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Self-regulated learning as a complex dynamical system: Examining students' STEM learning in a simulation environment

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ABSTRACT

Self-regulated learning (SRL) is essentially a complex dynamical system (CDS). However, no effort has been made to study SRL from a CDS approach in the context of science learning. In this study, we adopted the ideas and analytical techniques of complexity science to analyze SRL. Specifically, 74 ninth-grade students were asked to undertake an engineering design task in a computer-simulated environment. We compared the differences in the complexity of the SRL process and the regularity of SRL behaviors between the high and low performers. We found that the SRL processes of the high performers were more complex than those of the low performers. In general, the low performers demonstrated a higher degree of repetition of SRL behaviors than the high performers. The low performers were also more likely to exhibit a behavior repeatedly than the high performers. This study extends the literature on the dynamics of SRL in both theoretical and methodological dimensions.

1. Introduction

There has been a growing recognition that self-regulated learning (SRL) plays a central role in influencing students' performance across various learning or problem-solving contexts (Azevedo & Gašević, 2019; Boekaerts et al., 2005; Greene & Azevedo, 2007; Järvelä et al., 2020; Pintrich, 2004; Winne, 2019). In particular, SRL refers to a cyclical process whereby students purposefully govern *when* and *how* to use self-regulatory strategies to achieve learning goals, proactively monitor *what* and *why* specific strategies work or fail, and efficiently determine *where* to go next accordingly (Pintrich, 2000; Winne, 2019; Zimmerman, 2000). The process of SRL is influenced by a wide range of factors, which include the characteristics of the learning context, an individual's demographic, cultural, or personality characteristics, and the individual's strategic regulation of their internal environments such as cognition, metacognition, motivation, and emotion (Pintrich, 2004). The emergence of SRL behaviors or products is an aggregate result of interactions between those factors. Therefore, SRL is essentially a complex dynamical system, comprising interdependent components whose roles and inter-component relations continuously emerge through internal and external feedback loops (Kaplan & Garner, 2020; Koopmans, 2020). Examining SRL as a complex dynamical system could provide insights that go beyond simple cause-effect relations between SRL components and performance. However, limited studies have investigated SRL from a complex dynamical system (CDS) approach, which is rooted in complexity science (Koopmans, 2020; Richardson et al., 2014). One reason is that the application of CDS in educational research is still nascent, and the other reason lies in the challenge of viewing the SRL process as emergent and not-fully-predictable, which requires an epistemological shift from researchers (Kaplan & Garner, 2020).

In addition, research in the SRL field has relied extensively on atemporal methods to study how specific SRL components relate to students' performance, focusing on the frequency, magnitude, quality, or interaction of such components (Coco & Dale, 2014; Järvelä et al., 2020). Accordingly, researchers use summary statistics such as mean and standard deviation to describe SRL processes, leaving the temporal variations of SRL components largely unexplored (Azevedo & Gašević, 2019; Paans et al., 2019; Winne, 2019). Moreover, the inferential statistics for studying SRL phenomena are typically based on certain assumptions such as linearity assumption, homogeneity of variance, and normal distribution of data sets. In terms of the linearity assumption, which assumes that all causal inferences remain constant in direction throughout time (Xu et al., 2020), it is often violated when investigating variables with complex dynamics. SRL process is no exception since the interrelationships among SRL components are not necessarily *linear*, and the measured data may contain non-random fluctuations that are not

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normally distributed (Richardson et al., 2014). Therefore, it is methodologically important to explore the complex nature of SRL processes through nonlinear analytic methods, among which recurrence quantification analysis (RQA) is gaining popularity (Coco & Dale, 2014; Marwan & Webber, 2015; Wallot & Grabowski, 2019; Xu et al., 2020). As noticed by Richardson et al. (2014), 'there is now substantial evidence that suggests it is potentially one of the most robust and generally applicable methods for assessing the dynamics of biological and human behavior' (pp. 273–274). Specifically, RQA is a nonlinear analysis method that allows researchers to quantify the temporal structure and patterns of learning behaviors but requires no assumptions about linearity and data distribution (Richardson et al., 2014; Wallot, 2019). To our knowledge, there has yet no effort to study SRL as a complex dynamic system using the RQA method. Thus, the present study aims to fulfill this gap. The current literature on SRL is centered around students' interactions with computer-based learning environments, where learning or problem-solving behaviors can be recorded in real-time as they occur (Azevedo & Gašević, 2019; Coco & Dale, 2014; Greene et al., 2019; Järvelä et al., 2020; Lajoie et al., 2019; Li et al., 2021). We also situate this study in a computer-based environment since learners' trace data is crucial to study SRL dynamics. This study provides researchers with methodological insights on the analysis of SRL dynamics. Findings from this study could also deepen our understandings of the complexity and regularity of SRL processes and consequently students' performance differences.

