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On the Instructional Sensitivity of CAD Logs*

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Computer-aided design (CAD) logs provide fine-grained empirical data of student activities for assessing learning in engineering design projects. However, the instructional sensitivity of CAD logs, which describes how students respond to interventions with CAD actions, has rarely been examined. For the logs to be used as reliable data sources for assessments, they must be instructionally sensitive. This paper reports the results of our systematic research on this important topic. To guide the research, we first propose a theoretical framework for computer-based assessments based on signal processing. This framework views assessments as detecting signals from the noisy background often present in large temporal learner datasets due to many uncontrollable factors and events in learning processes. To measure instructional sensitivity, we analyzed nearly 900 megabytes of process data logged by our Energy3D CAD software as collections of time series. These time-varying data were gathered from 65 high school students who solved a solar urban design challenge using Energy3D in seven class periods, with an intervention occurring in the middle of their design projects. Our analyses of these data show that the occurrence of the design actions unrelated to the intervention were not affected by it, whereas the occurrence of the design actions that the intervention targeted reveals a continuum of reactions ranging from no response to strong response. From the temporal patterns of these student responses, persistent effects and temporary effects (with different decay rates) were identified. Students' electronic notes taken during the design processes were used to validate their learning trajectories. These results show that an intervention occurring outside a CAD tool can leave a detectable trace in the CAD logs, suggesting that the logs can be used to quantitatively determine how effective an intervention has been for each individual student during an engineering design project.

Keywords: computer-based assessment; instructional sensitivity; data-intensive research; computer-aided design; time series analysis; engineering design; educational data mining; learning analytics

1. Introduction

High-quality assessments of deep learning hold a critical key to improving learning and teaching. Their strategic importance was highlighted by President Obama in March 2009: "I am calling on our nation's Governors and state education chiefs to develop standards and assessments that don't simply measure whether students can fill in a bubble on a test, but whether they possess 21st century skills like problem solving and critical thinking, entrepreneurship, and creativity" [1]. However, the kinds of assessments that the President wished for often require careful human scoring that is far more expensive to administer than multiple-choice tests [2]. Computer-based assessments, which rely on the learning software to automatically collect and sift learner data through unobtrusive logging [3], are viewed as a promising solution as digital learning becomes increasingly prevalent. Educational data mining and learning analytics [4] represent the latest development in this field towards the direction of *big data* applications [5, 6].

1.1 Instructional sensitivity and educational assessment

While there has been a lot of work on computer-based assessments for science education [7–11], some of which addressed complex problem solving skills [12–15], one foundational question remains under-explored thus far: To what extent can the logged learner data reveal the effect of an instruction?

There are two main categories of evidence for determining the *instructional sensitivity* of an assessment tool: judgmental evidence and empirical evidence [16]. Computer logs provide empirical evidence based on user data recording—the logs themselves provide empirical data for assessment and their *differentials* before and after instruction provide empirical data for evaluating the instructional sensitivity. Like any other assessment tools, computer logs must be instructionally sensitive [17] if they are to provide reliable data sources for measuring student learning. In some cases, insensitivity could indicate the ineffectiveness of the learning software in translating instructional outcomes into human–computer interactions that can be logged and analyzed. Hence, the study of instructional sensitivity may also help learning software developers improve their products.

Throughout this paper, we will use the term "instructional sensitivity" as it is commonly used in the literature [17–20]. This does not mean that our assessments are limited to measuring only the effects of traditional instruction, however. In fact, we

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intend our theoretical framework (described in Section 2) to cover the study of all types of interventions, including those carried out by humans (such as teacher instruction or group discussion) or generated by the computer (such as adaptive feedback or intelligent tutoring [21, 22]). In this phase of our research, we focus only on human interventions. Studying the instructional sensitivity of learner data to human interventions will enlighten the development of effective computer-generated interventions for teaching complex science and engineering practices in the future (which is another reason, besides cost effectiveness, why research on automatic assessment using software logs is so promising).

Another important thing to keep in mind is that, as the effect of an intervention may differ from one student to another, the instructional sensitivity of an assessment item is not an "either/or" question—it must be gauged by statistically considering the responses from an ensemble of students. An item can be said to be completely insensitive if none of its indicators shows any difference before and after the intervention for all students, or strongly sensitive if they all show observable differences for all students. Between these two extremes, an item should be generally considered as instructionally sensitive if a sizable percentage of students react to a meaningful intervention. Increasing the instructional sensitivity is the goal of both instructional materials and assessment tools development.

1.2 *Instructional sensitivity of design logs*

Earlier studies have used computer-aided design (CAD) logs to capture the designer's operational knowledge and reasoning processes [23–25]. Those studies were not intended to understand the learning dynamics of engineering design [26] taking place within a CAD system, however. Different from them, this study addresses the instructional sensitivity of CAD logs, which describes how students react to interventions with CAD actions. This is a complex, dynamical learning process that involves the interactions among students, instructors, tools, and artifacts.

The study of instructional effects on design behavior and performance is particularly important, viewing from the perspective of teaching science through engineering design [27–30], a practice now mandated by the newly established Next Generation Science Standards of the United States [31, 32]. A problem commonly observed in precollege engineering projects is that students often reduce engineering design challenges to construction or craft activities that may not truly involve the practice of science [33, 34]. This suggests that other driving forces acting on learners, such as hunches and desires for how the design artifacts should look, may overwhelm the effects of instructions on learning and using science in design work. Hence, the research on the sensitivity of design behavior to science instruction requires careful analyses to detect the changes. The insights obtained from studying this instructional sensitivity may result in the actionable knowledge for developing effective instructions that can reproduce or amplify those changes.

This work is based on a time series mining method [35, 36] that we have recently developed to collect and analyze large process data generated by students through using our Energy3D CAD software (http://energy.concord.org/energy3d). Preliminary results have been reported in an earlier paper [37]. The results have demonstrated that the process analytics based on CAD logs can reveal various student behavior patterns that may have profound cognitive implications, such as iterative cycles of inquiry and design.

2. Theoretical framework

Computer-based assessments can be viewed as operational procedures for detecting signals from the noisy background often present in large temporal learner datasets due to many uncontrollable and unpredictable factors and events in deep learning processes over a significant period of time. This view leads to a useful theoretical framework that borrows many ideas, concepts, and methods from signal processing to inspire, guide, and organize our research, as described in the following subsections.

2.1 *A black-box approach to studying complex learning dynamics*

Our research is concerned with a student learning science and engineering concepts and skills through creating 3D computer models that function in cyberspace using a modern CAD tool such as Energy3D that supports both virtual construction (to create structures) and virtual experimentation (to test functions). The research subject is a complex dynamical system comprising three interacting subsystems: the learner, the CAD tool, and the artifacts, which are connected through the design loop (Fig. 1). Each subsystem has its own governing rules. For example, the learner is motivated by various factors such as prior knowledge and personal interest, the user interactions with the CAD tool are determined by its user interface, and the design artifacts are created to meet the specifications.

Each learner has some degree of inertia and autonomy that may be opaque to researchers and is constantly influenced by planned or random events. Each uses the CAD tool in unique ways to design different artifacts, sometimes unexpectedly.

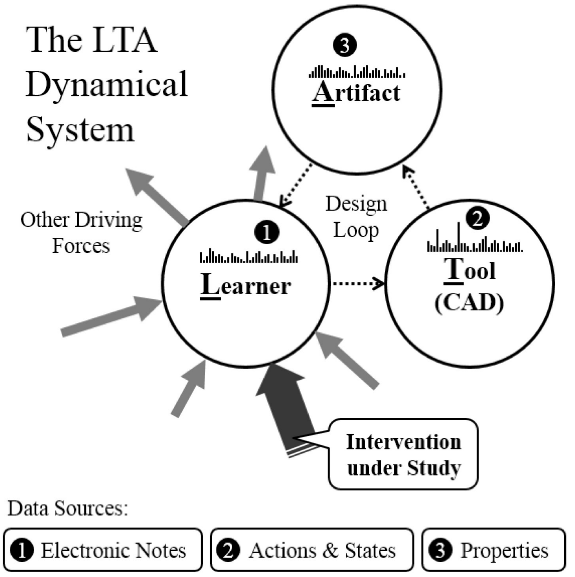


Fig. 1. Our research subject is a dynamical system consisting of three interacting subsystems: the learner, the tool (CAD), and the artifacts (LTA). The learner responds to interventions and uses the CAD tool to create or revise the design artifact. Our intervention analysis will be based on different data sources produced by these subsystems, as illustrated above.

As such, the reaction to the same intervention may vary from learner to learner or even from design to design. In other words, the learner-tool-artifact (LTA) system may respond to instructional inputs with numerous possibilities that are not feasible to enumerate or predict *a priori*. From the assessment point of view, this complicated open-ended nature of the LTA system suggests that it would be theoretically favorable to treat it as a *black box*, meaning that the system should be studied in terms of its inputs, outputs, and transfer characteristics as the accurate knowledge of its internal workings cannot be exactly known (in contrast to this view, most curricular instructions are developed with a *white box* mindset that assumes students would follow them precisely and learning would progress as hoped).

2.2 Time series analysis

Time series analysis [38] provides an experimental approach to studying the complex behaviors of this black box by examining the effects of the inputs (the interventions) on the outputs (the changes of system behaviors after the interventions). Figure 2 shows two hypothetical scenarios (that have been confirmed using student data, as discussed in later sections).

