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Longitudinal clustering of students' self-regulated learning behaviors in engineering design

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ABSTRACT

It is vital to develop an understanding of students' self-regulatory processes in the domains of STEM (Science, Technology, Engineering, and Mathematics) for the quality delivery of STEM education. However, most studies have followed a variable-centered approach, leaving open the question of how specific SRL (Self-regulated Learning) behaviors group within individual learners. Furthermore, little is known about how students' SRL profiles unfold over time in STEM education, specifically in the context of engineering design. In this study, we examined the change of students' SRL profiles over time as 108 middle school students designed green buildings in a simulation-based computer-aided design (CAD) environment. We identified three distinct SRL profiles using a longitudinal clustering approach: reflective-oriented, adaptive, and minimally self-regulated learners. In addition, we found that students with different profile memberships differed significantly in their design performance. Specifically, adaptive self-regulated learners outperformed minimally self-regulated learners on design completeness, whereas reflective-oriented self-regulated learners demonstrated higher design efficiency than minimally self-regulated learners. This study provides researchers with both theoretical and methodological insights concerning SRL dynamics. Findings from this research also inform practitioners about the design of adaptive interventions.

1. Introduction

Self-regulated learning (SRL) has become an important topic in the fields of education and psychology in the last three decades (Azevedo & Gašević, 2019; Boekaerts, Maes, & Karoly, 2005; Schunk & Greene, 2018; Steffens, 2006; Winne, 2019). As indicated by researchers, one of the primary goals of education should be fostering students' SRL skills (Greene, 2018; Greene, Costa, & Dellinger, 2011; Winne & Hadwin, 1998; Zimmerman, 2000). Self-regulated students can effectively activate and monitor their behaviors, cognition, and affect, and thus are more likely to succeed in achieving personal goals than those who lack adequate self-regulatory skills (Yang, Chen, & Chen, 2018). In a broad sense, we live in an age in which lifelong learning is becoming more and more important. Learning beyond formal education contexts requires self-regulatory skills to a greater extent (Steffens, 2006). In parallel to the rising interest in self-regulated learning, STEM (science, technology, engineering, and mathematics) education is increasingly

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gaining global attention because it plays a critical role in driving innovation and productivity growth (DeCoito, 2016). It is noteworthy that SRL can serve as an effective approach for students to improve their performance in STEM disciplines, and SRL skills are teachable (Barak, 2012; Greene et al., 2019, p. 101201). For instance, experienced engineering teachers nowadays are increasingly emphasizing self-regulated learning among students instead of merely focusing on the technical side of engineering work (Barak, 2012). For the successful and quality delivery of STEM education, it is vital to develop an understanding of students' self-regulatory processes in the domains of STEM, especially in specific STEM activities and tasks.

Examinations of students' SRL processes have typically focused on group differences, the relative contribution of each separate type of SRL behaviors and the many interaction, mediator, and moderator effects among them (Jang et al., 2017; Li & Zheng, 2018; Shell & Soh, 2013; Zimmerman, 2008). Most studies in the SRL field have followed a variable-centered approach, leaving open the question of how specific SRL behaviors or strategies group within individual learners (Greene et al., 2011; Jang et al., 2017; McCardle; Hadwin, 2015). A person-centered approach allows us to identify and classify learners who share common patterns of learning behaviors or self-regulatory characteristics. It is also more suitable than traditional variable-oriented statistical approaches to examine if students favor one or two SRL behaviors over others. While research on individual profiles in SRL is emerging, researchers have proposed that SRL profiles are dynamic per se (Jang et al., 2017; Shell & Soh, 2013). Students shift their learning profiles across different domains and even within a course in response to contextual factors (Shell & Soh, 2013). Furthermore, Jang et al. (2017) claimed that the change of SRL profiles occurs in more fine-grained task environments. They argued that students' learning profiles must be updated based on learners' interactions with specific tasks in order to provide immediate and dynamic feedback. However, little is known about how students' SRL profiles unfold over time in STEM education, specifically in the context of engineering design. This study aims to address this gap by examining the time-course nature of SRL profiles in engineering design, which is one of the first in this context to our knowledge. Moreover, we focused on engineering design tasks since the outcome of engineering design includes not only the acquisition of domain knowledge but also a practical solution to a real-world problem. In addition, engineering design tasks are usually ill-structured problems with no clear procedural or predetermined solution path. Examining the changes of SRL profiles in such tasks could provide researchers insights about how students choose many different solutions to solve a genuinely unique problem. In order to understand how SRL profiles unfold, "SRL cannot be measured as aggregated across time and tasks, nor can it be measured as a single learning event" (McCardle & Hadwin, 2015, p. 60). Therefore, this study applied a longitudinal person-centered learning analytics approach (Xing, Lee, & Shibani, 2020; Zhu, Xing, & Popov, 2019), which allowed us to track and identify developmental patterns among different SRL profiles. This study provides researchers with both theoretical and methodological insights. Findings from this research may also inform practitioners about the design of adaptive interventions.

2. Theoretical framework

2.1. Self-regulated learning and engineering design

Self-regulated learning (SRL) is a widely adopted paradigm of research in the scientific literature that claims students' ability to engage in self-regulatory processes is critical to task performance in STEM domains (Nelson, Shell, Husman, Fishman, & Soh, 2015; Shell & Soh, 2013; Zimmerman & Martinez-Pons, 1988; Zimmerman & Schunk, 2011). Specifically, 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, 2019). In particular, this study used Zimmerman's (2000) model of SRL as a theoretical framework to examine students' self-regulatory processes, which consisted of three cyclical phases: forethought, performance, and self-reflection. We used this model because it can appropriately explain students' behaviors in light of our research context, i.e., engineering design. In the forethought phase, students identify the requirements of a learning task (task analysis), set learning goals, and develop plans to achieve their goals. The performance phase involves the actions taken to complete the task that are consciously controlled and monitored by students. In the self-reflection phase, students evaluate whether their behaviors/efforts yield the expected performance and make adjustments correspondingly. It is noteworthy that the three phases are recursive and weakly sequenced, which means that the output of earlier stages update the conditions in which a student works during subsequent activities (Winne & Hadwin, 1998; Zimmerman, 2000). For example, the output of the forethought phase (i.e., one's perception about the task features and requirements) provides the conditions in which a student could generate plans and take actions during the performance phase. However, the three phases do not necessarily unfold in linear order, but rather, may occur simultaneously and dynamically as students engage in a task (Pintrich, 2000; Zimmerman, 2000).