2. Theoretical background

2.1. Self-regulated learning as a complex dynamical system

Self-regulated learning is a multidimensional process whereby students perceive, interpret, control, and monitor their internal and external conditions to achieve their predetermined goals (Greene & Azevedo, 2007; Hooshyar et al., 2019; Pintrich, 2004; Winne, 2019). In terms of internal conditions, the predominant SRL theories describe the process by referring to four main components (i.e., cognition, metacognition, motivation, and emotion) and their interactions (Azevedo & Gašević, 2019; Greene & Azevedo, 2007; Pintrich, 2000; Zimmerman, 2000). Regarding external conditions, SRL researchers have recognized the influences of available resources, instructional cues, time, and the local context (Greene & Azevedo, 2007; Li et al., 2018). All of these factors can influence an individual's strategic regulation of learning process and their ability to achieve desirable goals. As such, the process of SRL exhibits the three key features of complex dynamical systems, i.e., interconnectedness, non-ergodicity, and nonlinear dynamics (Heino et al., 2020; Richardson et al., 2014). First of all, the many components of SRL are closely interconnected. SRL components such as cognition, emotion, and behaviors interact with each other over time, yielding the internal dynamics in the human mind and reflecting the very nature of the learning process (Engelmann & Bannert, 2021; Li, Chen, et al., 2020; Li et al., 2022). Furthermore, SRL process is non-ergodic, which means that students can vary significantly in their changes of SRL behaviors, and even the same individual could experience radical changes in cognition or emotions over time. It would be misleading and inaccurate to draw individual-level inferences from group-level data about SRL (Heino et al., 2020). In addition, SRL process also manifests the characteristic of nonlinear dynamics of any complex dynamical systems, considering that there are no clear linear causal relationships between SRL components. Although the patterns of interactions among SRL components are recognizable, none of these patterns alone can predict a determined outcome (Marchand & Hilpert, 2020).

In an attempt to understand the complex SRL dynamics, researchers have been making a great effort to gather multidimensional data about SRL (Lajoie et al., 2019; Winne, 2019). In fact, a growing interest in SRL research is to unravel the temporal dynamics of SRL components by collecting and analyzing multimodal multichannel data with various methodologies such as physiological sensors, eye-tracking, facial expressions of emotions, log files, concurrent think-aloud, and discourse analysis (Azevedo & Gašević, 2019). However, modeling multimodal multichannel data about SRL can be theoretically, methodologically, and practically challenging. To name a few of these challenges: embodiment of theoretical assumptions in data streams, temporal alignment of multimodal multichannel SRL data sources based on different sampling rates, and complexity in dealing with missing, noisy or messy data (Azevedo & Gašević, 2019). Moreover, as pointed out by Winne (2019), "a different model or theory may devalue or even disregard data instrumented according to another theory or model" (p. 286). As a result, an important question naturally arises: Are there valid, reliable, and cost-effective methods to study the temporal dynamics of SRL that move beyond the multimodal multichannel approach? In the present paper, we argued that the CDS approach to SRL and corresponding analytical techniques have the potential to address this question. SRL is basically a complex dynamical system. Clearly, researchers can gain additional insights into the SRL process by adopting ideas and methods of complexity science. For instance, recurrence quantification analysis, a CDS method that is widely used in social and personality psychology, enables researchers to reveal the underlying dynamics of SRL process by describing the aggregated functioning of its components (Koopmans, 2020; Richardson et al., 2014; Wallot, 2017).

2.2. Recurrence quantification analysis

Recurrence quantification analysis (RQA) is a powerful technique used to quantify the complexity and regularity of the temporal patterns of a single or multiple time-series, especially when the time-series is the result of multiple interdependent variables (Marwan & Webber, 2015; Wallot, 2017; Wallot & Leonardi, 2018). In particular, RQA allows researchers to reveal information about the multiple underlying variables by analyzing the observable one-dimensional time-series. As such, RQA is applicable to analyze a SRL system, given that it consists of the interplays of multiple interdependent constructs (i.e., behavior, cognition, metacognition, emotion, and motivation) and the SRL behavioral sequence is usually directly observable. RQA has a solid mathematical foundation, which is the theorem of higher-dimensional reconstruction by the time-delayed embedding method proposed by Takens (1981). As observed by Webber and Zbilut (2005), 'what this theorem states is that the topological features of any higher-dimensional system consisting of multiple coupled variables can be reconstructed from but a single measured variable of that system' (pp. 33–34). This is done by reconstructing a multidimensional space where time-delayed copies of the one-dimensional time-series act as surrogate dimensions in that space (O'Brien et al., 2014; Wallot, 2019; Webber & Zbilut, 2005). Readers can find more details about the mathematical and computational foundations of RQA from the research of Marwan and Webber (2015).

With regard to the time-delayed embedding method, there are two parameters that are essential for the reconstruction of a potentially multidimensional system from a single one-dimensional time-series (Wallot, 2019). One is the delay parameter τ, which refers to the lag at which the time-series is plotted against itself. The delay parameter is usually estimated through the mutual average information function to "ensure that reconstructed dimensions of the phase-space are relatively orthogonal and deliver non-confound information about the temporal structure in a time-series" (Wallot, 2017, p. 374). Once an appropriate delay parameter is obtained, it is further used to estimate the other parameter, i.e., the embedding dimension. The embedding dimension parameter indicates the number of times the time-series is plotted against itself (Wallot, 2019). It is an estimate of the dimensionality of a potentially multidimensional system (Wallot & Leonardi, 2018), while dimensionality represents the number of underlying subcomponents, with each subcomponent contributing to one reconstructed dimension. In the context of SRL, dimensionality refers to the number of SRL components activated in learning or problem-solving. For instance, some students may actively manipulate more SRL components (e.g., self-instruction, attention focusing, self-evaluation, causal attribution, management of outcome expectations, and emotion regulation) than those who lack self-regulatory skills. As a result, the dimensionality of a SRL system for the competent self-regulated learners is assumed to be larger than that of those less competent.