Time series analysis in this study aims at two goals:

1. *Instructional sensitivity*: The goal is to evaluate the effects of different interventions on different variables, such as different learners, different processes, acquisition of different concepts and skills, and so on.
2. *System identification*: The goal is to characterize the LTA system through observing its responses to inputs that are deliberately designed to probe certain characteristics of the system. The two goals have considerable overlaps but are distinct in that the former has an emphasis on instruction as stimuli to the system and the latter has an emphasis on intrinsic learning dynamics within the system. This paper will focus on the study of instructional sensitivity, but with system identification in the background. This combined perspective is helpful because we are ultimately interested in knowing what kinds of interventions are more

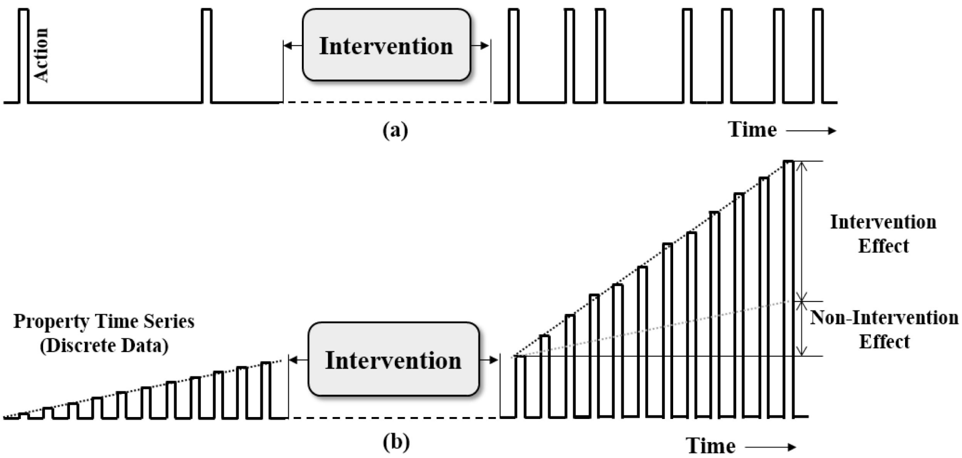


Fig. 2. A schematic illustration of the effect of an intervention on: (a) the frequency of a certain type of learner action, in which case the intervention increases the frequency of the action, and (b) the value of a certain property of the design artifact, in which case the intervention accelerates the increasing of the value.

effective for what kinds of students working on what kinds of projects with what kinds of tools.

3. Types of response data

The responses of different learners to an intervention vary considerably. The purpose of this research is to characterize the responses recorded in the CAD logs (which include three types of data—student notes, student actions, and artifact properties, as shown in Fig. 1) and use the time series data to investigate the following questions: (1) *Susceptibility*: What sub-processes are more notably changed by the intervention? (2) *Persistence*: For how long does an intervention effect last to regulate learner behavior? (3) *Variation*: What students are more responsive to the intervention?

To answer these questions, we obtain from the time series data a *response function* that describes the reaction of the learner to the intervention about a design aspect (for a definition of the response function, see Box 1). The shape of a response function represents the persistence or the decay of an intervention effect (Fig. 3).

Box 1: According to the linear response theory widely used in physics and signal processing, a response function $R_x(t)$ describes the susceptibility of a variable x of a dynamical system to an intervention:

$$x(t) = \int_{-\infty}^{t} R_x(t-\tau)I(\tau)d\tau$$

where $x(t)$ is the time series of the studied variable and $I(\tau)$ is the intervention function. In the case of an impulse input, $I(\tau) = \delta(\tau - t_0)$, where δ is the Dirac delta function that equals zero if not at time t_0, the observed time series after the intervention time t_0 becomes the response function: $R_x(t) = x(t + t_0)$.

In the following subsections, we will discuss possible responses to interventions from three categories of learning and design aspects.

3.1 *Effects on design actions*

The action category addresses how an intervention

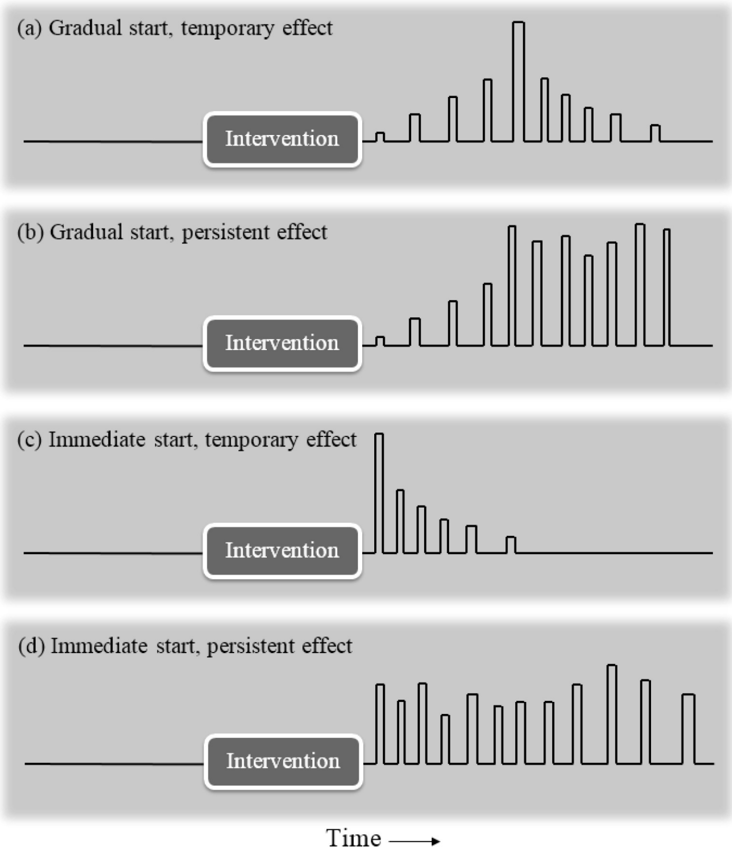


Fig. 3. Four possible response functions that may be derived from the time series data: (a) gradual start, temporary effect; (b) gradual start, persistent effect; (c) immediate start, temporary effect; and (d) immediate start, persistent effect.

alters students' design behaviors with a CAD tool. For example, if students are unaware of a feature, a reminder would likely increase its use.

An important fact that we must keep in mind when evaluating the results across the board, however, is that the data for studying the instructional sensitivity in this category depend considerably on the usability and capability of the software features. The action using an easy-to-use feature may appear more frequently in the logs than the action using an awkward-to-use feature. The type of action that constantly results in interesting changes in the design artifact (such as visually dramatic changes in the CAD software's 3D scenes due to construction or destruction activities) may appear more often in the logs than the type of action that does not immediately cause significant changes on the computer screen (such as certain virtual experimentations involving delicately adjusting parameters to optimize a design iteratively or incrementally). The advantage of time series analysis is that it allows us to track each type of action individually. In this way, an action can be assessed in its own context.

The characterization of the instructional sensitivity per action type provides a picture of distribution across the action space created by the user interface of the CAD software. The data sources for this category are the action time series that record the timestamp, type, target, and parameters of the actions taken during a design project. Some of the data types are shown in Table 1.

3.2 Effects on design artifacts

A design artifact is the *cumulative* result of a sequence of continuous design actions, but the actions may not measure the properties and performance of an artifact—more actions do not necessarily entail higher performance. As the performance of an artifact often represents that of its designer, it is important to understand its instructional sensitivity. *The artifact category* addresses how an intervention changes the structures and functions of students' design artifacts. In our research, the time series analysis of artifacts is performed through post-processing the intermediate products recorded by Energy3D. In this way, we can extract the time series data of any artifact property that may shed light on learning progress.

The characterization of the instructional sensitivity per artifact property provides a picture of distribution across the problem space created by the design challenge. Effective interventions around a design aspect should result in improvements of the corresponding artifact properties (but not others) over time.

3.3 Effects on design thinking

A unique feature of Energy3D is that it enables students to take electronic notes to report their (simulated) experimental results with their designs, record the data, and document their rationales at each design step. These notes are saved automatically and synchronously to the design intermediates. In the meantime, their compilation processes are logged in a mechanism similar to tracking changes in a word processor. These features record a trajectory of design thinking, expressed in words, in parallel with design actions. In our classroom study, we required students to take notes diligently as this practice would give them opportunities to reflect on their own designs. These notes provide invaluable data sources to probe what students thought, as opposed to what they did—which were captured in the action and artifact time series. The documentation category addresses how an intervention may affect students' design thinking processes. For example, did the usages of certain science keywords in the documentation increase as a result of an instruction on using science concepts in design?

4. Research settings and design

4.1 The research participants

Sixty-eight 9th graders (27 boys and 41 girls) in three physics classes (E, F, and G) at a high school in Massachusetts, where the state education standards mandate engineering contents be incorporated in the science curriculum [39], participated in this research in June 2013. Each student used a notebook computer to run Energy3D and worked individually in the classroom. The project took seven class periods (approximately 45 minutes per period) to complete. After all the data were collected and cleaned, 65 out of the 68 students were determined to have produced sufficiently complete data for analyses.

Table 1. Some examples of action data

Action classes	**Data expressions**	**Examples**
Add/remove an element	{x}	{Add Wall}, {Remove Roof}
Revise an element	{x}	{Edit Wall}, {Move Building}, {Undo}
Toggle a Boolean state	<x>	<Heliodon>, <Solar Map>, <Shadow>
Set a value	[Attribute: x]	[Camera: (–47, 22, 54) (0.98, 0.15, 0.05)], [Time: 6/30:11]
Write a note	[Note: x]	[Note: 787]

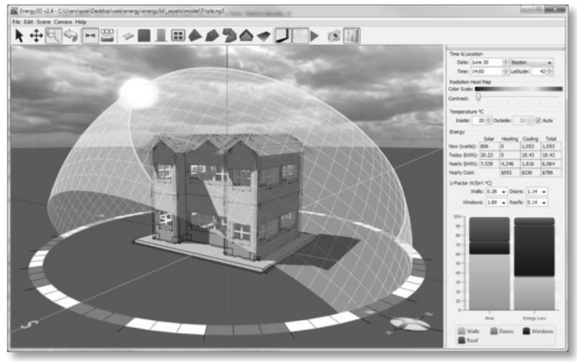
4.2 The Solar Urban Design Challenge

The Solar Urban Design Challenge [40] requires students to consider solar irradiance as it varies over seasons and locations [41–43] and apply these concepts to solve open-ended problems using two integrated simulation tools, the Heliodon Simulator (Fig. 4(a)) and the Solar Irradiation Simulator (Fig. 4(c)), of Energy3D. These features, similar to those in contemporary CAD software such as Autodesk's Ecotect [44], distinguish Energy3D from pure computer-assisted drafting activities in which students draw structures whose functions cannot or will not be verified or tested within the drafting software. As such, the negative side effects of using CAD in classrooms previously reviewed by some authors [45], such as circumscribed thinking, premature fixation, and bounded ideation [46], can be mitigated by these embedded science simulations as their visualizations provide feedback to stimulate iteration.