In the context of engineering design, students develop an individualized perception about the task features and requirements in the first phase of forethought. For instance, students need to understand the task requirements of harnessing renewable energy to build a specific type of building that is green and architecturally attractive within a certain budget. 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; Xing, Pei, Li, Chen, & Xie, 2019; Zheng et al., 2020). In particular, the formulation behaviors refer to transforming the task requirements into design actions such as "add wall" or "add trees" in designing a resource-efficient house. The analysis behaviors consist of the operations performed to analyze the features of a design artifact. For instance, students need to calculate the energy use and the budget during the house design process if the task has specific requirements for such components. With regard to the reformulation behaviors, they are triggered when students notice that the design state space needs to be revisited and changed to meet design goals. Taking the house design as an example, students may need to edit walls constantly if they find that the structure/function variables or ranges of values are not satisfactory. The third phase of SRL (i.e., self-reflection) involves students evaluating their design performance and determining how to modify their plans and use of strategies for achieving higher performance. The SRL model in engineering design is shown in Fig. 1. This model is developed based on Zimmerman's (2000) three-phase SRL model and the model proposed by Zheng et al. (2020) for explaining student SRL behaviors in engineering education.

2.2. Profiling self-regulation behaviors

Whereas most research has concentrated on group effects on SRL behaviors (Bannert & Mengelkamp, 2008; Järvelä; Malmberg, & Koivuniemi, 2016; Lajoie et al., 2015), there is a growing interest in shifting research focus away from group differences toward learners' profiles and changes over time (Greene et al., 2019, p. 101201; Hong, Bernacki, & Perera, 2020; Jang et al., 2017; Wong, Khalil, Baars, de Koning, & Paas, 2019). The profiling of learners provides us the opportunity to identify and classify learners with distinct patterns of learning behaviors. The profiling approach also enables researchers to develop a deep understanding of the complex and reciprocal relationships between different SRL behaviors in a holistic manner. From a profiling perspective, the identification of a student as being self-regulated includes a constellation of SRL behaviors, not simply effort or use of a specific strategy. As noticed by Shell and Soh (2013), recent years have witnessed an increasing research focus on profiles as researchers benefit from the profile framework. Specifically, Shell and Soh (2013) utilized a profiling approach to understand differences in SRL strategies among post-secondary STEM students. They identified five profiles: strategic, knowledge-building, surface learning, apathetic, and learned helpless. Ning and Downing (2015) revealed four distinct types of students with differential SRL strategy orientations: competent, cognitive-oriented, behavioral-oriented, and minimally self-regulated learners. In particular, Ning and Downing (2015) examined differences in university students' SRL strategy orientations with latent profile analysis and explored profile differences in students' academic performance.

Aligned with the modern SRL research that considers SRL as events rather than general tendencies, some scholars situated their studies concerning the examination of SRL profiles in specific learning or problem-solving contexts. As an example, Bouchet, Harley, Trevors, and Azevedo (2013) used the expectation-maximization algorithm to find the optimal number of categories of students as they learned about the circulatory system with an agent-based intelligent tutoring system. Greene et al. (2019, p. 101201) investigated the temporal nature of self-regulation in science learning by leveraging the multimodal online interaction trace data from 408 college students enrolled in an introductory biology class. Using latent profile analysis, Greene et al. (2019, p. 101201) identified three groups of students who systematically differed in the frequency of their enactment of SRL activities. In a recent study conducted by Zheng et al. (2020), four types of students with distinct patterns of SRL behaviors in engineering design were identified. Specifically, students were clustered into one of four groups: competent, cognitive-oriented, reflective-oriented, and minimally self-regulated learners, using K-means cluster analysis. In addition, Hong et al. (2020) performed latent profile analyses to find three metacognitive learning profiles (i.e., infrequent metacognitive processing, planning and self-evaluation, and monitoring via self-assessment) among 1326 students accessing digital learning resources on a biology course site.

It is noteworthy that studies examining SRL profiles in specific contexts rely on digital trace data instead of students' self-reported measures of self-regulatory strategies. While self-report data provide important information about students' subjective perceptions of learning, they cannot capture how students actually employ learning strategies (Bernacki, 2018), or how learning activities are strategically adapted to specific contexts (Hadwin, Nesbit, Jamieson-Noel, Code, & Winne, 2007). Since researchers are reaching a consensus that SRL processes are cyclical, temporal, and adaptive, it is thus crucial to augment self-reports of SRL with fine-grained trace data about actual student actions (Hadwin et al., 2007; Järvelä & Bannert, 2019, p. 101268). Trace data, by its nature, is used to 'trace' a student's actions in a task (Bernacki, 2018). Trace data can not only be used to capture the adaptations of students' learning activities at a precise level, but also is critical to test theoretical assumptions about SRL such as its temporal nature (Bernacki, 2018; Greene et al., 2019, p. 101201). Consistent with the contemporary SRL methodologies, we used trace data, i.e., log files, to add depth to our understandings of SRL profiles in this study.

