Traversing the Barriers to Using Big Data in Understating How High School Students Design

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The context of this paper is a "large learner data" project that seeks to respond to existing challenges by introducing educational data mining and learning analytics into K-12 engineering design research. To probe deeply into student learning, we are developing and refining computational techniques to analyze large process analytics datasets generated through a CAD-based software, Energy3D, that logs design process data as students complete an assigned design challenge, such as a net-zero energy efficient building. We are combining these process analytics with demographic data and pre/post-tests of science and design knowledge. In this paper, we revisit three illustrative research cases to reflect on our experiences and lessons learned with navigating big data, generating useful data visualizations, and integrating process analytics with traditional performance assessment methods to relate design actions to knowledge and learning outcomes.

Aims

The context of this paper is a "large learner data" project that seeks to respond to existing challenges by introducing educational data mining and learning analytics [1] into K-12 engineering design research. Through a five-year collaboration, we are applying a data-intensive approach to study student design learning and performance. The project involves engaging secondary students with Energy3D (http://energy.concord.org/energy3d), a computer-aided design (CAD) software tool for designing energy efficient solutions for the built environment based on Earth science, physical sci-

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ence concepts, and engineering principles required by the Next Generation Science Standards (NGSS) ETS1 [2].

To collect large learner data, Energy3D automatically logs design process data as students complete an assigned design challenge, such as a net-zero energy efficient building. This includes fine-grained information on student actions, experimentation results, electronic notes, and design artifacts. For a single student, process data over the duration of a project can sum up to 20 megabytes, ranging from 200 to 2,000 construction and analysis actions. To probe deeply into student learning, we are developing and refining computational techniques to analyze these large process analytics datasets. These techniques are being used to reconstruct the entire learning trajectory for each individual student with high resolution, providing a holographic method for assessing his/her performance. We are combining these process analytics with demographic data and pre/post-tests of science and design knowledge.

To date, we have produced research findings that focus on investigating common patterns of student design behaviors (e.g., using scientific experimentation to make design choices, making trade-offs, idea fluency, and reflection), as well as how patterns of design behaviors are associated with science and design learning outcomes measured using traditional performance assessment methods. Throughout these experiences we have been traversing the challenges of relating design actions (as logged in Energy3D) and knowledge (as evidenced in Energy3D performance and measured via pre/post-tests), and how these relationships offer explanations of learning outcomes. In this paper, we revisit three illustrative research cases to reflect on our experiences and lessons learned with navigating large learner data, generating useful data visualizations, and integrating process analytics with traditional performance assessment methods. We feel that sharing our reflections is a critical contribution to a larger discussion on what it means to gather, analyze, interpret, and eventually use large learner data to guide improvements in how students design.

Significance

In the context of K-12 science education, engineering design is a complex cognitive process in which students learn and apply science and design concepts to solve open-ended problems to meet specified criteria. Our understanding of what K-12 students learn from engineering design is limited [3]. A 2008 literature review concluded that many K-12 engineering education projects lacked data collection and analysis to provide reliable evidence of learning [4]. The Committee on Standards for K-12 Engineering Education found “very little research by cognitive scientists that could inform the development of standards for engineering education in K-12” [5]. Similarly, how K-12 students learn and apply science concepts in engineering design processes is a fundamental interest in the learning sciences. Through engineering design projects, students practice science as they gather and analyze data through experiment-based inquiry and apply this knowledge to conceive, compare, and optimize solutions. Although previous research suggests that engineering design is an effective pedagogical approach to promoting science learning [6][7][8][9], there are also concerns about the so-called “design-science gap” [10] that fails science learning in design projects [6][7]. Overall, there is considerable need for approaches that can accurately and efficiently assess student design performance and learning of both science and design inquiry in engineering design projects.

There is a rich history of techniques for understanding how people design; however, most of these have been implemented in postsecondary and professional contexts and many emphasize research, not assessment. A common approach is to capture “think aloud” data to conduct verbal protocol analyses of design processes or design cognition [11]. Often verbal data is translated into visualizations to explore design behavior patterns such as structure-function-behavior design cognition diagrams [ ], process timelines [13][14][15], and linkography diagrams [16]. Some also use observation and video-based analyses [17][18]. Another approach involves using design documentation such as journals to analyze relationships between design processes and design performance [19] or conduct latent semantic analyses to characterize designer performance [20]. Others use technology-based tools that support documenting and reflecting on design processes [21][22]. Some performance-based methods include using concept maps to assess student understanding of the engineering design process [23], asking students to explain the relative importance of various design activities [24], asking students to critique a design process timeline and identify process improvements [25], and using design scenarios to assess problem formulation capabilities [26][27].