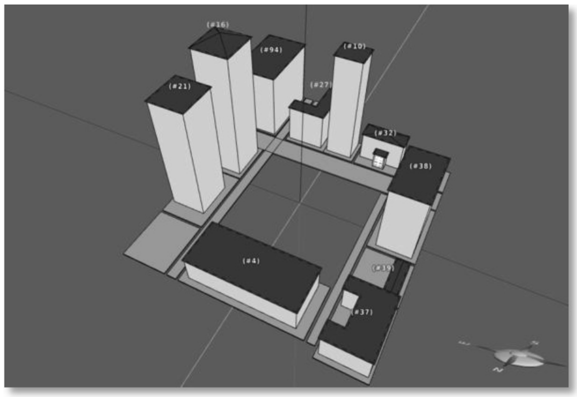
In the design challenge, students construct a number of buildings within a square city block surrounded by a number of existing buildings of different heights (Fig. 4(b)), with the goals of exploiting solar energy to achieve energy efficiency of the new construction. To save time, students need not add windows as it is assumed that the window areas are proportional to the wall areas of the buildings. Each student is required to consider alternatives and create at least three different design solutions, from which he or she picks one to represent his/her final design. The complexity of this design problem stems from three aspects:

1. the inter-building shadowing among the new buildings and the existing buildings (unmodifiable);
2. the intra-building shadowing of the new buildings that depends on their own shapes;
3. seasonal differences in the Sun path between summer and winter situations.

Students must use systems thinking to take all these factors into account and make trade-off decisions among multiple competing variables. Simulations that provide quantitative results are essential for students to make design choices.



(a)



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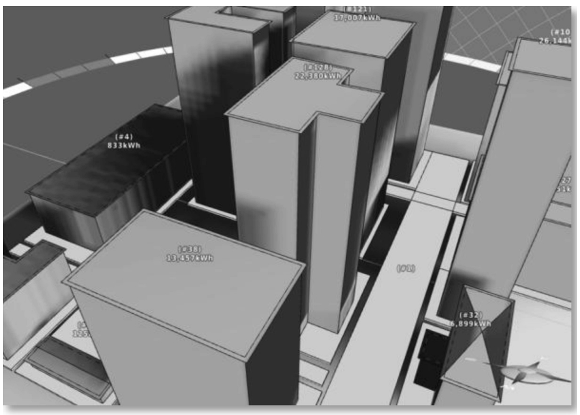


(c)

Fig. 4 (a) The user interface of Energy3D with the Heliodon Simulator open in the scene to visualize the Sun path at a given location and time; (b) the Solar Urban Design Challenge requires students to design a city block to meet a set of criteria and constraints; (c) the heat map of daily solar irradiation on the surfaces of some structures in a dense urban area generated by the Solar Irradiation Simulator.

4.3 The intervention

In earlier classroom trials of the Solar Urban Design Challenge, we observed that many students spent much more time on designing unique building shapes rather than exploring solar irradiation—even though the specifications explicitly include requirements for solar energy performance. Solar design in this study is critically important because it is this step that provides opportunities to learn about the iterative cycle of engineering design through data-driven scientific inquiry using the built-in simulators. Students will not fully attain the learning goals if they underperform in the solar design tasks. Because of this importance, we arranged an intervention that intended to steer the students to the right track in the middle of the project. In this way, the instructional sensitivity of CAD logs can be examined in the context of the so-called "design-science gap" [34, 47], a problem that frequently fails science learning in design projects.

This intervention was a 10-minutes lecture by one of the authors (SN), given about two class periods after the students started the project. The lecturer demonstrated the applications of the simulators. He explained how the solar energy input may depend on the path of the Sun in the sky as well as the shape of the building and its location relative to others. He also discussed the interpretation of a solar irradiation heat map generated by Energy3D. Before his intervention, all students had finished their first designs. Hence, the differences between the first design and the subsequent ones can be used to measure the instructional effect.

It is noteworthy that, although the teacher was present in the classroom all the time and had certainly intervened in many ways, SN's instruction was the only intervention regarding solar design. The teacher's interventions can be considered as other driving forces as depicted in Fig. 1.

4.4 Data intensity and quality control

Students' actions were logged every two seconds (if an action had occurred). Thus, action logs may contain a total of 3,000–5,000 lines of data. Students' intermediate artifacts were logged less frequently—every 20 seconds if there was any change to the current CAD model. Thus, an artifact log folder may contain a total of 300–500 intermediate files. The data collected from the students add up to nearly 900 megabytes. More than 20 megabytes of data were recorded from the most active student. To analyze this sheer volume of process data, a visual analytics program was written in Java to automatically process the datasets and visualize the results with graphs so that researches can rapidly identify patterns and trends.

To control the quality of the process data, it is important to minimize the side effect of the learning curve of the tool. As with any other tool, there is a learning curve for Energy3D, however simple and intuitive its user interface may be. Our strategy to confine this side effect was to begin the project by giving a real-time demonstration that covered the basics of Energy3D. Students were then given 30 minutes to learn and explore the tool freely before working on the Solar Urban Design Challenge. Only after they started to work on the challenge were the processes logged. This reduced some random exploratory data not pertinent to solving the challenge. To ensure that the data collection was not interrupted by possible Internet connection problems, each student was given a USB drive onto which all the learner data were stored.

5. Temporal data patterns

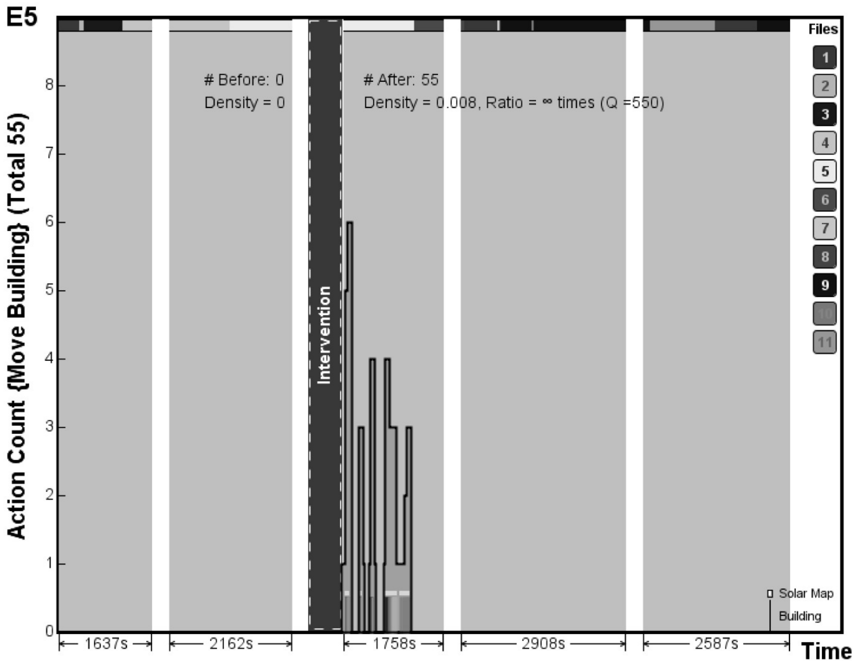
In this section, we will focus on analyzing a number of selected students and discussing the temporal patterns in their data. These students were selected on the basis that the temporal patterns of each one of them represent a class of design behavior.

5.1 Instructionally sensitive actions

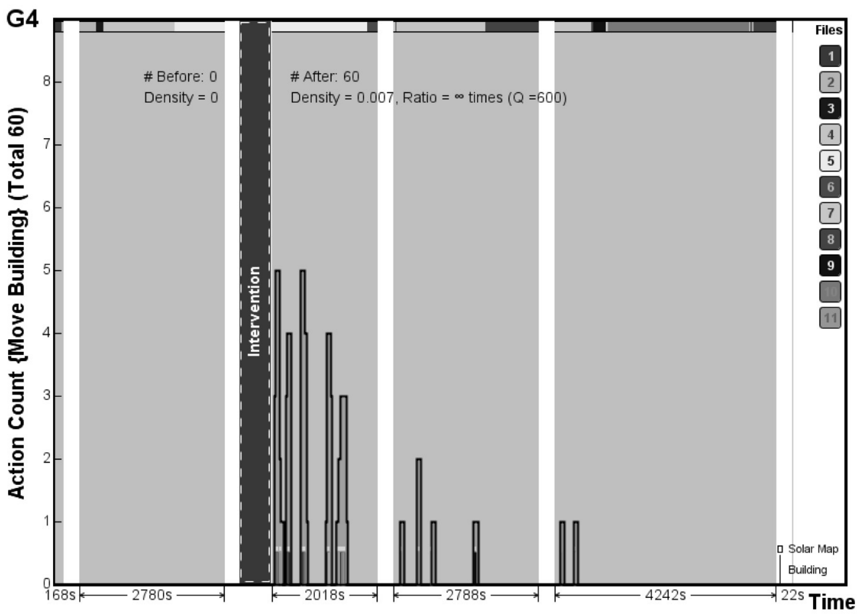
Among many different types of design actions, we chose to study a subset that is most critical to the design challenge. For instance, site layout has a big impact on solar heating in buildings, as neighboring tall buildings can block the sunlight in different ways at different times [43, 48]. As the Sun moves differently in the sky in different seasons, a layout may have different solar energy gains in the winter and summer. The existing buildings in the provided template (Fig. 4(b)) were carefully designed such that the southwestern and southeastern parts of the city block are the best locations to erect the required skyscrapers that can yield optimal solar heating in both winter and summer situations. However, this was not disclosed to students and cannot be seen without careful analysis using the simulators. To discover an energetically favorable layout, students have to frequently move the buildings around to experiment with many different layouts in order to find an optimal solution that is satisfactory for both winter and summer, based on evaluating the simulation results of the solar heating of all the new construction in those layouts (Fig. 4(c)). If the logs show no action of moving buildings, it is almost certain that the student did not consider site layout and it can be concluded that he or she did not accomplish the learning goals. Hence, the instruction stressed the importance of moving buildings.