It is noteworthy that the overarching goal of RQA is to examine the repetition of elements or patterns in a time-series since recurrence is a fundamental property of dynamical systems. The examination of recurrence patterns can be more accurate when analyzing the co-ordinates in the reconstructed multidimensional system compared to the values of the observable time-series per se (Marwan & Webber, 2015; Wallot, 2019; Wallot & Leonardi, 2018). RQA can also be computed on categorical series of finite states. Therefore, it provides an analytic framework for studying the recurrence patterns of students' behavior sequences (Xu et al., 2020). Recurrence plot (RP) is a core concept of RQA, which is generated by plotting a time-series on both the x and y-axis of a two-dimensional grid. Specifically, RP is used to visualize repeating structure or patterns by comparing all the elements of a sequence with themselves (Wallot & Leonardi, 2018). As an illustration, Fig. 1 shows the recurrence plots of two participants. The x and y-axis are both a participant's behavior sequence, with recurrence points (i.e., dots marked with black color) in the RP indicating when the same behavior within the sequence reoccurs. That is, recurrence points do not represent specific values but rather show the position where a specific value repeats itself. Recurrence plot is symmetrical about its main diagonal because each value within a behavior sequence is recurrent with itself (Wallot, 2017). In particular, the adjacent points forming vertical or horizontal lines suggest that an individual performs a repetitive behavior such as planning, whereas the diagonally adjacent points indicate that a behavioral pattern reoccurs. As shown in Fig. 1, the behaviors of participant B are more structured than that of participant A since the RP of the prior contains more diagonal lines.

In addition, RQA provides multiple metrics to quantify the recurrence patterns. The most commonly used metrics are percent recurrence (%*REC*), percent determinism (%*DET*), average diagonal line length (ADL), laminarity (%LAM), and trapping time (TT) (Wallot, 2017; Webber & Zbilut, 2005). The definitions and meanings of these metrics are shown in Table 1. Plenty of terms have been used to describe these RQA measures, including but not limited to regularity, predictability, stability, flexibility, and complexity (Jenkins et al., 2020;Marwan et al., 2002; Wallot, 2017). For the purpose of this paper, we used the term of regularity throughout.

Table 1
The most common measures of recurrence quantification analysis.

Variable	Definition	Meaning
Percent recurrence (%*REC*)	The density of recurrence points in a recurrence plot (RP). %*REC* = Sum of recurrent points in the RP / size of RP	The repetitiveness of the elements in a sequence
Percent determinism (%*DET*)	Proportion of recurrent points forming diagonal lines in the RP. %*DET* = Sum of diagonally adjacent recurrent points / sum of recurrent points	How many of the repetitions occur in connected trajectories
Average diagonal line length (*ADL*)	Average length of diagonal lines in the RP	How long the average repeating trajectory is
Laminarity (% LAM)	Proportion of recurrent points forming vertical line structures. %LAM = Sum of vertically adjacent recurrent points / sum of recurrent points	How many of the repetitions occur in vertically connected trajectories
Trapping time (TT)	Average length of vertical lines in the RP	How long the average vertical line is

Marwan et al. (2002) and Wallot (2017).

In the context of SRL, % *REC* denotes the proportional degree to which an individual performs the same behaviors over time (see Table 2). %*DET* is another measure of state regularity that, captures the degree to which the same sequences of SRL behaviors occur over time. In other words, a higher %*DET* value suggests a more structured or predictable pattern of SRL behaviors (Jenkins et al., 2020). With regard to ADL, it is the average length of repeating patterns of SRL behaviors. In terms of % LAM, it measures the extent to which an individual gets stuck in a behavior. % LAM will increase if a student consecutively performs a specific behavior more often. The last RQA measure of TT, analogous to ADL, denotes the average length of repeating behaviors. For instance, the TT equals five if an individual conducts a behavior repeatedly for five times. In sum, researchers can gain a deep understanding of the temporal structure of SRL behaviors by describing and analyzing those RQA measures.

2.3. The current study

The purpose of this study is to examine the temporal structure of

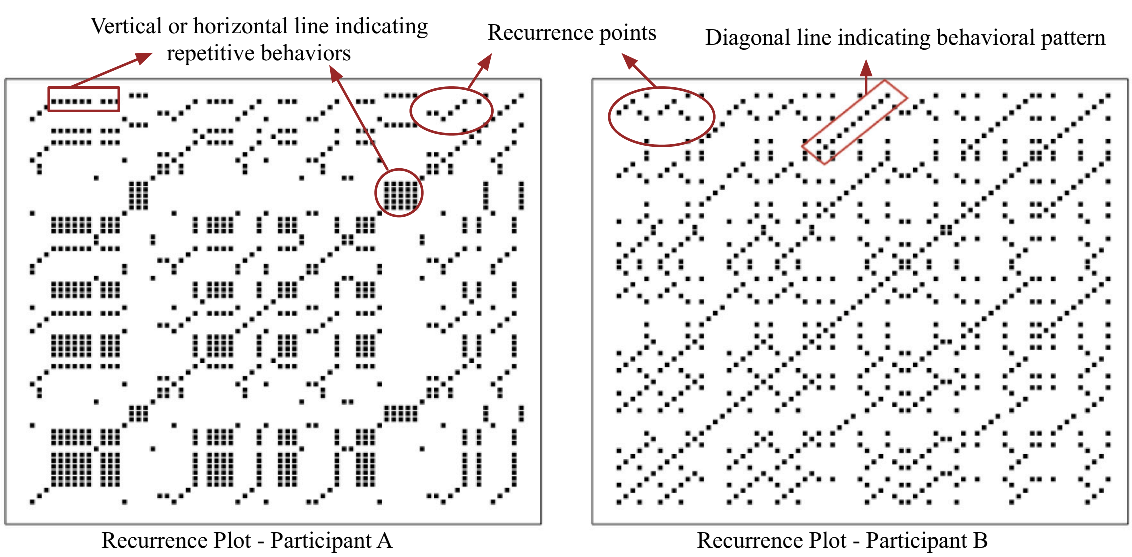

Fig. 1. Illustration of recurrence plots.