2.3. Examining the change in SRL profiles

As pointed out by Nelson et al. (2015), recent studies about profiling students' self-regulation behaviors have not followed a systematic theoretical and empirical course. Studies vary in how many SRL profiles are identified and how researchers label different profiles. In addition, research has suggested that students demonstrated specific patterns of SRL behaviors as a function of contextual factors and task progress (Entwistle & McCune, 2004; Nelson et al., 2015; Shell & Soh, 2013). Students may shift profiles in different stages of learning or problem-solving in response to changes in task situations. That is, the adoption of profiles is a dynamic process in

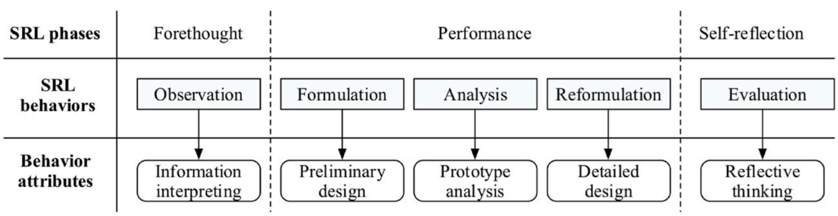

Fig. 1. The SRL model in engineering design.

which students display different learning patterns based on their interactions with highly specific tasks (Nelson et al., 2015). As an example, Fryer and Vermunt (2018) used a longitudinal person-centered analytical framework (latent profile transition analysis) to examine the changes in students' use of regulation strategies across their first-year of study at university. Specifically, they clustered students into four homogenous groups, which were labeled Low Quality (low deep strategies), Low Quantity (low strategy use), Average (moderate strategy use), and High Quantity (intense use of all strategies). They found that students in the Average group mainly remained in this group across one year, with a retention rate of 93%. However, only 40% of students in the Low-Quantity group displayed the same profile at the end of the experiment. Beyond a broad profile analysis, Fryer and Vermunt's (2018) research provided insights into students' transitions between different strategy use profiles and added a unique perspective on future directions of research in SRL.

Considering that there are limited studies that can be referred to, we take other sources of variation into account by introducing relevant research on the motivational aspect of self-regulated learning. In Tuominen-Soini, Salmela-Aro, and Niemivirta's (2011) research, four groups of students with distinct motivational profiles were identified: indifferent, success-oriented, mastery-oriented, and avoidance-oriented. Moreover, they examined the change in students' motivational profiles within a school year and found that students' motivational profiles were substantially stable. They came to conclude that students' motivation, especially achievement goal orientation, is an enduring disposition that reflects their generalized beliefs and tendencies to favor certain outcomes in the contexts of achievement and learning. Another example is Hayenga and Corpus's (2010) research designed to examine the change of individual profiles of intrinsic and extrinsic motivations over the course of an academic year. Contrary to Tuominen-Soini's et al. (2011) findings, they found that half of the sample students shifted their motivational profiles during the academic year. Although these studies did not focus specifically on self-regulation behaviors, they provided a foundation for asking important questions concerning the change in SRL profiles (i.e., patterns of self-regulatory behaviors) in the context of engineering design, such as whether or not students' SRL profiles are stable dispositions, how students shift their SRL profiles during specific tasks, and how different cohorts of students at different age stages or in various disciplines unfold their SRL profiles.

In sum, researchers have suggested that the SRL profile is malleable; however, studies outside the realm of SRL behaviors have proved that students' profiles are relatively stable individual dispositions though student changed their profiles at times (Entwistle & McCune, 2004; Jang et al., 2017; Nelson et al., 2015; Shell & Soh, 2013; Tuominen-Soini, Salmela-Aro, & Niemivirta, 2011). The change of SRL profiles is still an underexplored area of research but is one that has the possibility to deepen our understanding of the complex range of SRL processes. In addition, to our knowledge, no studies have situated the examination of the change of SRL profiles in a specific task, especially in the context of engineering design.

2.4. The present study

While emerging research on profiling students' self-regulation behaviors offers new insights into the generalized tendencies of students' self-regulatory learning processes, little is known about the transitions of students' SRL profiles in specific tasks. It is crucial to address questions concerning individual learning trajectory over time through a person-centered approach and classify students into homogenous groups with similar profiles using longitudinal designs. A longitudinal approach to investigating the change in SRL profiles has not been used in the context of engineering design as students design green buildings in a simulation-based computer-aided design (CAD) environment. The aim of our study is to address this gap by profiling students' SRL behaviors longitudinally and examining whether or not students in different longitudinal clusters differ in their design performance as they design a specific type of green building with a CAD tool. Specifically, we address the following research questions:

(1) Do students display different self-regulated learning (SRL) behaviors that characterized them into distinct groups in the context of engineering design?
(2) How do student SRL behaviors unfold in engineering design?
(3) Do students with different SRL profiles differ in their performance, i.e., design completeness and design efficiency?

3. Method

3.1. Participants

The sample was comprised of 111 ninth-grade students who participated in a larger project focusing on modeling and simulation of engineering design in a CAD environment. Nine students did not complete the task in the current study, leaving a sample of 102. The students came from a suburban high school located in the Northeastern United States. They 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 5 years' experience in mentoring engineering design projects. According to the information provided by the 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. We had obtained the students' consent prior to the study; therefore, they were fully aware of the purpose and the procedures of this study.

3.2. Research design

This study adopted a non-experimental research design in general, relying on quantitative research methods. In particular, we used a descriptive-longitudinal approach to examine the changes of SRL profiles for each student, based on which we identified certain groups of students who shared similar transition patterns of SRL profiles across the problem-solving process.

3.3. Learning context and task

Energy3D is a simulation-based environment for engineering design (see Fig. 2) supporting the design, construction, and analysis of green buildings that harness solar energy to achieve self-sustainability (Xie, Schimpf, Chao, Nourian, & Massicotte, 2018). The project was launched in 2008 and we started to collect empirical data from March 2015 to understand how students learn to solve engineering design challenges and to develop STEM competencies. In particular, Energy3D allows users to sketch a realistic-looking house structure with 3D modeling tools such as walls, windows, roofs, solar panels, and trees. It also provides information for users to evaluate the energy performance of a house for any given day in a year. In Energy3D, students begin a task by determining useful information (i.e., observation) via the examination of available functions such as rotating building, changing date and time, and showing axes, shadow, and heliodon. They then formulate an initial solution by adding walls, windows, roofs etc. In order to meet design requirements, they need to perform a series of analyses, for example, computing solar energy, net energy, and the total cost of the design. Afterwards, students reformulate their design solutions (e.g., edit windows, change the position of house, and add more trees) based on the outputs of the analyses. Moreover, the embedded prompts ask students to reflect on their design performance throughout the process. All operational behaviors of students are automatically captured and recorded in Energy3D log files.