Of all the four temporal patterns hypothesized in Fig. 3, two of them were unambiguously identified from the student data. Figure 5 shows two response functions that can be categorized as Pattern (c) (immediate start, temporary effect), but with different decay rates. In the case shown in Fig. 5(a), the intervention effect lasted only for the remainder of the class period immediately following the intervention. No {Move Building} action was logged in the subsequent two class periods. In the case shown in Fig. 5(b), the occurrence of the {Move Building} action gradually diminished in the following three class periods. In both cases, no {Move Building} action was ever recorded before the intervention.

Figure 6 shows two examples of Pattern (d) (immediate start, persistent effect) that logged over 100 {Move Building} actions. In both cases, the solar irradiation heat map was turned on at every move, indicating that the students might be experi-



(a)



(b)

Fig. 5. The fast (a) and slow (b) decay behaviors (Pattern (c) in Fig. 3) from the time series graphs of the {Move Building} action for two students E5 and G4. The light gray bands separated by white gaps represent different class periods. The black vertical bar in the middle represents the intervention event. The array of small color rectangles near the top edge represents the sequence and transition of files students worked on. A tiny white dot in the middle of a histogram bar indicates that the solar irradiation heat map was generated in that event.

menting with the solar layouts (if the heat map is not shown, moving a building will not result in any visible change with regard to solar irradiation that will elicit further experimentations).

Patterns (a) and (b) with a gradual start were not evident in the action data. This makes sense because the {Move Building} action requires no effort to master—informed students can immediately resort to actions upon instruction. A pattern of gradual start may be more likely to be found from the data if the action command requires some initial effort to learn.

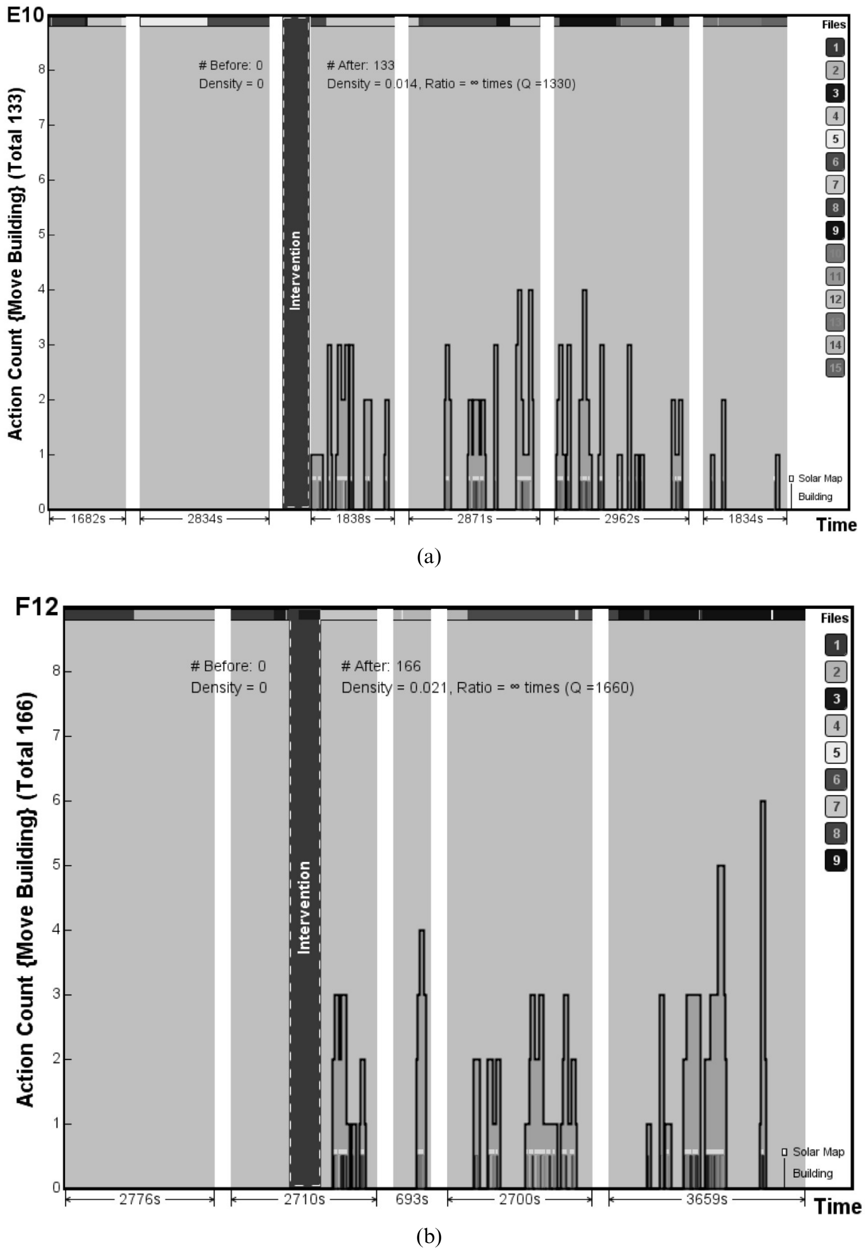


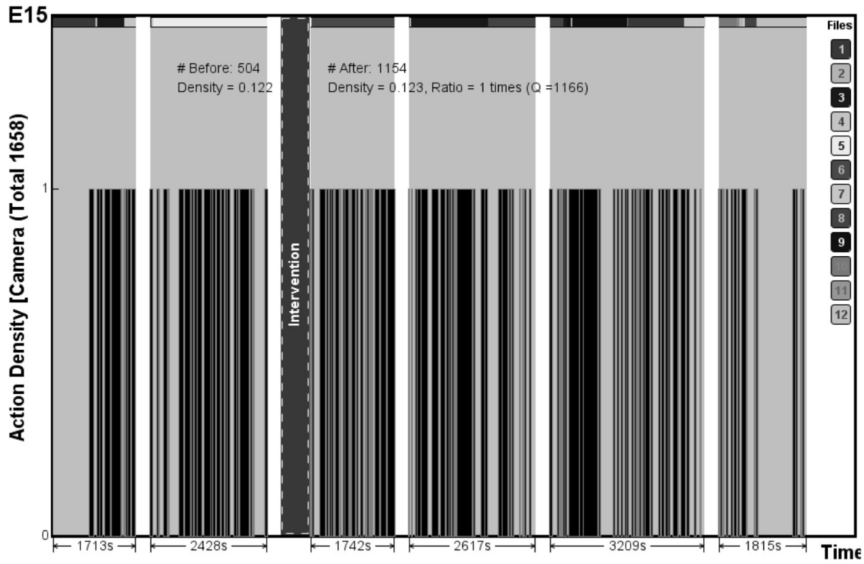
Fig. 6. Two examples of Pattern (d) that show the persistent effect of the intervention. For an explanation of the visual elements in these graphs, see Fig. 5.

5.2 Instructionally insensitive actions

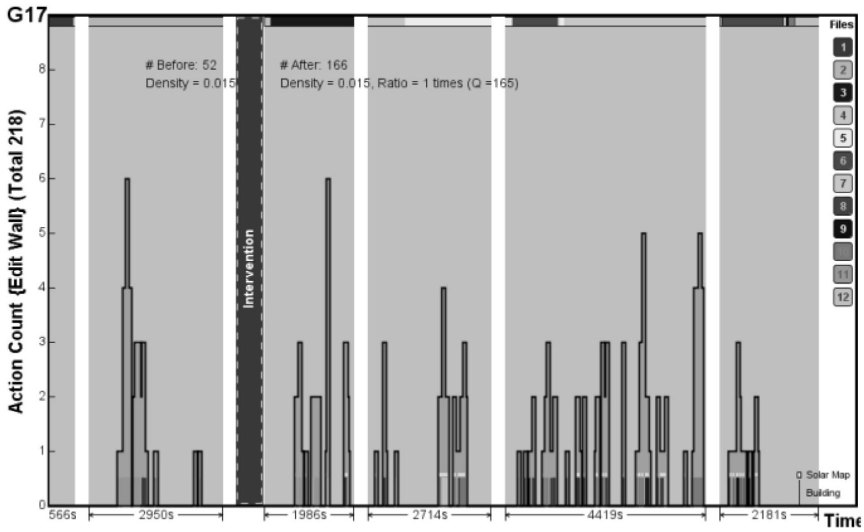
It is also interesting to examine the temporal patterns of the actions that are not sensitive to the intervention. Figure 7(a) shows that the action density of rotating the 3D view (a basic action in all 3D software) before and after the intervention, not surprisingly, had no apparent difference for student E15. Figure 7(b) shows that the action density of editing walls of student G17 was not affected by the intervention, either. The exact definition of action density will be introduced in Section 6.1.

5.3 Instructional sensitivity of artifact performance

We examined the relationship between performance improvement of design artifacts and the intervention. This subsection presents two interesting cases in which the process data show that the students went through iteration between winter and summer simulations (more on this design aspect in Section 7) and arrived at their optimal solutions. Both students discovered that a tall building with a larger south-facing side and smaller west/east-facing sides receive more solar energy in the winter and less in the summer (more in Section 7). Figure 8 shows all the milestone designs of the two students.



(a)



(b)

Fig. 7. (a) The action density of rotating the 3D view was not affected by the intervention, (b) neither was the action of editing walls. Different from histograms in (b) and previous graphs in Figs 6 and 7, graph (a) is a density plot in which a thin vertical line of a fixed height is drawn wherever there is an event.

A challenge for time series analysis of artifacts is that the results must accurately reflect the evolution of artifact performance. This requires that the automatic analysis incorporates data mining rules based on disciplinary knowledge. For example, in order to visualize these students' design trajectories, we calculated the following weighted aspect ratio that characterizes their design rationale:

$$S = \sum_{i=1}^{N} w(i) \frac{L_{\mathrm{EW}}(i)}{L_{\mathrm{NS}}(i)}, w(i) = \frac{H(i)}{\sum_{j=1}^{N} H(j)},$$

where N is the total number of new construction in the block, $L_{\mathrm{EW}}(i)$ is the length of the i-th building along the east-west direction, $L_{\mathrm{NS}}(i)$ is the length of the i-th building along the north-south direction, $H(i)$ is the height of the i-th building, and $w(i)$ is the weight factor that represents the contribution of the height of the i-th building among the new construction. A taller building has a larger contribution to the overall solar performance. In the cases of the two students, the increasing trend of the S-factor, as shown in Fig. 9(a), indicates that their optimizations were on the right track.