Table 2
The RQA measures in the context of SRL.

Variable	Meaning in SRL	Explanation
Percent recurrence (%*REC*)	How often does an individual show the same SRL behavior?	The degree to which the same SRL behavior reoccurs over time. For instance, the SRL behavior of formulation may reoccur 20 times in a behavioral sequence, while the analysis behavior reoccurs 30 times. %REC = Sum of recurrences / N (N − 1), where N refers to the length of the behavioral sequence.
Percent determinism (%*DET*)	To what extent do repetitions of SRL behaviors occur in the form of behavioral patterns?	Examples of the SRL behavioral patterns include "FO-AN-RE-EV", "RE-EV-RE-EV", and "FO-AN-EV". %DET captures the degree to which the SRL behavioral patterns reoccur over time.
Average diagonal line length (*ADL*)	How long is the average repeating pattern of SRL behaviors?	Examples of the repeating patterns of SRL behaviors include "FO-AN-RE-EV" and "RE-EV-RE-EV". ADL refers to the average length of these repeating patterns.
Laminarity (%LAM)	To what extent do repetitions of SRL behaviors occur in repeating sequences of the same behavior?	Examples of the repeating sequences of the same SRL behavior are "FO-FO-FO-FO", "RE-RE-RE-RE-RE", and "AN-AN-AN". %LAM captures the degree to which the repeating sequences of the same SRL behavior reoccur over time.
Trapping time (TT)	How long is the average repeating sequence of the same SRL behavior?	TT refers to the average length of the repeating sequences of the same SRL behavior.

Note: FO = formulation, RE = reformulation, AN = analysis, EV = evaluation.

students' SRL processes and behaviors in STEM (Science, Technology, Engineering, and Mathematics) learning by leveraging the affordances of RQA. In particular, we situate our study in the context of engineering design, since we introduced a domain-specific SRL model to explain students' learning in engineering design in previous studies (Li, Du, et al., 2020; Zheng et al., 2020). The SRL model in engineering design, which was adapted from the three-phase model of SRL (Zimmerman, 2000), was shown in Fig. 2. Specifically, students begin an engineering design task by developing an understanding of the task features and requirements in the forethought phase of SRL. For instance, an engineering design task may require students to build a green building (a type of building that generates the same amount of energy as it consumes) within a certain budget in a computer-aided design environment. Students need to familiarize themselves with the task environments and connect environment-relevant information with specific task requirements. Learning behaviors that occur in this phase are usually referred to as observation behaviors in the context of engineering design. In the performance phase, students generally conduct three types of behaviors (i.e., formulation, analysis, and reformulation) to accomplish their design goals (Howard et al., 2008; Li, Chen, et al., 2020; Zheng et al., 2020). The formulation, analysis, and reformulation behaviors contribute to the processes of preliminary design, prototype analysis, and detailed design, respectively. In the self-reflection phase, students evaluate their design performance and determine how to proceed for achieving predetermined goals.

In the present study, we are interested in how high and low performers differ in the complexity of SRL process and the temporal patterns of SRL behaviors as they complete an engineering design task. Examining the differences between these two performance groups could enable researchers to make a direct comparison of SRL features and develop a clear understanding about how the differences in SRL features may lead to performance differences. Specifically, this study addresses the following research questions: (1) Do high performers differ from low performers in the complexity of their SRL processes when solving an engineering design task? (2) Are there differences in the temporal patterns of SRL behaviors between high and low performers?

In line with the research of Wallot (2017), we consider the number of dimensions of an SRL system (i.e., dimensionality) as the operational definition of its complexity. To be specific, we use RQA to discern the number of dimensions that best capture the fluctuations observed in the time-ordered behavior durations. Time-ordered durations of behaviors reflect the continuous adjustments learners made in response to changing internal and external conditions (Greene et al., 2019). Therefore, the time-series data is suited for the analysis of SRL process to reconstructing a potentially multidimensional system. Moreover, when we mention the regularity of SRL behaviors, we refer to their temporal structure represented by the RQA measures. Based on SRL theory, we hypothesize that high performers would demonstrate a more complex SRL process than low performers, given that high performers are usually those who can effectively manage SRL components (e.g., attention-focusing, strategic planning, and emotion regulation) to accomplish learning tasks. In other words, we hypothesize that the dimensionality of the SRL systems of high performers will be significantly larger than that of low performers. Moreover, we assume that repeating behaviors indicate uncertainty in problem-solving; therefore, we hypothesize that the percent recurrence (%REC), trapping time (TT), and laminarity (%LAM) of high performers will be significantly smaller than that of low performers. However, high performers are expected to show more repeating behavioral patterns than low performers. For this reason, we hypothesize that the percent determinism (%DET) and the ADL of high performers will be significantly larger than that of low performers. This study is exploratory in nature. Nevertheless, this study has the potential to advance the research in SRL both theoretically and methodologically.