In this study, students were tasked with designing a Ranch-style house (see Fig. 3) with specific requirements. Specifically, a Ranch-style house should meet the following requirements: houses need to demonstrate curb appeal; the ratio of the total area of windows to the floor area must be between 0.05 and 0.15; tree trunks must be at least 2 m away from the walls of the house; the roof overhang must be less than 50 cm wide; the area of the house needs to be between 150 and 200 m^2, and the height needs to be between 4 and 6 m. In addition, the budget for the house should be within $200,000. Last but not least, the house should produce renewable energy to achieve sustainable development throughout a calendar year.

Before designing the house, students were required to finish a pre-test pertaining to their science knowledge on the construction of green buildings. Students familiarized themselves with the Energy3D platform through a researcher-guided practice case. Furthermore, a two-page print-out of instructional materials, which specified the design requirements and important notes, was provided to the students in order to promote an accurate understanding of the task. Students were then asked to accomplish the task independently. Students could ask for help in case they encountered technical issues. On average, they spent 100–160 min finishing the task in the science course during regular school hours.

3.4. Measures

Test of Science Knowledge on Green Buildings. An 18-question test was developed to assess students' science knowledge related to the construction of green buildings. In particular, the test items were drawn from green building science textbooks (Montoya, 2010). A panel of green building science experts, high school science teachers, engineering design professors, and learning scientists reviewed the items to ensure that they were appropriate and valid. Specifically, the items covered the following areas of scientific knowledge: sun path and insolation, spatial and geometric measures, and heat transfer and representations. Students' responses were scored using a 5-level scoring rubric developed to differentiate different levels of scientific sophistication in students' design justifications. The internal consistency has been confirmed in our previous work with a Cronbach's alpha value of 0.82.

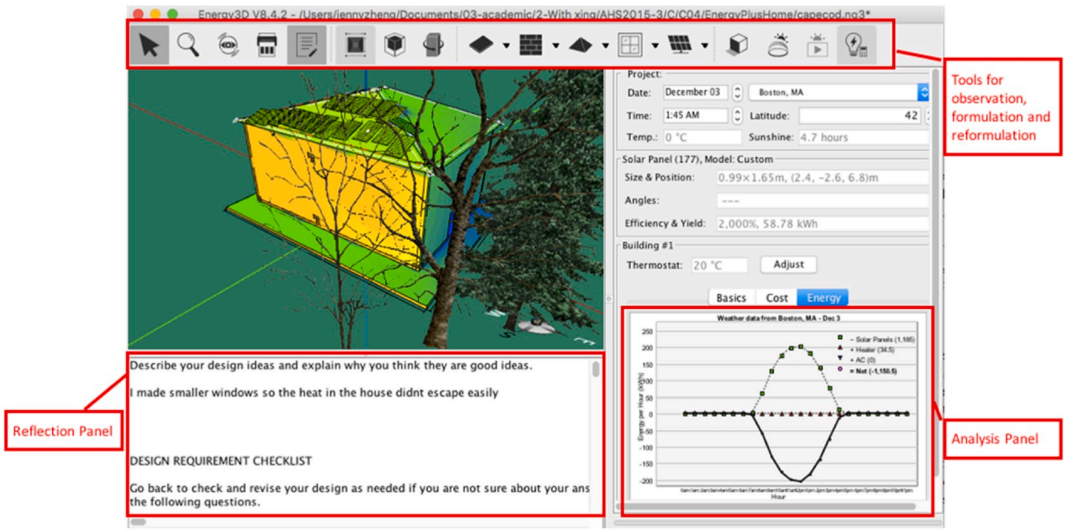

Fig. 2. Interface of Energy3D.

Fig. 3. An example of Ranch-style house.

Design Completeness. Design completeness refers to the number of good design ideas that either make the house architecturally attractive or improve the energy efficiency of the house. Specifically, the number of good design ideas was coded by two independent researchers from students' subjective reflections in their answers to two broad questions: Describe your design ideas and explain why you think they are good ideas, and explain how you improve energy efficiency of the house. The intercoder reliability was 0.86.

Design Efficiency. Design efficiency is measured by the duration of one's design process. The log files of Energy3D recorded the timestamps of the onset and offset of each navigational behavior as well as the whole process. For the interest of this paper, we examined how fast students with different SRL profiles accomplished the task.

3.5. Data preparation

The purpose of data preparation is to create aggregate events from raw trace data following the practice of Greene et al. (2019, p. 101201). As pointed out by Greene et al. (2019, p. 101201), such aggregation that typify similar activities into less granular classes "can be helpful when it matters less what specific example of SRL processing learners enact than whether or how often they are enacting a type of SRL processing (p. 2)". Moreover, the aggregated categories were better predictors of student learning than the finer-grained activity data (Greene & Azevedo, 2009). As mentioned earlier, the Energy3D project unobtrusively collects detailed information about students' engineering design activities. In particular, the log files of the Energy3D contained at least three primary descriptive fields for each event: student identifier, timestamp, and event code. From this fine-grained, temporally identified data of student activities, we aggregated similar events to map the larger categories of SRL behaviors in engineering design, i.e., observation, formulation, reformulation, analysis, and evaluation. We counted the frequencies of these five types of SRL behaviors. Given that students took different amounts of time to complete this project, we calculated the percentages of behaviors for the overall task period as well as three equally segmented periods of each student's design process. Those data served as the basis for our longitudinal clustering models.

3.6. Data analysis

We used an agglomerative hierarchical clustering algorithm to identify distinct student groups based on their SRL behaviors. The agglomerative hierarchical clustering method is a bottom-up approach that begins from individual data points and iteratively merges them to create bigger groups. Each data point starts as a cluster by itself, and the two closest clusters then begin to merge into one progressively until there is only one cluster. During the merging process, the linkage criteria refers to how the distance between clusters is calculated in order to identify closest clusters. In this paper, we adopted Ward linkage, which defines the distance between two clusters as the sum of squared differences when both groups merge. Equation (1) represents how merging cost is calculated when A and B group into one cluster.

$$\Delta(A,B) = \sum_{i \in A \cup B} (x_i - c_{A \cup B})^2 - \sum_{j \in A} (x_j - c_A)^2 - \sum_{k \in B} (x_k - c_B)^2 \tag{1}$$

where c_j is the center of cluster j. Lowest Δ is then identified within each step to determine which two clusters to merge.

