limitation is that we built SRL network in terms of behaviors rather than mental activities. In addition, the SRL networks illustrate the group differences, but researchers still need to make inferences about why specific interaction patterns of SRL behaviors occur and how these patterns account for students' performance. Moreover, it is possible that one behavior stimulates the occurrence of two other SRL behaviors simultaneously, which requires a new level of complexity in our thinking about SRL dynamics.

For research moving forward, it would be interesting to shift the focus from the quantity of SRL behaviors to their qualities. For example, this study found that the success-oriented group and the mastery-oriented group showed no difference in the number of the evaluation behaviors. Zimmerman (2000) differentiated two distinctive types of criteria that students use to evaluate their task performance: previous performance, and normative. Previous performance criteria consist of comparisons of current performance with earlier levels of one's behavior, whereas normative criteria involve social comparisons with the performance of others. It is highly possible that the mastery-oriented group is predisposed to using previous performance criteria, and the success-oriented group tends to use normative criteria for self-evaluation. The mechanisms underlying the presence of SRL behaviors need to be revealed in a more qualitative approach. Moreover, much work remains to be done when it comes to linking engineering design activities to a specific type of SRL behaviors due to the context-dependent nature of SRL. As a closing remark, the network approach opens a range of new questions and possibilities. For one, an informative feature of the network is node centrality, which refers to the importance of a node or how focal one specific variable or node is in the network (Bringmann et al., 2016; Freeman, 1978). Of particular interest for future research is to examine how much information a node (e.g., reformulation) receives from the other nodes, and how much information a node (e.g., evaluation) sends to other nodes. It would also be fruitful to explore how fast an SRL behavior such as analysis can be reached from the other behaviors in the network when taking closeness centrality into account. Another possible avenue for future research is to examine the SRL behavioral network in other domains and learning contexts.

Credit author contribution statement

Shan Li: Writing - original draft, Conceptualization. Hanxiang Du Chen: Methodology, Formal analysis, Writing - original draft. Wanli Xing: Conceptualization, Methodology, Writing - review & editing, Supervision. Juan Zheng: Writing - review & editing. Guanhua Chen: Formal analysis. Charles Xie: Project administration, Software.

Declaration of competing interest

The authors declare that they have no conflict of interests.

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