The average daily solar energy density over all the new buildings is another performance indicator that can be calculated from these students' artifacts:

$$\rho = \frac{1}{N}\sum_{i=1}^{N}\frac{E(i)}{V(i)},$$

where $E(i)$ is the total solar energy radiated on all the surfaces but the roof of the i-th building and $V(i)$ is its volume. Figure 9(b) shows the evolution of average daily energy densities in the winter and in the summer over the four milestone designs. The results show steady improvements of solar performance after the intervention in both cases. G3's solar design outperformed G8's because her *S*-factor was greater.

6. Population data patterns

In education practices, no instruction has exactly the same effect on different students. The statistics of student data often reveals a continuum of responses to the same instruction. This section will present our findings based on the data from the 65 students.

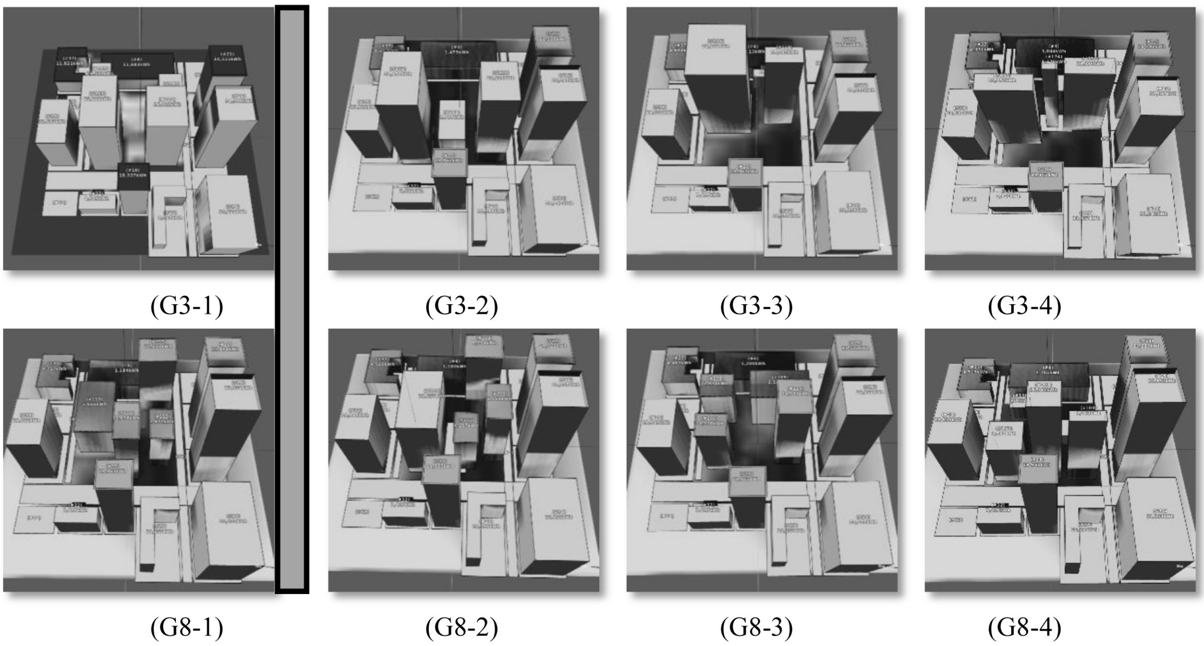


Fig. 8. The first row are the designs of students G3 and the second row are those of G8. Designs G3-1 and G8-1 were created before the intervention. G3-4 and G8-4 were picked by the students as their best designs.

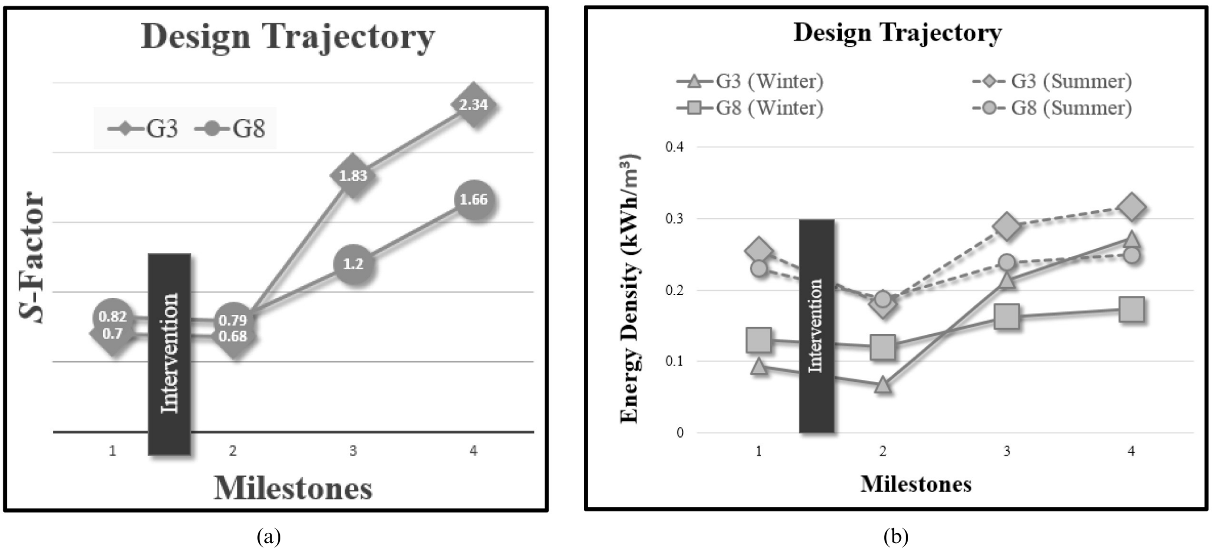


Fig. 9. The trends of solar optimization in the data from G3 and G8 show that the intervention may have boosted the performance of their design artifacts, conforming to the pattern illustrated in Fig. 2(b). (a) The S-factor (defined in Section 5.3); (b) the average daily solar energy density radiated on the new construction.

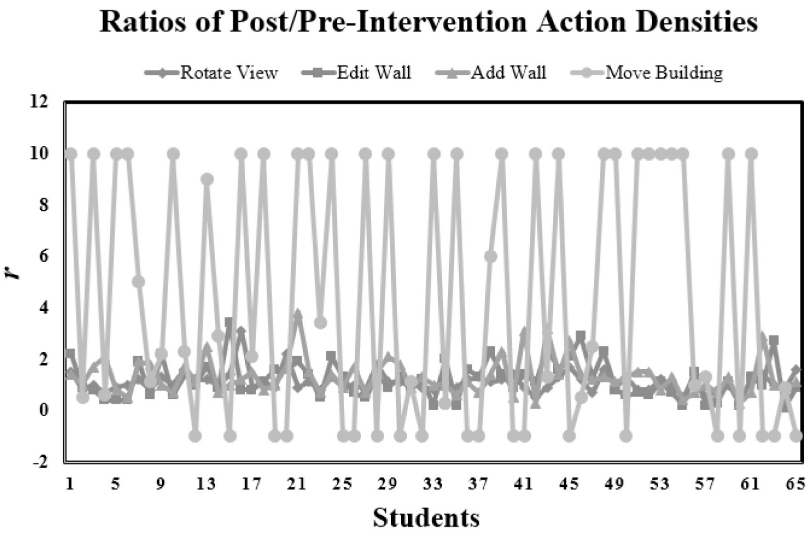
6.1 Changes of action densities

One attribute of the data that characterizes the change of a design behavior due to the intervention is the ratio of the action density after the intervention to the action density before the intervention:

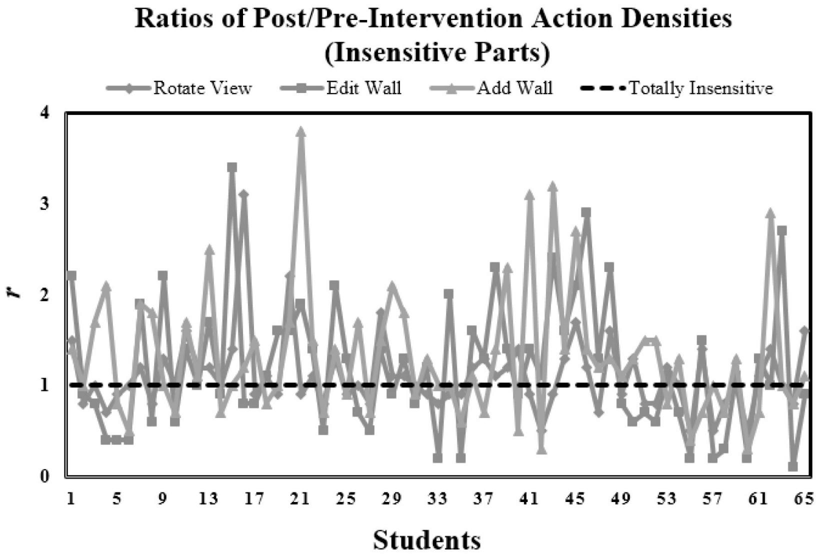
$$r(A) = \frac{N_{\text{after}}(A)/T_{\text{after}}}{N_{\text{before}}(A)/T_{\text{before}}},$$

where $N_{\text{after}}(A)$ is the number of times action A was recorded after the intervention, $N_{\text{before}}(A)$ is the number of times action A was recorded before the intervention, T_{after} is the length of time after the intervention, and T_{before} is the length of time before the intervention. There are a few special cases for calculating this ratio:

1. When $N_{\text{before}}(A) = 0$ and $N_{\text{after}}(A) > M$, $r(A)$ is infinity, but in our calculation, the result is set to a number much larger than the rest of the data (such as 10) to make it outstanding. The parameter M is the minimum number of recorded actions for them to be considered as non-random data. M was chosen to be 20 in this study.
2. When $N_{\text{before}}(A) = 0$ and $N_{\text{after}}(A) < M$, $r(A)$ is set to –1.
3. When $N_{\text{before}}(A) \neq 0$ and $N_{\text{after}}(A) < M$, $r(A)$ is set to 0.