The agglomerative hierarchical clustering algorithm assumes no particular number of clusters as opposed to some top-down divisive approaches such as the k-means clustering algorithm. Its calculating process could be visualized as a dendrogram, which is helpful to understand the hierarchical relationships of identified clusters of all steps. In this paper, we used gap statistics (Tibshirani, Walther, & Hastie, 2001) to appraise clustering results and determine the number of clusters. The basic idea of gap statistics is to compare the total intra-cluster variation of a particular cluster number k against its expected values under a distribution with no obvious clustering patterns, which is also known as a null reference distribution. By comparing the gap between such variations and null reference distributions of different k values, an optimal number of clusters can be determined. The total intra-cluster variation is given by equation (2), which involves the calculation of the squared Euclidean distance between any pair of data points within clusters.

$$W_K = \sum_{k=1}^{K} \frac{1}{2n_k} \sum_{i,j \in C_k} (x_i - x_j)^2 = \sum_{k=1}^{K} \frac{1}{2n_k} \sum_{i \in C_k} (x_i - \mu_k)^2 \tag{2}$$

where n_k and μ_k are the number of points in and the average of cluster C_k respectively. The gap statistic is then given by equation (3).

$$Gap(K) = \frac{1}{B}\left[\sum_{b=1}^{B} \log\left(W_{Kb}^{*}\right)\right] - \log(W_K) \tag{3}$$

where W_{Kb}^{*} is the total intra-cluster variation of a Monte Carlo sample from the reference distribution and $B = 10$ in this study. Equation (4) denotes the standard deviation of the B simulations after accounting for simulation error.

$$s_K = \sqrt{1 + \frac{1}{B}} sd(K) \tag{4}$$

The number of clusters could then be chosen by finding the smallest K value that satisfies the requirement that $Gap(K) \geq Gap(K + 1) - s_{K+1}$.

Furthermore, we divided students' engineering design processes into three equal time periods since students may shift SRL profiles in different stages of learning. We then performed the agglomerative hierarchical clustering algorithm for each of the periods. We examined the longitudinal changes of students' SRL profiles across the three subprocesses. It is worth mentioning that latent transition analysis (LTA) is an alternative to our approach. In latent transition analysis, however, "transitions are expressed as probabilities indicating the likelihood of changing (i.e., transitioning) from one latent status to another" (Li, Cohen, Bottge, & Templin, 2016, p. 183). Researchers determine transition patterns by observing any large and meaningful probabilities in the transition matrices (Ryoo, Wang, Swearer, Hull, & Shi, 2018). In this study, we traced the changes of SRL profiles at the individual level. Although our approach is labor-intensive, it is superior to LTA since the changes of SRL membership are clearly identified for each student without probabilistic-based inferences.

4. Results

(1) Did students display different self-regulated learning (SRL) behaviors that characterized them into distinct groups in the context of engineering design?

We performed agglomerative clustering to identify students' overall SRL profiles in engineering design. We used gap statistics to choose the optimal number of clusters. Fig. 4 shows the dendrogram, which groups similar cases with a given distance metric

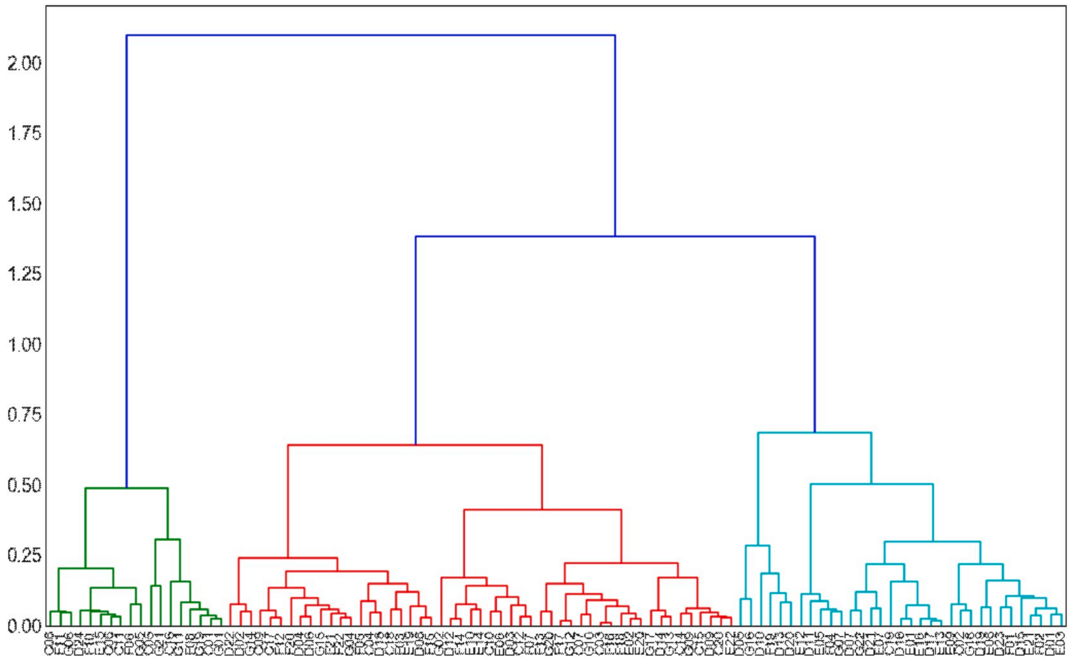

Fig. 4. Dendrogram of the clustering result on overall SRL profile.

(Euclidean distance in this case) and generates a tree structure showing the similarity between clusters.

Fig. 5 (left) suggests three distinct groups by balancing between the maximization of gap statistics and parsimony of the model. The three identified clusters were also colorized in Fig. 4. Fig. 5 (right) visualizes how those groups of students differentiate each other in terms of Observation and Evaluation behaviors as specified in our SRL model (Fig. 1).