Translating these research-focused approaches for use as assessments in K-12 contexts is a significant challenge. While each approach has strengths, each requires time-consuming data collection, data management, and data analysis procedures, often involving extensive human labor. An additional challenge is that the complexity and open-endedness of a design task can make it difficult to discern design patterns or correlate patterns to performance. For example, a pattern that looks like “gaming the system” in an inquiry activity [28] may be a legitimate search in a vast problem space for meaningful alternatives in a design project. For design, performance is not based on "getting the right answer" because multiple solutions are possible; rather, performance needs to be a function of understanding students' growth in knowledge and skills necessary for informed designing [29]. Collectively, these issues can significantly limit scale-up and broader use of existing approaches in K-12 classrooms [30].

Opportunity: Large Learner Data and Technology-based Assessments

Information technology-based assessments offer a cost-effective solution for scaling up educational research. Large amounts of relevant data, real time feedback, and scalable and personalized support can be achieved now with the use of these technologies [31]. Similar to the Energy3D project, researchers have used technology-based assessments to study inquiry within interactive media and games [32][33][34][35]. These approaches have rarely been exploited for assessing design, a process that includes inquiry but is fundamentally distinct in many ways [36].

While we anticipate many affordances of integrating technology-based assessments into research on how people design, we also expect this will come with its own set of challenges. Some of these challenges may be unique to open-ended tasks such as engineering design that might make it necessary to combine learning analytics with human-based qualitative analysis to be able to draw strong conclusions about student learning [37]. As Socha et al. [38] note, some challenges may due be the complexity and scale of the data itself such as being able to navigate a complex dataset that combines multiple modes of data (e.g., activity logs, reflection notes, video playbacks) which traverse fine-grained to more macro-level units of analysis; some challenges may be the nature of the cross-disciplinary collaboration, which may be a requirement for these kinds of endeavors, which will likely involve negotiating among different perspectives (e.g., quantitative-qualitative, software programming-educational research dynamics).

In this paper we focus on sharing lessons learned from using large learner data to identify, develop, and test approaches for assessing design performance and learning through engineering design projects in secondary school. In the following sections, we describe Energy3D, which serves as simulated engineering design environment for this project. We then present three illustrative cases of research studies to critique and debrief on our experiences with using large learner data to understand how secondary students learn design.

Method: Energy3D as a curriculum and research platform

Energy3D is a free, open-source software that allows students to create 3D buildings and simulate energy consumption [39]. The software offers a simple 3D graphical user interface for drawing buildings, and evaluating their performance using cost and energy (solar and heat) simulations (see Figure 1).

As a learning experience, Energy3D provides computer-aided engineering tools for students to design, analyze, and construct green buildings that utilize renewable energy. For a given design challenge, students can quickly sketch up a realistic-looking building and then evaluate its energy performance for any given day and location (see Figure 1). Energy3D can rapidly generate energy consumption simulations (i.e., time graphs, heat maps, and a solar simulator) based on computational physics to allow students to make informed design decisions. Students can use a notepad tool to describe and reflect on their designs and science simulations. At the end of the design, Energy3D allows students to print out a design, cut out the pieces, and use them to assemble a physical scale model.

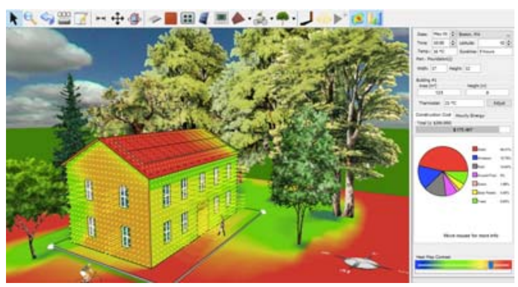

Fig. 1 Energy3D performance calculated (e.g., energy & cost).

As a research platform, Energy3D logs all design process data in a non-intrusive way as students complete an assigned design challenge. This includes fine-grained information on student actions, experimentation results, electronic notes, and design artifacts. This interaction data is translated into a JSON data stream for each student with a list of all interactions including: (1) the date / time the action was carried out; (2) the file in which the action was carried out; (3) the description of the action (e.g. Add, Edit, Move, Resize, Notepad, etc.); and (4) the object towards which the action was directed. Energy3D also has the capability of reproducing the design process as a video display, similar to time-lapse photography, which integrates both activity log and notepad data.

These fine-grained CAD logs of large learner data possess all four characteristics of "big data" [40]: high volume, high velocity (data is collected in real time to support rapid feedback), high variety of data types (from learner actions to simulation data and experiment results), and high veracity (data is comprehensive and accurately documented to ensure fair and trustworthy assessments of student performance).