3. Methods

3.1. Participants

The participants consisted of 74 ninth-grade students (39.2% females) who came from a suburban high school in the Northeastern

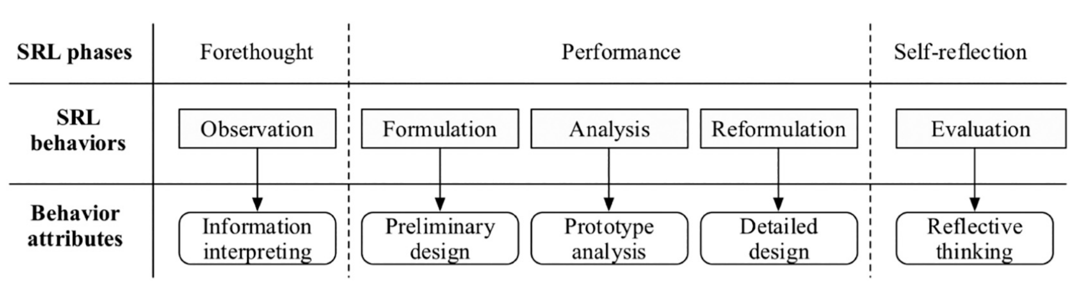

Fig. 2. The SRL model in engineering design.

United States. In terms of the racial demographics of the school, the majority viewed themselves as Caucasian (57.5%), with African American comprising 25.7%, Hispanic 7.8%, Asian 6.1%, multi-race 2.8%, and Pacific Islander 0.2% of the whole population. Furthermore, 30% of the students were from economically disadvantaged backgrounds. Prior to the study, we had obtained research ethics approval from the institutional review board. In addition, all parents provided consent for their children's participation in this study. Moreover, we explicitly explained the research purposes and procedures to the students; therefore, they were aware of the potential benefits and risks of the study. Students had free choice to quit the study whenever they wanted. They all participated in this study in Fall 2019. However, eight students did not finish the task, and the data of 5 participants were not saved, leaving a sample of 61 for data analysis.

3.2. Learning environment and task

This study was part of a larger research project aiming to study the best practice to support science and engineering education in Aladdin, a simulation-based computer-aided design (CAD) environment (https://intofuture.org/aladdin.html). Aladdin, previously known as the Energy3D platform (Xie et al., 2018), supports the design, simulation, and analysis of green buildings that harness solar energy for their maintenance. In Aladdin, students play the role of solar engineer to provide an optimal solution regarding the arrangements of solar panels and to meet customers' additional requirements such as annual energy production and payback period.

In this study, students were given the task of Solarize Your School (SYS), which required them to turn their school buildings into a power generator. We first created a computer-simulated reality environment in Aladdin, whereby a physical, real-world environment of students' campus was replicated on computers (see Fig. 3). Students could interact with the computer-simulated reality environment using virtual tools such as show sun shadows, add solar panels, and simulate sun paths. Moreover, students were told that the task was for a competitive bid held by the town where the school was located in. The advertised requirement for bidders was to design a solar array on the roofs of the school buildings. The solar array needed to generate more than 400,000 kWh of electricity per year with a payback period shorter than ten years. Therefore, the SYS task provided students with a deeply situated learning experience as it exploited the affordances of a real-world context, and it was designed to address an authentic meaningful problem. During the task, students were asked to work individually on their own laptops for the bidding.

3.3. Procedure

Students were invited to participate in this study consecutively for six days during their regular school hours. We provided a training session to help students get familiar with the Aladdin environment on the first day of the study. The training session was approximately 45 min. In the following three days, students spent 45 min per day learning about important solar science concepts that are essential in understanding how to design an efficient solar array. These concepts include but are not limited to Sun path, projection effect, air mass, weather effect, and solar radiation pathways. Meanwhile, students used Aladdin to explore how the Sun moves across the sky as the Earth orbits the Sun and rotates around its own axis, how the Sun path changes from season to season, and how the length of the day varies. In addition, students investigated how the Sun's position relative to a surface on the Earth affects the intensity of sunlight and why the intensity depends on the time of the day and the weather. At the end of the science learning session, students were asked to apply what they had learned to solve a practical problem, i.e., find a position for a solar panel around a house that generates electricity the most throughout a year.

Afterwards, students had another two days to work on the SYS task. As aforementioned, students played the role of solar engineers to design cost-effective solutions that power their school with solar energy under certain constraints. For instance, three different types of solar panels were available for engineering design activity. Nevertheless, students could only select one type of solar panel for their design. To optimize the return on investment (ROI), students needed to carefully choose solar panels given that different solar panels had different efficiencies, dimensions, and costs. Students also needed to adjust the location and