(a)



(b)

Fig. 10. (a) The distribution of the ratios of post/pre-intervention action densities for four types of actions across 65 students. (b) The same graph without the {Move Building} data showing a magnified view of the insensitive data that fluctuate around one (which corresponds to a totally insensitive case).

$r(A) = 1$ indicates that the instruction had no effect on the design behavior, $r(A) > 1$ indicates that the instruction had a positive effect, and $r(A) < 1$ indicates that the instruction had a negative effect.

The ratio $r(A)$ has an additional meaning that is significant—the sum $\sum_A r(A)$ also measures the change of design activity over time. Typically, students are more likely to be engaged at the beginning of a project. Hence, the post-intervention action densities could be lower than the pre-intervention ones as the intervention in our case occurred in the middle of the project. If a student had lost interest in pursuing the design project and became inactive later, the $r(A)$'s and their sum would be likely to be lower than one. In the opposite case, large $r(A)$'s indicate lasting effects of engagement, which, in turn, translate into high fidelity of the learner data (in general, the fidelity of computer logs decreases rapidly when students are disengaged).

Figure 10 shows the distribution of the ratios of four types of actions, "Rotate View," "Edit Wall," "Add Wall," and "Move Building," across the 65 students. The first three types were the most common actions in the data. Just as expected, the data fluctuate around one for the first three types of actions, because in practice they have little to no correlation with the intervention (see Fig. 10(b) for a clearer view of this fluctuation). The fact that many data points from the first three types of actions are close to one highlights the statistical reliability of the temporal data. For instance, as students must constantly rotate the view in order to work in the 3D space, the action should not change dramatically as they move forward (unless they were disengaged in the later stage of the project). This consistency is confirmed for most students and can be seen in Fig. 10(b).

Figure 10 also illustrates the importance of instructional sensitivity of an assessment item. For example, as the "Edit Wall" or "Add Wall" action data are not susceptible to the instruction on solar design, they probably should not be used to assess student performance on solar design.

6.2 t-test results of action density changes

Another way to investigate the changes of action densities due to the intervention is to run a t-test that compares the ratios of the number of a target action against the total number of actions before and after the intervention. The results show that there is a highly significant difference for the {Move Building} action: $t(64) = 5.02$, $p < 0.0001$, with an effect size $d = 0.62$. In comparison, $t(64) = -1.93$, $p = 0.06$ for the {Add Wall} action and $t(64) = -3.15$, $p < 0.01$ for {Edit Wall} action, indicating that they are not as statistically significant.

6.3 A continuum of responses

For the "Move Building" action, Fig. 10 shows that 26 students responded to the instruction ($r = 10$), 20 students did not respond at all ($r \leq 0$), and the rest were in the middle (these include four students whose r values are close to zero, meaning that their action densities of {Move Building} actually decreased after the intervention). This distribution suggests that the instructional outcome is not an on/off variable—it is a continuum ranging from no effect to strong effect as pointed out by Popham [18]. To visualize Popham's continuum, we computed the following quantity:

$$Q(A) = r(A)N_{\text{after}}(A).$$

The Q value distinguishes those data points that fall into special case (1), discussed in Section 6.1. Figure 11 shows the distribution of student number as a function of the Q value, revealing a wide range of degrees to which students reacted to the intervention.

6.4 Distribution of response patterns

The distribution of the ratio of post/pre-intervention action densities defined in Section 6.1 is a time average of the instructional effect and does not depict a statistical picture about the temporal shape of the data, such as Patterns C (temporary effect) and D (persistent effect) described in Section 5. To complete the picture, Figure 12 shows the distribution of the patterns. Among the 65 students,

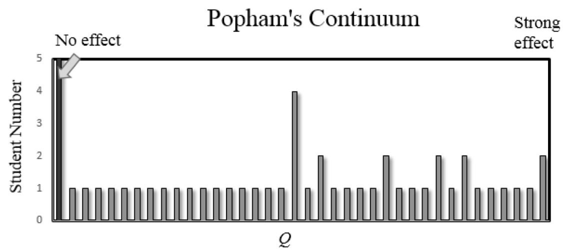


Fig. 11. A continuum of instructional effect constructed from the "Move Building" action data from 65 students.

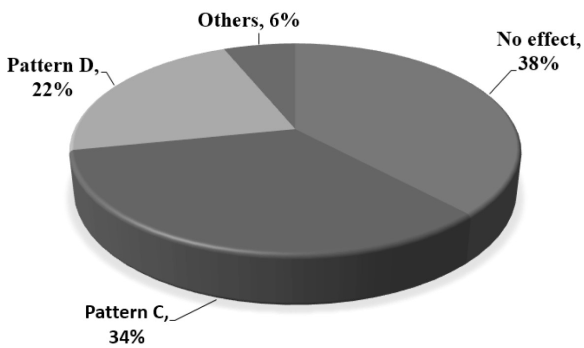


Fig. 12. The distribution of patterns among 65 students.

38% did not respond to the intervention. Pattern C was the most common behavior among the responding students—accounting for 34% of the students. Pattern D was found from a smaller number of students—accounting for 22%. About 6% cannot be clearly categorized because of insufficient data.

7. Validation of the results using student notes

To determine the accuracy of the action and artifact data for measuring student performance, we examined the electronic notes that students took during the design processes. This section presents two cases.

7.1 Student G3

Figure 13(a) shows the time locations of the following four notes taken by G3, overlaid onto her {Move Building} time series graph.

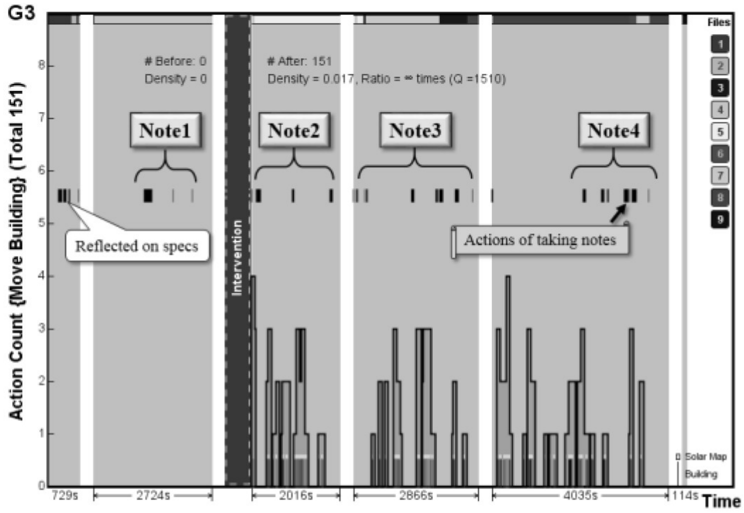
- *Note 1* (before intervention)
  "I first put the buildings so that there was a courtyard in the middle that got sunlight. When I read #2 on the directions I realized that we are trying to get the most amount of sunlight on the buildings in winter and least in summer. I then had to delete the buildings I had and completely recreate them in a different place because for some unknown reason this program does not have anything that allows you to move whole buildings or walls or foundations! This was the best place I could find where all the buildings fit with plenty of green space and the most sun in the winter. Also when in this position they do not cut off sunlight for the surrounding buildings."
- *Note 2* (after intervention)
  "I learned how to move around buildings!!!! This makes life so much easier!!!!! I decided that the two smaller buildings are stores so they don't care about sun but the taller buildings are apartments so I will try to make them have the most sun. I am now just moving my buildings around to get them the most sun in the winter and least in the summer. I tried to make the front wall the tallest and make the other walls shorter to lessen the amount of sun they got in the summer but I had to change it back because they didn't get enough sun in the winter."
- *Note 3*
  "Before just placing buildings I will look at what area of ground receives the most light. I made it so that the tallest buildings were the hottest in the winter but that made them very hot in the summer. I decided to pretty much ignore this fact because I didn't want to take away heat in the winter. I decided that they should use solar panels to make use of all the sun they get!"
- *Note 4*
  "I have decided to now focus on making the numbers OK in the summer and in the winter rather than making the numbers really good during one season and horrible during the other. I built the high rises so that the side that had the most sun in the summer was very thin to minimize the amount of sun it got. I made the side that got sun in the winter long and thick so that it got the most possible sun. This did a lot to maximize the amount of sun in winter and minimize the amount of sun in the summer. I put another tiny tall building in between the others to get the most winter sun on that side. I made the low rise buildings in the shade because it doesn't matter as much that they have sun because they are businesses rather than living areas. I tried to make it so that the low buildings shaded the tall ones as much as they could in the summer but it didn't do much. This is the design that I chose out of the three because it has the best temperature as far as hot in winter and cold in summer. I used the most strategy when placing the buildings and it follows the requirements the best."

This student's Note 1 shows that she was unaware of the functionality for moving buildings before the intervention, which explains why there was no {Move Building} action initially. She then learned about the functionality from the intervention and was excited about it (see Note 2). Rather than exploring peculiar shapes as many students did, she spent much of her time on the solar design, especially on searching a solution that works both in the winter and in the summer. She not only moved buildings to different locations but also changed their shapes. The time series in Fig. 13(b) shows the increasing use of the {Resize Building} feature after the intervention. Figure 13(c) shows the increasing actions of switching between summer and winter simulations. Using the Solar Irradiation Simulator, she discovered the importance of the aspect ratio of a high-rise building to optimal solar heating in both seasons. She concluded that G3-4 in Fig. 8 was her optimal design. To summarize, the results from analyzing her actions and artifacts match well with her design thinking recorded in her notes.