Results: Three illustrative cases

We are using Energy3D to investigate: (1) patterns and relationships in engineering design processes and how these are associated with prior knowledge, design performance, project duration, demographic factors, and learning outcomes, (2) the effect of engineering design process on science learning outcomes (e.g., to what extent does design iteration contribute to science learning of energy concepts), and (3) the effect of science inquiry processes on engineering design outcomes (e.g., scientific experimentation via Energy3D simulations and how these relate to design choices and revisions).

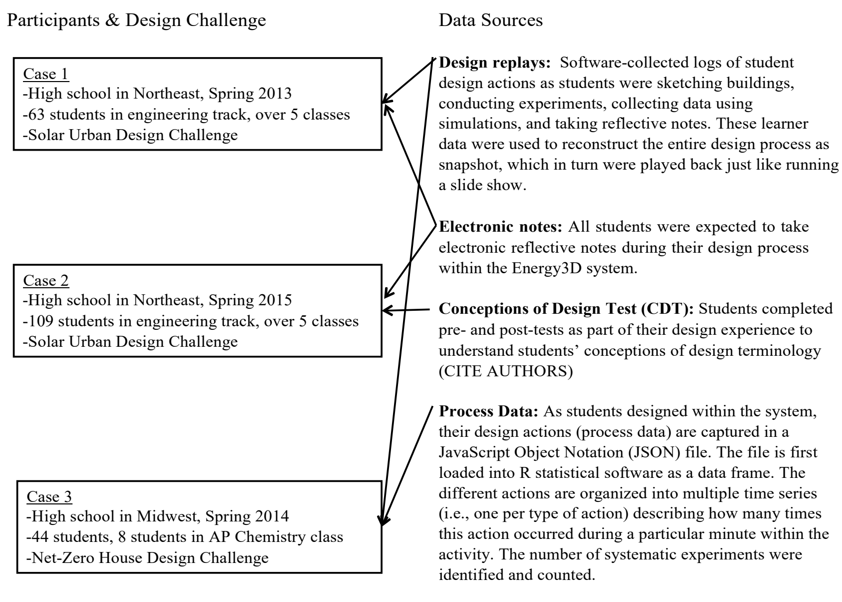

Fig. 2. Overview of three illustrative cases – context, participants, design challenge, and data sources.

Over the past two years we have conducted multiple studies in which students use Energy3D to complete a design challenge. Here we focus on three studies, summarized in Figure 2. Each study has been previously published, and as such we provide only limited details relevant for the purposes of this paper. Overall, each case speaks to different research approaches and lessons learned regarding: conducting multimodal analyses linking micro and macro grain data, integrating process data (internal to Energy3D) with pre/post-test data (external to Energy3D), pursuing targeted analyses using single data modes, and generating visualizations to support both human and computer-based pattern analyses.

As shown in Figure 2, the context for the three cases was either a high school in the Midwest or one in the Northeast. The number of participants ranged from 63 to 109 students: Case 1 (n = 63), Case 2 (n = 109), and Case 3 (n = 44). While the number of participants may appear small, each Energy3D log file is on the order of thousands of design actions. Students in both contexts completed either one or both of two design challenges. One challenge, Net-zero House, involved designing an energy-efficient single-dwelling home [30]; the other, Solar Urban Design, involved designing an energy-efficient urban block, in which each building could impact the energy-efficiency of adjacent buildings [39]. For both scenarios, students were provided with a one-page handout that summarized design requirements and provided instructions on how to open, use, and save files on Energy3D. Teachers were provided with similar curricular resources. Each design challenge project was implemented during regularly scheduled class hours, and teachers were encouraged to link the project to other curricular goals including NGSS standards.

Large learner data was collected for each design challenge from every student. As shown in Figure 2, this encompassed a variety of data sources and data types. Data sources included (1) data automatically collected through Energy3D (i.e., process data, electronic notes), (2) data collected through Energy3D with additional post-processing (i.e., design replays, design performance), and (3) data external to Energy3D (i.e., conceptions of design pre/post-test). In the following sections, we summarize these three cases to illustrate data visualization outcomes and discuss lessons learned.

Case 1: Science Connections through Tradeoffs

For this exploratory study, we were interested in understanding connections between science inquiry and design, in particular students' use of Energy3D science experiments in relation to informed design behaviors [29] such as balancing benefits and trade-offs [41]. A first step was to identify which automatically generated Energy3D data would allow directly investigating these relationships. Energy3D log files document student process data at a very fine or micro-level grain size – e.g., Add, Edit, Move, and Test. Most coding frameworks on design cognition or design processes articulate design activities at a larger grain size such as problem formulation or idea fluency, which are likely comprised of sequential combinations of finer grain actions. Given our research goals, we selected the design replays and electronic notes (see Figure 2).