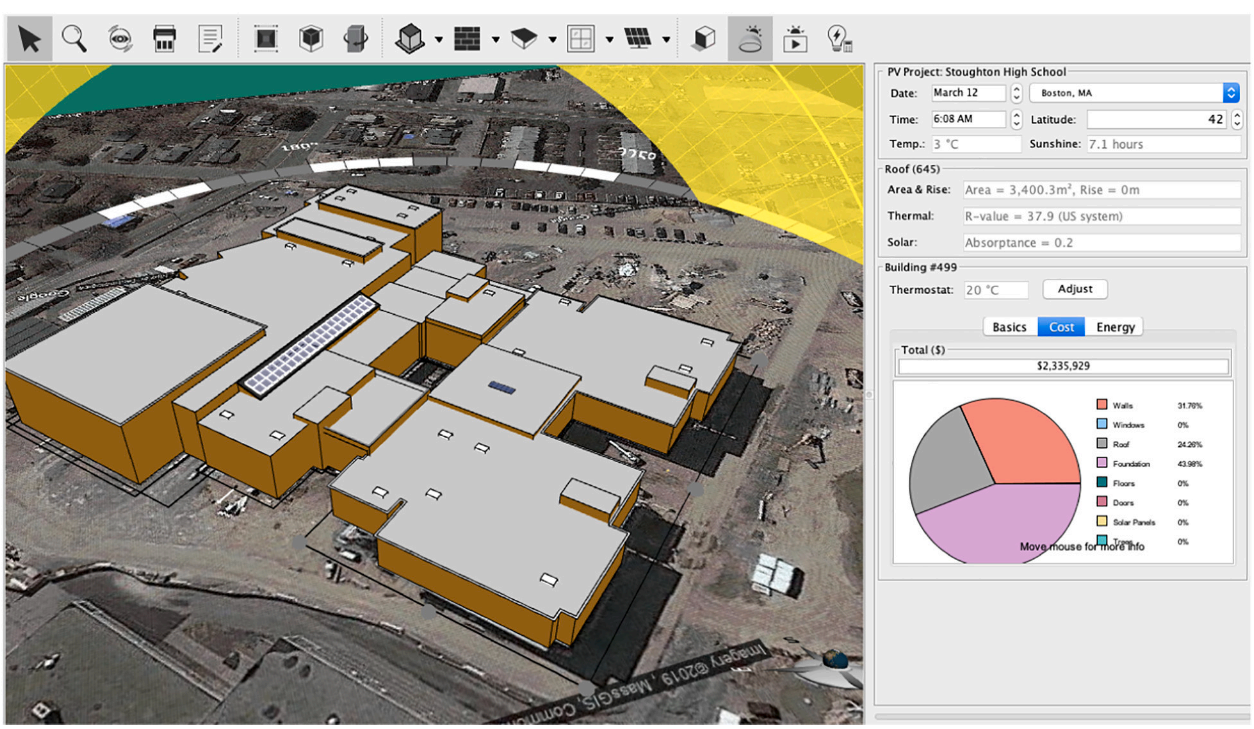

Fig. 3. The computer-simulated reality environment.

orientation of solar panels, as well as the distance between adjacent rows of tilted solar panels, since all of them could affect the output of solar energy. On average, students spent 135 min completing the task, with their design behaviors and corresponding timestamps being automatically recorded in the log files of Aladdin. Moreover, Aladdin stored the annual energy production and payback period into the log files for each student when they finished the task.

3.4. SRL behaviors

We examine students' engineering design behaviors within a SRL framework based on the following considerations. First, engineering design tasks are usually ill-structured problems with no clear procedural and predetermined solutions. The process of engineering design represents a good example of SRL scenario where students purposefully control and monitor their behavioral, cognitive, metacognitive, and affective aspects of learning to fulfill personal goals (Pintrich, 2000; Winne, 2019; Zimmerman, 2000). Moreover, the outcome of STEM education includes not only the acquisition of domain-specific knowledge and skills but also the development of SRL competency to supporting long-term growth in students' STEM achievement. Examining students' engineering design behaviors through the lens of SRL theories would help researchers develop a deep understanding of the quality delivery of STEM education. Furthermore, we introduced a SRL model to illustrate how students' engineering design processes are superimposed over the SRL phases (Li, Chen, et al., 2020; Li, Du, et al., 2020; Zheng et al., 2020). We classified five types of SRL behaviors (i.e., observation, formulation, analysis, reformulation, and evaluation) in engineering design. The sample activities for each type of SRL behavior are shown in Table 3. It is noteworthy that the engineering design task involves the possible use of 38 types of activities, which were automatically recorded in the log files as students approached the task. Students conducted 325 activities on average in the engineering design process. We extracted the information of SRL behaviors from the log files.

3.5. Data processing and analysis

To address our first research question, we created a series of behavior durations for each participant. In particular, the duration of each behavior was obtained by subtracting the timestamp of the behavior itself from the subsequent one. Considering that behavior duration is a continuous variable, and there exist complicated fluctuations in the dynamics of students' cognition, metacognition, emotion, and motivation behind the observed series of behavior durations, we followed the time-delayed embedding procedure to reconstruct the time series' phase-space (Wallot, 2017; Wallot & Leonardi, 2018). In other words, we reconstructed the multidimensional dynamics from the one-dimensional series of behavior durations by plotting the time-series against itself at a certain time delay (Wallot, 2017). As behavior durations are not an equally sampled time-series, we set the delay parameter as 1 (i.e., $d = 1$) following the instructions of Wallot and Grabowski (2019). According to Wallot and Grabowski (2019), the interevent times do not contain redundant information that might be inherent in equally sampled signals; therefore, a value of 1 for the delay parameter is sufficient to estimate a correct dimensionality of the dynamics of the time-series.

Table 3
Sample activities for each type of SRL behavior.

SRL behaviors	Sample activities
Observation	Rotate building; show shadow, axes, and heliodon
Formulation	Add foundation, rack, and solar panels
Analysis	Compute solar energy, net energy, and the total cost of the design; animate sun; generate energy graphs
Reformulation	Edit rack; change the azimuth and the base height for all racks
Evaluation	Make notes; make subjective and structural reflection

Specifically, the dimensionality of the phase-space was estimated for each student using the false-nearest-neighbor function (Wallot, 2017). The R packages of 'tseriesChaos', 'nonlinearTseries', and 'crqa' were used to perform the analyses. We then compared the difference in dimensionality between high- and low-performing groups.

To answer the second question, we used categorical-RQA (Coco & Dale, 2014; Jenkins et al., 2020; Wallot, 2017) to explore the temporal structures of the one-dimensional behavioral sequence, which consisted of different categories of engineering design behaviors. We performed the analysis using the 'crqa' package (Coco & Dale, 2014). Afterward, we examined how high and low performers differed in the variables of interest, i.e., the RQA variables in Table 1.

4. Results

4.1. Do high performers differ from low performers in the complexity of their SRL processes when solving an engineering design task?