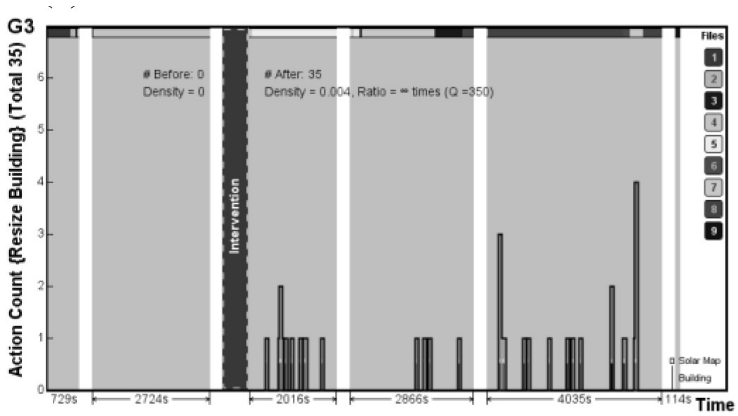
7.2 Student G8

Figure 14(a) shows the time locations of the following four notes taken by student G8, overlaid onto her {Move Building} time series graph.

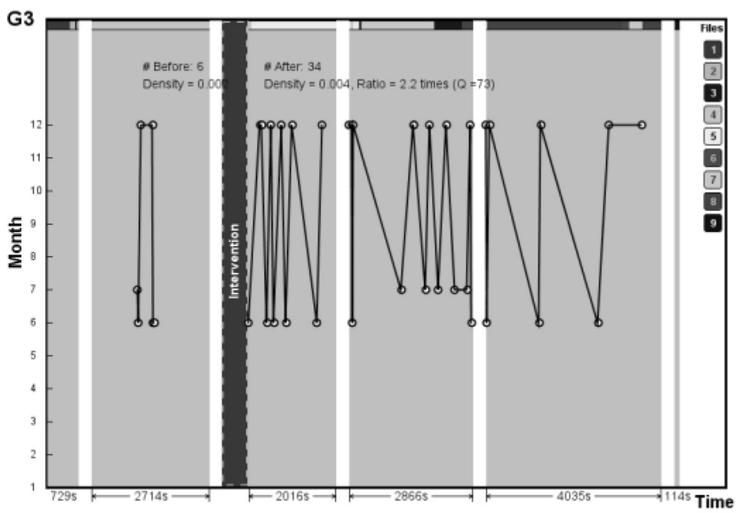
- *Note 1* (before intervention)
  "While building this city complex, I made some short, some tall, and some medium size buildings.



(a)

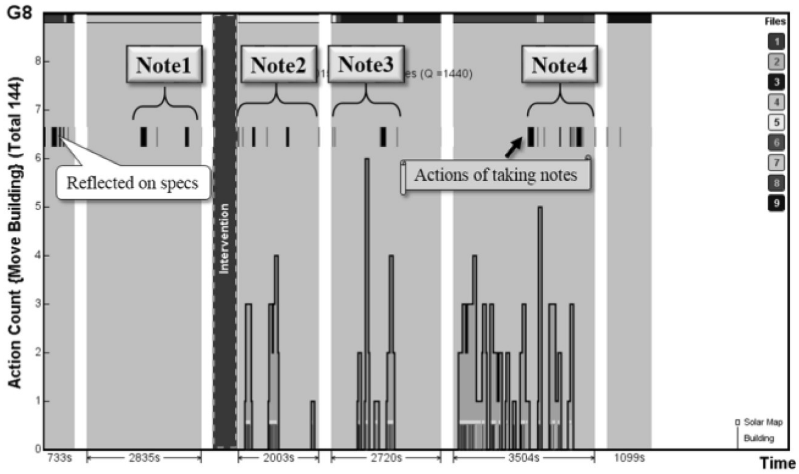


(b)

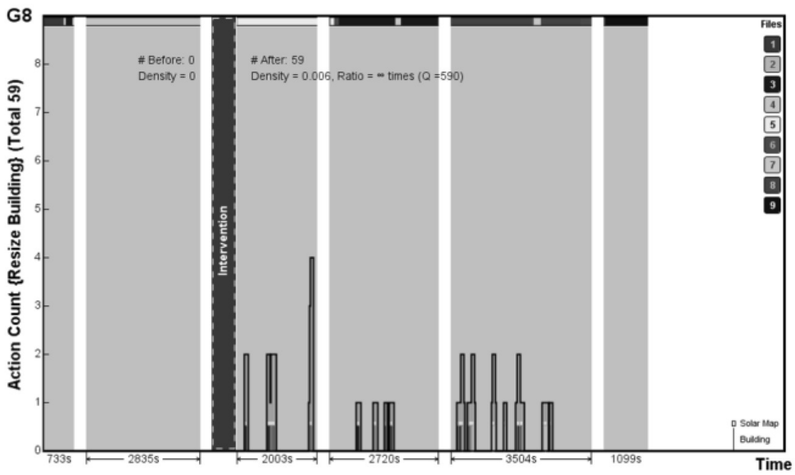


(c)

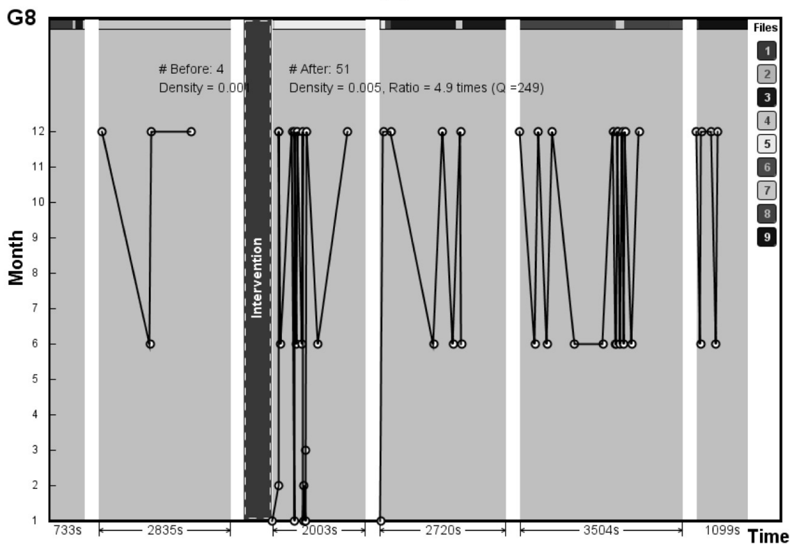
Fig. 13. (a) The time locations of the notes that student G3 took, relative to the {Move Building} actions. The first segment of the note-taking actions was the result of a reflection on the specifications required at the beginning of the project. Its purpose was to test how well students understood the design challenge. (b) The time series of {Resize Building}, indicating that G3 used this feature frequently to reshape the buildings in search of optimal design for both winter and summer situations. (c) G3's actions of switching between summer and winter simulations.



(a)



(b)



(c)

Fig. 14. (a) The time locations of the notes student G8 took, relative to the {Move Building} actions. (b) The time series of {Resize Building}, indicating that G8 used this feature frequently to reshape the buildings. (c) G8's actions of switching between summer and winter simulations.

I wanted to spread them out so that 20% could still be green, open space. I just focused on having fairly good amounts of shade in the summer and light in the winter."

- *Note 2* (after intervention)
"To make my buildings cool in the summer I moved them around until they had little amounts of red and more blue and green. Then for the winter I tried the opposite by getting as red as I could. I tried to find a good balance between the seasons."
- *Note 3*
"On this design I put my tallest buildings in the front [south] where the gaps were so that they could have the most heat in the winter and the least in the summer. Then I put the shorter longer buildings in the back for the same reason. I think this made for a pretty good balance for both the winter and the summer."
- *Note 4*
"For this design I was kind of just trying some different things moving the buildings so they would be hidden from the sun in the summer and right in front of it in the winter. I also played around with the thickness and thinness of buildings. I found that the thicker they were the hotter they were both in the summer and the winter so again I tried to find a balance. Then I put some little stores in the back whose heat doesn't matter. I chose this design of the three because my main buildings were my focus and I got a good balance of heat in the winter and the summer. The little stores in the back were more for visual effect and requirements of the number of buildings but my main buildings were places right near the front to get a lot of sun in the winter and be mostly blocked from the sun in the summer. This design was more thought out than my other ones which were more random."

Similar to G3, G8 correctly identified the southern part of the city block to be the favorable area for setting up high-rise buildings using the results from both winter and summer simulations. This is well articulated in her four notes and illustrated in her final design (G8-4 in Fig. 8).

8. Discussion

One of the compelling reasons for using CAD logs in performance assessment is that their fine-grained, temporal nature may provide more reliable, more comprehensive, and more personalized process data for finding evidence of deep learning related to problem solving and design creativity, as opposed to pre-/post-tests that only measure the differences between student knowledge at the beginning and at the end or analysis of finished products that only evaluate the final representations of student work. However, this assessment approach brings a technical challenge—*deep learning generates big data* and large datasets are difficult to analyze and visualize. As the conceptual, curricular, and procedural complexities of a learning activity increase, such as in the cases of inquiry and design-based learning processes, the complexity of learner data increases. Determining the instructional sensitivity of computer logs, which is a differential effect in the temporal dimension, becomes even more complex. This is a data-intensive challenge that requires some serious computation. Ultimately, this research direction will merge with machine learning, a branch of artificial intelligence that creates and studies systems capable of dynamically learning from user-generated data [9, 49].

As an exploratory step in this direction of data-intensive research [50, 51], we have tested the instructional sensitivity of CAD logs to human interventions in real classrooms. This research approach represents a promising development in assessment methodology and technology. The same approach can be applied to test the instructional sensitivity of CAD logs to computer-generated interventions. In this way, the effectiveness of digital instructional scaffolding can be evaluated. Although this research focuses on CAD for engineering education, our theoretical framework and research methodology can be readily generalized and applied to analyze other types of learning processes as well.

9. Conclusion

Based on nearly 900 megabytes of process data generated by 65 high school students engaged in an engineering design challenge, this paper demonstrates that CAD logs are instructionally sensitive and, therefore, can serve as an effective instrument for assessing complex engineering design processes. The results suggest that high-volume, high-variety software logs can be used to detect the effects of what happens outside the computer on individual students. This leads to a vision of using fine-grained software logs as alternative data recorders to capture and evaluate the effects of various kinds of interventions that drive complex learning dynamics. This approach is highly scalable because computer logging happens behind the scenes and data analysis can be automated. The proposed theoretical framework for computerized assessments based on signal processing lays a foundation for creating adaptive feedback based on dynamically analyzing learner data, which is the ultimate goal of this research.