(2) How did students' SRL behaviors unfold in engineering design?

We are particularly interested in how students unfolded their SRL behaviors during their engineering design process. Because the three-profile solution appears to have the best coherence, we decided to anchor our examination of longitudinal profiles in the three-profile framework. Specifically, we performed the agglomerative hierarchical clustering algorithm to cluster students into three groups for each of the three subprocesses.

As shown in Fig. 6, there were no clear differences in SRL patterns between the three clustering groups in the first section of engineering design. The three groups all engaged extensively in the observation behaviors (e.g., rotating building, showing axes, changing seasons and time), which was characterized as the forethought phase of SRL. As time went by, students displayed distinct problem-solving patterns as reflected in how they changed their focus on different SRL behaviors. In particular, students who relied on the evaluation behavior emerged in the second section (N = 34, including those demonstrated relatively high and moderate evaluation behavior), although the majority (N = 68) still focused highly on the observation behavior. In the third section, 38 students demonstrated relatively high evaluation but low observation behaviors, 39 students performed moderate evaluation and observation behaviors, and only 25 students showed relatively low evaluation but high observation behaviors. In general, students diverted their efforts from the SRL behavior of observation into the evaluation behavior as they solved the task gradually.

Moreover, we identified three groups of students by examining students' transitions between different SRL profiles across the problem-solving process through a person-centered longitudinal perspective. Results are shown in Table 1. The first group was labeled as reflective-oriented self-regulated learners. This cluster of students maintained a high level of reflective thinking over the course of engineering design, demonstrated by extensive use of evaluation behaviors but relatively less observation behaviors in the second and third sections. This group consisted of 22 students. We did not take the first section into account because each of the three groups focused on observation-related behaviors in this section. Students in the second group included those who dramatically changed their profiles from the second to the third section and who kept a balance between the use of evaluation and observation behaviors in both sections. We labeled this group as adaptive self-regulated learners since students reacted to their task progresses with adaptive responses. There were 30 students in this group. For the last group, it had 50 students and was labeled as minimally self-regulated learners who used relatively fewer evaluation behaviors but more observation behaviors in general.

(3) Did students with different SRL profiles differ in their performance, i.e., design completeness and design efficiency?

The results in Table 2 show that adaptive self-regulated learners ($M = 4.21$) performed significantly better than minimally self-regulated learners ($M = 3.15$) on design completeness while controlling for their prior levels of science knowledge, $F\,(2, 98) = 3.474$, $p = .035$. There were no differences in design completeness between neither reflective-oriented and minimally self-regulated learners nor adaptive and reflective-oriented self-regulated learners. In terms of design efficiency, Table 2 demonstrated that reflective-oriented self-regulated learners ($M = 2419.36$) spent significantly less time than minimally self-regulated learners ($M = 3874.76$) while controlling for their prior levels of science knowledge, $F\,(2, 98) = 3.699$, $p = .028$. There were no differences in design efficiency between other groups.

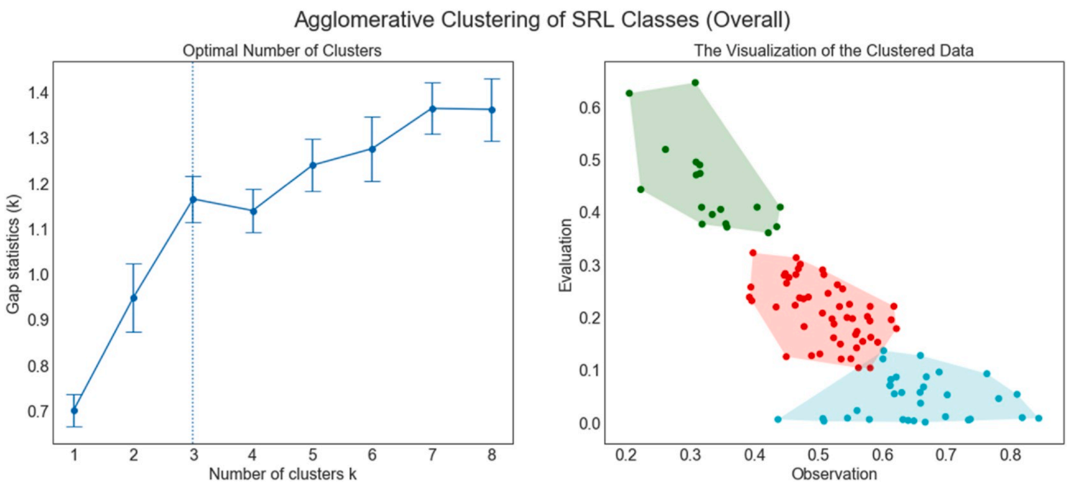

Fig. 5. Number of clusters selection and clustered data visualization on overall SRL profile.

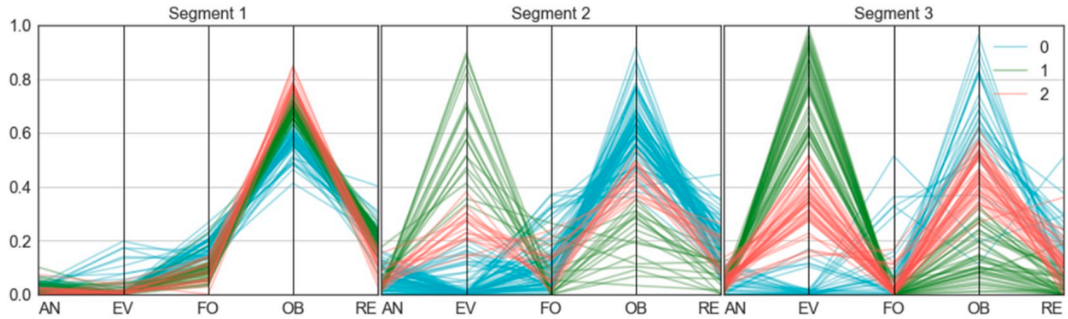

Fig. 6. Parallel coordinates of longitudinal clustering results. Note: AN = Analysis, EV = Evaluation, FO = Formulation, OB = Observation, RE = Reformulation. The labels of 0, 1, 2 represent three different groups. However, the numbers of students in the same group (e.g., group 0) are different for the three segments, since students shift their SRL memberships across the problem-solving process. The clustering results for segment 1, 2, and 3 demonstrate the changes of SRL profiles over time.