We first applied the k-means algorithm to identify homogeneous subgroups of students based on their performance. Specifically, a standard k-means algorithm was used on the two performance indices (i.e., annual energy production and payback period) to find centroids that minimize the total within-cluster variation. In this study, annual energy production refers to the total amount of electrical energy generated by solar arrays over a year, while payback period is the amount of time it takes to recover the cost of the investment in solar arrays. The number of clusters was set as two since we were interested in comparing the differences between low- and high-performing groups. In addition, we performed a series of exploratory data analyses to find that the cluster sizes became unbalanced as we increased the number of clusters. Therefore, the 2-cluster solution was optimal and conceptually meaningful. The results in Table 4 showed that there were 39 and 22 students that could be identified as low and high performers, respectively. Students in the low-performing group failed to reach the goal of engineering design in this study. Low performers produced a relatively smaller amount of annual energy compared to high performers, but they took a longer time than high performers to recoup the customers' investment.

We then used the RQA to reconstruct the multidimensional system of SRL from the one-dimensional series of behavior durations, whereby the dimensionality of the reconstructed SRL system for each student was obtained. We then compared the difference in the dimensionality between low and high performers. As shown in Table 5, the SRL system of high performers had a significantly larger dimensionality ($M = 6.95$) than that of low performers ($M = 5.49$), $p < .05$, suggesting that higher performers differed with low performers in the complexity of SRL processes when completing the engineering design activity. The effect size of the difference was medium to large with Cohen's $d = 0.56$ (Cohen, 1988).

4.2. Are there differences in the temporal patterns of SRL behaviors between high and low performers?

We performed the categorical-RQA on the behavior sequence of each student. In doing so, the most commonly used RQA measures for quantifying the temporal patterns of a sequence were obtained for each student (Jenkins et al., 2020; Marwan et al., 2002; Wallot, 2017). In particular, the RQA measures included percent recurrence (%*REC*), percent determinism (%*DET*), average diagonal line length (ADL),

Table 4
The centroids of low- and high-performers regarding annual electricity and payback.

Group	Annual electricity	Payback period	Number
Low performing	210,494.85	20.97	39
High performing	484,484.86	13.60	22

Table 5
Group differences in the variables of interest between low- and high-performers.

	Group	*M*	*SD*	*t*	*df*	*p*	Cohen's *d*
Dimension	Low	5.49	2.71	−2.096	59	0.040*	0.56
	High	6.95	2.46				
%REC	Low	33.11	13.01	2.346	59	0.022*	0.67
	High	25.93	7.99				
%DET	Low	80.01	8.22	2.295	59	0.025*	0.60
	High	74.64	9.70				
ADL	Low	3.82	0.91	0.801	59	0.426	0.22
	High	3.62	0.89				
%LAM	Low	89.29	5.49	2.101	28.62	0.045*	0.60
	High	84.53	9.79				
TT	Low	5.39	1.86	0.811	59	0.421	0.22
	High	5.01	1.55				

* $p < .05$.

laminarity (%LAM), and trapping time (TT). We used *t*-tests to compare the differences in these RQA measures between low and high performers. We found that high performers demonstrated a significantly lower recurrence rate of SRL behaviors ($M = 25.93$) than low performers ($M = 33.11$), $p < .05$, Cohen's $d = 0.67$. Similar to the recurrence rate, the determinism of SRL behaviors for high performers ($M = 74.64$) was also significantly lower than that of low performers ($M = 80.01$), $p < .05$, Cohen's $d = 0.60$. Moreover, high performers were significantly lower in the measure of laminarity ($M = 84.53$) than low performers ($M = 89.29$), $p < .05$, Cohen's $d = 0.60$. The effect sizes for those differences were all medium to large (Cohen, 1988). In addition, the results showed that high and low performers had no significant differences in the RQA measures of ADL and TT (see Table 5).

5. Discussion

In this study, we found that the SRL processes of high performers were more complex than low performers, given the significant difference in the dimensionality of SRL system between the two performance groups. In other words, a larger number of components made up the SRL system of high performers when compared with low performers. Such components may include different types of cognitive activities (e.g., insight, causation, tentativeness, or differentiation), motivations (e.g., self-efficacy, self-concept, achievement goal orientation, interest, or task values), and emotions, for instance, curiosity, enjoyment, boredom, or relief. It is quite possible that a different set of components act together to yield a unique SRL system for each student. For instance, the SRL system of an individual may consists of mainly strategic planning and self-reflection, while the SRL system of another student involves the processes of self-motivation and emotion regulation. Therefore, caution is needed in interpreting this result. Although RQA with the time-delay embedding method allows us to retrieve the multidimensional dynamics of SRL from time-ordered behavior durations, the concept of dimensionality only reflects the statical structure of the data rather than specific SRL dimensions such as cognitive, metacognitive, motivational, and affective aspects of learning (Wallot, 2017). Clearly more research is needed to unravel the components of an SRL system and their relative importance to students' performance so that instructors can diagnose learning process in a comprehensive manner and deliver targeted interventions accordingly. This study shows for the first time that the number of SRL components can be referred through a novel analytical technique of RQA. But we acknowledge that this study is at the very early stage of this direction. Future research will benefit from advanced mathematical modeling techniques along with the collection and analysis of multimodal multichannel data about SRL.