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References

1. The White House, Remarks by The President to the Hispanic Chamber of Commerce on a Complete and Competitive American Education, Washington, D.C., 2009.
2. L. Darling-Hammond and F. Adamson, *Developing Assessments of Deeper Learning: The Costs and Benefits of Using Tests that Help Students Learn*, Stanford Center for Opportunity Policy in Education, 2013.
3. U.S. *Department of Education, National Educational Technology Plan 2010: Transforming American Education: Learning Powered by Technology*, Office of Educational Technology, U.S. Department of Education, Washington DC2010.
4. G. Siemens and R. S. J. d. Baker, Learning analytics and educational data mining: towards communication and collaboration, *The 2nd International Conference on Learning Analytics and Knowledge*, Vancouver, British Columbia, Canada, 2012.
5. M. Bienkowski, M. Feng and B. Means, *Enhancing Teaching and Learning Through Educational Data Mining and Learning Analytics: An Issue Brief*, Office of Educational Technology, U.S. Department of Education, Washington, DC2012.
6. U.S. Department of Education, *Expanding Evidence Approaches for Learning in a Digital World*, Washington, DC2013.
7. J. Clarke-Midura, C. Dede and J. Norton, *Next Generation Assessments for Measuring Complex Learning in Science*, Rennie Center for Education Research & Policy2011.
8. M. A. Sao Pedro, R. S. J. D. Baker, J. Gobert, O. Montalvo and A. Nakama, Leveraging machine-learned detectors of systematic inquiry behavior to estimate and predict transfer of inquiry skill, *User Modeling and User-Adapted Interaction,* 2011.
9. M. A. Sao Pedro, R. S. J. D. Baker, O. Montalvo, A. Nakama and J. D. Gobert, Using text replay tagging to produce detectors of systematic experimentation behavior pattern, *The Third International Conference on Educational Data Mining*, Pittsburgh, PA, USA, 2010, pp. 181–190.
10. P. Horwitz, Interactive technology for formative assessment: How we got here and what comes next, *New Frontiers in Formative Assessment*, P. E. Noyce and D. T. Hickey (Eds), Cambridge, Massachusetts: Harvard Education Press, 2011.
11. K. W. McElhaney and M. C. Linn, Investigations of a complex, realistic task: Intentional, unsystematic, and exhaustive experimenters, *Journal of Research in Science Teaching,* **48**, 2011, pp. 745–770.
12. S. Greiff, S. Wüstenberg, D. V. Holt, F. Goldhammer and J. Funke, Computer-based assessment of complex problem solving: Concept, implementation, and application, *Educational Technology Research and Development,* **61**, 2013, pp. 407–421.
13. E. L. Baker and R. E. Mayer, Computer-based assessment of problem solving, *Computers in Human Behavior,* **15**, 1999, pp. 269–282.
14. R. E. Mayer, A taxonomy for computer-based assessment of problem solving, *Computers in Human Behavior,* **18**, 2002, pp. 623–632.
15. H. F. O′Neil, S.-H. Chuang and G. K. W. K. Chung, Issues in the computer-based assessment of collaborative problem solving, *Assessment in Education: Principles, Policy & Practice,* **10**, 2003, pp. 361–373.
16. W. J. Popham, Instructional insensitivity of tests: Accountability's dire drawback, *Phi Delta Kappan,* **89**, 2007, pp. 146–155.
17. M. S. Polikoff, Instructional sensitivity as a psychometric property of assessments, *Educational Measurement: Issues and Practice,* **29**, 2010, pp. 3–14.
18. W. J. Popham, *Everything School Leaders Need to Know About Assessment*, Corwin, 2010.
19. M. A. Ruiz-Primo, R. J. Shavelson, L. Hamilton and S. Klein, On the evaluation of systemic science education reform: Searching for instructional sensitivity, *Journal of Research in Science Teaching,* **39**, 2002, pp. 369–393.
20. M. A. Ruiz-Primo, M. Li, K. Wills, M. Giamellaro, M.-C. Lan, H. Mason et al., Developing and evaluating instructionally sensitive assessments in science, *Journal of Research in Science Teaching,* **49**, 2012, pp. 691–712.
21. H. M. Ghadirli and M. Rastgarpour, A web-based adaptive and intelligent tutor by expert systems, *Advances in Intelligent Systems and Computing*, **177**, 2013, pp. 87–95.
22. D. Diziol, E. Walker, N. Rummel and K. R. Koedinger, Using intelligent tutor technology to implement adaptive support for student collaboration, *Educational Psychology Review,* **22**, 2010, pp. 89–102.
23. R. C. W. Sung, J. M. Ritchie, H. J. Rea and J. R. Corney, Automated design knowledge capture and representation in single-user cad environments, *Journal of Engineering Design,* **22**, 2011, pp. 487–503.
24. R. C. W. Sung, G. Robinson, P. N. Day, J. M. Ritchie, J. R. Corney and T. Lim, Automated design process modelling and analysis using immersive virtual reality, *Computer-Aided Design,* **41**, 2009, pp. 1082–1094.
25. Y. Ishinoa and Y. Jin, An information value based approach to design procedure capture, *Advanced Engineering Informatics,* **20**, 2006, pp. 89–107.
26. C. L. Dym, A. Agogino, O. Eris, D. Frey and L. Leifer, Engineering design thinking, teaching, and learning, *Journal of Engineering Education,* **94**, 2005, pp. 103–120.
27. J. L. Kolodner, D. Crismond, B. B. Fasse, J. T. Gray, J. Holbrook, M. Ryan et al., Problem-based learning meets case-based reasoning in the middle-school science classroom: Putting a learning-by-design curriculum into practice, *Journal of the Learning Sciences,* **12**, 2003, pp. 495–548.
28. C. Schnittka and R. Bell, Engineering design and conceptual change in science: Addressing thermal energy and heat transfer in eighth grade, *International Journal of Science Education,* **33**, 2011, pp. 1861–1887.
29. X. S. Apedoe, B. Reynolds, M. R. Ellefson and C. D. Schunn, Bringing engineering design into high school science classrooms: The heating/cooling unit, *Journal of Science Education and Technology,* **17**, 2008, pp. 454–465.
30. M. M. Mehalik, Y. Doppelt and C. D. Schunn, Middle-school science through design-based learning versus scripted inquiry: Better overall science concept learning and equity gap reduction, *Journal of Engineering Education,* **97**, 2008, pp. 71–85.
31. NGSS Lead States, *The Next Generation Science Standards: For States, By States*, The National Academies Press, Washington, DC, 2013.
32. National Research Council, *A Framework for K-12 Science Education: Practices, Crosscutting Concepts, and Core Ideas*, The National Academies, Washington DC, 2012.
33. C. E. Hmelo, D. L. Holton and J. L. Kolodner, Designing to learn about complex systems, *The Journal of the Learning Sciences,* **9**, 2000, pp. 247–298.
34. S. S. Vattam and J. L. Kolodner, On foundations of technological support for addressing challenges facing design-based science learning, *Pragmatics and Cognition,* **16**, 2008, pp. 406–437.
35. T.-c. Fu, A review on time series datamining, *Engineering Applications of Artificial Intelligence,* **24**, 2011, pp. 164–181.
36. P. Esling and C. Agon, Time-series data mining, *ACM Computing Surveys (CSUR),* 45, 2012.
37. C. Xie, Z. Zhang, S. Nourian, A. Pallant and E. Hazzard, A time series analysis method for assessing engineering design processes using a CAD tool, *International Journal of Engineering Education,* **30**, 2014, pp. 218–230.
38. G. E. P. Box, G. M. Jenkins and G. C. Reinsel, *Time Series Analysis: Forecasting and Control*, 4th edn, John Wiley, 2008.
39. Massachusetts Department of Education, Massachusetts

Science and Technology/Engineering Curriculum Framework, 2006.
40. C. Xie, *Solar Urban Design*, http://energy.concord.org/energy3d/projects.html, September 11, 2013.
41. J. Kanters and M. Horvat, Solar energy as a design parameter in urban planning, *Energy Procedia,* **30**, 2012, pp. 1143–1152.
42. M. Amado and F. Poggi, Towards solar urban planning: A new step for better energy performance, *Energy Procedia,* **30**, 2012, pp. 1261–1273.
43. J. Bouyer, M. Musy, Y. Huang and K. Athamena, mitigating urban heat island effect by urban design: Forms and materials, *Cities and Climate Change: Responding to an Urgent Agenda*, The World Bank, Washington, DC, 2011.
44. Autodesk, *Autodesk Ecotect Analysis: Sustainable Building Design Software*, ed, n. d.
45. P. Brown, CAD: Do computers aid the design process after all?, *Intersect,* **2**, 2009, pp. 52–66.
46. B. F. Robertson and D. F. Radcliffe, Impact of CAD tools on creative problem solving in engineering design, *Computer-Aided Design,* **41**, 2009, pp. 136–146.
47. X. S. Apedoe and C. D. Schunn, Strategies for success: Uncovering what makes students successful in design and learning, *Instructional Science,* **41**, 2013, pp. 773–791.
48. P. Littlefair, Passive solar urban design: Ensuring the penetration of solar energy into the city, *Renewable and Sustainable Energy Reviews,* **2**, 1998, pp. 303–326.
49. C. C. Hayes, A. K. Goel, I. Y. Tumer, A. M. Agogino and W. C. Regli, Intelligent support for product design: Looking backward, looking forward, *Journal of Computing and Information Science in Engineering,* **11**, 2011, p. 021007.
50. T. Hey, S. Tansley and K. Tolle, *The Fourth Paradigm: Data-Intensive Scientific Discovery*, Microsoft Research, Redmond, Washington, 2009.
51. J. P. Collins, Sailing on an ocean of 0s and 1s, *Science,* **327**, 2010, pp. 1455–1456.

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