Table 1
Longitudinal clustering of self-regulation behaviors.

	N	S1	S2 → S3
Reflective-oriented self-regulated learner	22	–	HE-LO (S2) → HE-LO (S3) ME-MO (S2) → HE-LO (S3) HE-LO (S2) → ME-MO (S2)
Adaptive self-regulated learner	30	–	LE-HO (S2) → HE-LO (S3) ME-MO (S2) → ME-MO (S3) HE-LO (S2) → LE-HO (S3)
Minimally self-regulated learner	50	–	LE-HO (S2) → LE-HO (S3) LE-HO (S2) → ME-MO (S3) ME-MO (S2) → LE-HO (S3)

Note: HE = High Evaluation, LE = Low Evaluation, HO = High Observation, LO = Low Observation, ME = Moderate Evaluation, MO = Moderate Observation; S1= Section 1, S2 = Section 2, S3 = Section 3, S2 → S3 = SRL profile transition from S2 to S3.

Table 2
Performance differences between students with different SRL profiles.

	M	*SD*	*F*	*p*	Pairwise Comparison
Design Completeness			3.474	.035*	
RSRL	4.05	1.91			
ASRL	4.21	2.02			ASRL > MSRL*
MSRL	3.15	1.76			
Design Efficiency			3.699	.028*	
RSRL	2419.36	1210.66			
ASRL	3269.43	1773.78			
MSRL	3874.76	2540.98			MSRL > RSRL*

Note: *$p < .05$. RSRL = Reflective-oriented self-regulated learner, ASRL = Adaptive self-regulated learner, MSRL = Minimally self-regulated learner.

5. Discussion

This study showed that students could be clustered into three groups in general based on the SRL behaviors they displayed in engineering design. The three groups identified from cluster analysis revealed a generalized tendency of SRL behaviors as students accomplished the task. Specifically, Fig. 5 demonstrated that students in distinct groups differed significantly in the behaviors of observation and evaluation. In particular, one group of students performed relatively more observation behaviors but fewer evaluation behaviors. In contrast, there is another group of students who performed more evaluation but fewer observation behaviors. Students in the last group conducted moderate behaviors of observation and evaluation. It is noteworthy that the behavior of observation belongs to the forethought phase of SRL, whereas the evaluation behavior falls into the self-reflection phase. In the forethought phase, students generated several perceptions concerning task requirements, task complexity, environmental factors, and the ability to perform actions in an anticipated way. The forethought phase sets the stage for performance in learning (Barnard-Brak, Paton, & Lan, 2010; Zimmerman, 2008). Moreover, researchers have reached a consensus that reflecting on one's learning or problem-solving activities is a key component of SRL leading to successful outcomes across settings (Schunk & Greene, 2018; Winne, 2019; Zimmerman, 2000). Although the performance phase is indispensable to SRL and successful outcomes, we did not find significant differences between the three groups. Taken together, our results demonstrated that three groups differed primarily in the behaviors of the forethought and self-reflection phases, which provided insights about the relative importance of different SRL phases and corresponding behaviors. As an example, Li, Zheng, Poitras, & Lajoie (2018) applied a data mining algorithm (i.e., conditional inference tree) to assess the relative importance of different SRL behaviors in predicting students' performance. They found that the behaviors of classification, prioritization, and summarization, which were coded in the self-reflection phase, were more important than the other behaviors in differentiating students' performance. In a future study it would be interesting to systematically review the extant literature about the relative contributions that each SRL phase made to students' learning.

A unique and significant contribution of this study is that we identified three SRL profiles of students: reflective-oriented, adaptive, and minimally self-regulated learners, using a longitudinal clustering approach. By labeling the first group as reflective-oriented self-regulated learners, we did not mean that this group was unquestionably superior to the other two groups. Students in the first group were not equivalent to competent self-regulated learners as recognized in many other studies (Ning & Downing, 2015; Zheng et al., 2020), considering that this group performed relatively fewer formulation, analysis, and reformulation behaviors when compared with the other two groups. With regard to minimally self-regulated learners, they were not those showing completely no SRL tendencies, but rather relied on observation behaviors across the design process. These findings were partially in line with Barnard-Brak, Paton, and Lan's (2010) research, which claimed that some students were forethought-endorsing or reflection-endorsing self-regulators. In particular, forethought-endorsing self-regulators were those who endorsed task analysis, goal setting, and environment structuring as key actions to success but did not concern themselves with the use of learning strategies and self-evaluation in their learning. Reflection-endorsing self-regulators highly endorsed self-evaluation behaviors which were typically associated with the self-reflection phase of SRL. Barnard-Brak et al. (2010) considered both forethought- and reflection-endorsing self-regulators as disorganized self-regulated learners who may simply view their current learning strategies and behaviors are the best approach to achieving their goals. The reflective-oriented and minimally self-regulated learners identified in the present research appeared to be reflection- and forethought-endorsing self-regulators, respectively. The two types of SRL learners were also explainable in the context of the theories (Zimmerman, 2000), since the model proposed by Zheng et al. (2020) for explaining student SRL behaviors in engineering design consists of three phases: forethought, performance, and self-reflection. It is noteworthy that Barnard-Brak et al. (2010) administered a self-report scale (i.e., the Online Self-Regulated Learning Questionnaire) to students enrolled in online degree programs, and our study examined the changes of SRL profiles using digital trace data as students accomplished an engineering design task in a simulation-based environment. Our study not only provided additional evidence regarding the transitions of students' SRL profiles but also informed future studies. Since SRL processes are cyclical, temporal and adaptive, it is critical that such processes are captured by examining the fine-grained tracing of digital learning events (Bernacki, 2018; Greene et al., 2011, 2019, p. 101201). Moreover, the task of engineering design is an ill-structured real-world problem, where there is no predetermined solution path and SRL behaviors are deemed essential to students' performance (Boekaerts et al., 2005).