Moreover, this study found that low performers showed a higher degree of both percent recurrence (%*REC*) and percent determinism (%*DET*) than high performers. Considering that %*REC* refers to the degree of repetition of SRL behaviors, this result suggests that low performers tended to repeat behaviors over time. Moreover, low performers demonstrated a more structured and predictable pattern of SRL behaviors than high performers, since %*DET* captures the degree of repetition of SRL behavioral sequences (Jenkins et al., 2020). In sum, lack of regularity was observed in the behaviors of high performers, which could be well explained by the nature of engineering design. Engineering design tasks are ill-structured problems that have no predetermined solutions. Furthermore, engineering design is an iterative process whereby students need to refine their designs through successive versions. Students ultimately choose a version of a design that best meets design requirements and customers' needs. High-performing students may generate multiple, qualitatively different solutions during the iterative search for an optimal design. For this reason, the behaviors of high performers in engineering design are more creative and adaptive than low performers. Our explanation of this finding is in line with the contention of Koopmans (2020), who argued that the lack of regularity, in fact, creates opportunities for creativity and innovation.

In addition, low performers were significantly higher in the RQA measure of laminarity (% LAM) than high performers, suggesting that low performers were more likely to get stuck in a behavior, i.e., conducting a specific behavior repeatedly before moving on to the other behaviors. This finding was partially in line with the research of Lajoie et al. (2019), who found that low performers tended to get stuck in the orienting phase of SRL for long periods of time.

According to Lajoie et al. (2019), one explanation was that low performers were less successful at extracting meaningful information from the context so that they were unsure about the next steps in problem-solving. In a previous study (Li, Du, et al., 2020), we used a network approach to examine the differences in interaction patterns of SRL behaviors among three performance groups, i.e., unsuccessful, success-oriented, and mastery-oriented groups. We found that the unsuccessful group tended to perform the observation behavior repetitively in the design process. They were hesitant about how to proceed and consequently performed a behavior repeatedly until a decision was made, which corroborated the findings of the present study.

In short, findings from this study contribute to the emerging literature on the temporal structure of SRL by examining the complexity of SRL process and the regularity of SRL behaviors, specifically in the context of engineering design. This study informs future research on SRL and the design of scaffoldings for learners. First, researchers are encouraged to explore SRL using nonlinear analytic methods (e.g., RQA and network analysis) since they are on the rise in the field of educational psychology and most importantly, SRL process manifests complexity characteristics (Koopmans, 2020; Li, Du, et al., 2020; Li et al., 2022; Wallot & Leonardi, 2018). The analytical techniques rooted in complexity science might be important alternatives to traditional linear statistical methods. For instance, the nonlinear analytic method of RQA enables researchers to reconstruct a multidimensional system of SRL and to examine its characteristics even though researchers have to limit the number of operating variables in their experiments due to various constraints. At a practical level, the RQA method and our interpretations of the RQA measures in SRL can be easily transferred to other research contexts, given that researchers only need to collect the information of SRL behaviors and the time-ordered durations of those behaviors. There is also abundant of resources in the literature that support the implementation of the RQA method. As an illustration, Wallot (2017) developed a step-by-step tutorial in R to illustrate the processes and products of RQA. Moreover, this study informs the design of instructional interventions, early warning systems, and learning analytic dashboards. For example, instructors can offer timely interventions based on the RQA measures if they find the percent recurrence of an individual's learning behaviors exceeds a cut-off value. RQA also provides a useful visualization of students' SRL behaviors (i.e., recurrence plot), which can be implemented in learning analytic dashboard to increase students' awareness of the regularity of their problem-solving behaviors.

6. Conclusion

In this study, SRL is conceptualized as a complex dynamical system. Therefore, we adopted the ideas and analytical techniques of complexity science to analyze SRL phenomenon accordingly. In particular, we used RQA to examine the differences in the complexity of SRL processes and the regularity of SRL behaviors between high and low performers as they accomplished an engineering design task in a computer-simulated environment. We found that the SRL processes of high performers were more complex than low performers. The behaviors of high performers lacked regularity, whereas low performers were more likely to conduct a behavior repeatedly in the process of engineering design. This study extends the literature on the dynamics of SRL in both theoretical and methodological dimensions. Theoretically, this study provides researchers with a new perspective of SRL process that is complex, nonlinear, dynamically emerging, and continuously updated by internal and external feedback inputs. By introducing the CDS approach to the field of SRL, this study also opens up many fruitful lines of research that can potentially advance the development of SRL theories. For instance, it would be interesting to examine the shift of SRL components and their roles to performance at a fine-grained size, which could help understand how students adaptively manage the many components of SRL to succeed in learning or problem-solving. Moreover, the research on SRL will be more complete if researchers consider the overall features of a SRL system and the quality of SRL processes and behaviors simultaneously in a study. In addition, this study has significant methodological insights. Specifically, this study is the first to demonstrate how RQA can be used to analyze the temporal structure of SRL behaviors and how RQA measures can add new information about students' performance differences. Nevertheless, this study has several limitations that must be acknowledged. First, the nature of nonlinear analytic methods prevents us from making causal conclusions about how the regularity of SRL behaviors is related to task performance. A second limitation is the homogeneity of participants. They were all ninth-grade students, so we cannot make a conclusive argument that findings from this study apply to other populations. Finally, we relied on system log files and did not take into account any subjective data. Regardless of these limitations, this study offers a promising direction for the examination of the regularity of SRL behaviors and for the extensions of SRL theories, i.e., the development of a complex dynamical model of SRL. This study takes the first step toward this direction and implores SRL researchers to provide more theoretical insights and empirical evidence.

Declaration of competing interest

The authors declare that they have no conflict of interests.

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Ethical approval

Prior to the study, we had obtained research ethics approval from the institutional review board. In addition, all parents provided consent for their children's participation in this study. We explicitly explained the research purposes and procedures to the students; therefore, they were aware of the potential benefits and risks of the study.

Data access

Data collected for the project have not been made available through an open data repository given the Ethics requirements. However, the anonymized data in this study can be accessed upon reasonable request.

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