The presence of adaptive self-regulated learners showed that students could adopt quite different SRL profiles over time. This is in line with the research of Lau, Sinclair, Taub, Azevedo, and Jang (2017), who found that students exhibited different combinations of SRL behaviors across short time periods. However, Lau et al. (2017) failed to link the different combinations of SRL behaviors (transitions of SRL profiles) to students' task performance and did not clarify the patterns about how students shifted their SRL memberships. For instance, it was unclear whether or not students could shift to a diametrically opposed SRL profile in a short time. Our study added new evidence to the SRL research that students choose appropriate SRL profile membership and even SRL profiles that are at the two ends of the spectrum based on task situations and their developing views of the task.

In addition, we found that adaptive self-regulated learners outperformed minimally self-regulated learners on design completeness while controlling for their prior levels of science knowledge. This finding came as no surprise, as students with an adaptive profile performed both moderate observation and evaluation behaviors in general. They managed "what they have planned to do" (forethought) and "how their plan goes" (self-reflection) well during the task. Interestingly, we did not find significant difference in design completeness between reflective-oriented and minimally self-regulated learners. However, reflective-oriented self-regulated learners demonstrated higher design efficiency than minimally self-regulated learners, controlling for the influence of their prior knowledge in science. In alignment with Barnard-Brak's et al., (2010) arguments, our results suggested that reflective-oriented and minimally self-regulated learners should consider different SRL behaviors and strategies as being equally instrumental to them in order to achieve high performance on design completeness. Findings from this research also suggested that students with an adaptive SRL profile and minimal self-regulators should put more emphasis on evaluation behaviors if they want to solve the task in a more efficient way. In sum, there are different pathways leading to success which depend on how we define that success. In particular, we proposed that balanced SRL behaviors contribute to design completeness, whereas evaluation behavior associates with design efficiency in engineering design. Moreover, findings from this study were contrary to the research of Karlen (2016), who claimed that successful learners were more likely to have a similar SRL profile over time than less successful self-regulated learners. Our results revealed that both reflective-oriented and minimally self-regulated learners showed a similar SRL profile over time, but the former group reached their goals faster than the latter group. It is not the stability of SRL profiles but rather their quality that determines students' performance.

6. Conclusion

The present study contributes to the extant literature on self-regulated learning by examining changes in students' SRL profiles through a longitudinal approach. Although there have been some attempts to profile students' SRL behaviors, such attempts often failed to examine the underlying assumption for profiling students and clustering them into homogenous groups with similar learning patterns. In particular, the assumption that students demonstrate stable SRL profiles in terms of self-regulatory behaviors over time is overlooked, yet essential to profile analysis. We explicitly acknowledged the fact that students may change their SRL profiles over time in response to changes in task situations and their developing views of the task. Therefore, we integrated this fact into the way students' profiles were identified, i.e., grouping students based on their SRL profiles analyzed at three time points across the engineering design process. Adding to other studies focusing on the general tendencies of SRL behaviors, this study provided nuanced modeling of SRL dynamics. Specifically, we identified three groups of students: reflective-oriented, adaptive, and minimally self-regulated learners. We found that adaptive self-regulated learners outperformed minimally self-regulated learners on design completeness, whereas reflective-oriented self-regulated learners achieved their goals faster than minimally self-regulated learners while controlling for students' prior levels of science knowledge.

This study brings not only theoretical contributions to the advancement of SRL theories but also informs the design of adaptive interventions to students with different profiles. A strength of this study was that we used a longitudinal clustering approach to examine the change of students' SRL profile memberships, which advanced a nuanced understanding of students' strategic adaptations over time. This approach informs studies in other disciplines across various contexts, although we situated our study in engineering design. This study also has significant practical implications. First, this research informs the design of interventions for students with different SRL profiles. On one hand, intervention efforts should be tailored to meet the needs of unique groups of students. On the other hand, intervention strategies must be designed based upon the types of expected performance, for instance, design completeness and design efficiency. In addition, this research found that a portion of students showed a high degree of malleability in SRL behaviors, which means that interventions should be delivered adaptively at multiple time points along with the change of students' learning patterns. Findings from this research also help instructors realize the many aspects of engineering design performance. Future research will benefit from the practice of taking the nature of various performance matrices into consideration.

This study was not without limitations. A possible limitation was that the participants were all in their ninth grade and came from the same school in the Northeastern United States, which may affect the generalizability of our research findings. We clustered students based on how they unfolded SRL patterns over time but did not examine the underlying mechanisms about why some showed consistent patterns in learning and others changed their learning patterns dramatically. Moreover, students were required to design a green building in this study, which added some levels of uncertainty to our results because additional tasks may generate other interesting and important findings. Finally, this research used the system log files as a single data source to model students' SRL behaviors at multiple time points. Although the measurement method of log files can collect data automatically and continuously without interfering with the flow of students' designing processes, this approach is highly inferential, especially when it comes to connecting overt behaviors to specific SRL phases.

In closing, we identified several future directions toward examining the change of SRL profiles. SRL is a multidimensional construct which includes not only strategic behaviors but also other aspects such as metacognition, emotion, and motivation. It would be fruitful to take multiple SRL components into consideration in clustering students and to examine intraindividual differences in SRL profiles over time. For instance, students with a competent SRL profile may show a high level of metacognitive strategy knowledge, high frequency of strategy use, positive achievement emotions, and mastery-oriented motivation. Examining the changes of SRL profile that is multicomponent would provide researchers a comprehensive understanding of the dynamics of SRL processes. In addition, it is important to reveal why some students shift between different SRL profiles while others prefer a stable learning pattern over time, especially when taking student personality and social-cultural factors into consideration. Another line for future research is to detect, measure, and analyze the changes of SRL profiles using multimodal multichannel data about SRL behaviors with advanced learning technologies (Azevedo & Gašević, 2019). Moreover, a different cohort of students is required in future research to cross-validate our findings with regard to the three SRL profiles discerned across the process of engineering design.

Declaration of competing interest

The authors declare that they have no conflict of interests.

CRediT authorship contribution statement

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

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