Design replays are generated from Energy3D activity log and allow a researcher to observe a students' unfolding design process as a sequence of design actions captured within the software. Like a video, the design playbacks can be replayed multiple times either as a whole, from beginning to end, or as smaller episodes to support focused analysis on a sequence of design actions. Researchers can also set the playback speed. For example, a design replay can be observed in real time (e.g., an hour-long project as an hour-long video) or at a pace such as 10-second increments (e.g., an hour long project as a 6 minute video). The electronic notes are collected within Energy3D activity logs, and provide a place for students to write reflections, outcomes of experiments, ideas for what they could improve, and any other kinds of issue they want to document. Like all Energy3D data, the electronic notes are time stamped and logged in the system, and therefore integrated into the design replay function. In this way, researchers can observe a student's overall design process along with their evolving written comments. By combining design replays with the accompanying electronic notes we could "chunk" a student's design process into goal-directed design sequences, which could then be coded with existing empirically grounded frameworks.

A second challenge was determining useful coding frameworks that would easily map to the kinds of observable activities evident in the design replays and electronic notes. Valkenburg's coding scheme [42] provided a useful mechanism for characterizing sequences of design activities that link goals to moves (observed in the design replay) and reflections (observed in the electronic notes). For example, the electronic notes allowed us to see when a student was working towards a particular goal, such as optimizing a roof design, and the design replay allowed us to observe the associated design actions or "moves". Table 1 summarizes this coding scheme, which includes a code for denoting references to science concepts. It also illustrates how data sources were integrated to analyze patterns.

Table 1 Action visualization coding protocol [41]

Framework	Description	Source of evidence	'Symbol' in representation system
Design goal	The goal of a sequence of activities or the frame of actions	Student notes	⬭
Design moves	The activities students can do within the system (e.g., make, edit, delete, change shape, change orientation, simulation, etc.)	Design replays from log file	▽
Self-reflection	Reflection or thinking about the actions in relation to the goal or frame	Student notes - explanations that link goals to actions	◇
Science concept	Denotes existence of or reference to a science concept	Student notes - explanations	●

Data visualizations linking log files, data replays, and reflection notes

As shown in Table 1, an added benefit of Valkenburg's coding scheme [42] is the use of symbols that could be used to generate visualizations of interconnecting science and design inquiry processes. For example, each design episode began with a goal, represented with an oval. The triangles represent moves or student actions such as making, editing, or changing the shape of a roof. When a connection to a science concept is made, this can be indicated with a blue dot. Student reflections are signified with a diamond. By generating these visualizations we could quickly identify connections between science and design inquiry.

Full detailed analyses for two students through visualizations are available in previous work [41]. Design replays supported with detailed student reflective notes provided sufficiently detailed information for characterizing student design thinking and design behaviors. One of our research findings was how these visualizations showed a notable progression of student behaviors starting with idea generation and evolving to more sense-making behaviors, such as balancing benefits and tradeoffs.

The visualizations also made evidence meaningful applications of science learning when students attempted to balance design benefits and trade-offs. In a particular design episode [41], the student conducted experiments based on changes to iterative revisions to the roof and wall of his building, while reflecting upon the size and direction of window placement and the resulting solar gains. By mapping design and science inquiry moves and reflections into a combined representation we can see evidence of important design behaviors such as systematic experimentation and decision-making with a trade-off analysis. By deconstructing the design process and offering a visualization for the interdisciplinary research team, we were able to better articulate behaviors that were leading to science connections in students

Lessons learned

Overall, this study highlights many of our ongoing experiences with large learner data. It illustrates issues with navigating multi-modal data – the design replay and electronic notes are different types of data, although the design replay function allows integrating these different data types and streams in ways that leverage the benefits of each data source. The design replays also supported iterative refinement of our analysis approach. This case also illustrates challenges with mapping activity-level units of analysis (i.e., captured automatically in the system as Edit, Move, Resize, etc.) to process-level units of analysis (i.e., observed as design replays but translated into visualizations through coding). We are developing a sharper awareness of the non-trivial challenges of translating across different units of analyses, and how continuing down a pathway of technology-based assessments will require considerable work to build bridges between existing design inquiry frameworks and frameworks that can used for fine-grain analyses. This case also illustrates the value of generating visualizations as intermediate representations for identifying and characterizing patterns, even though these visualizations are manually created. These visualizations enabled our research team to collectively understand features of design performance and learning and investigate new kinds of visualizations that can support discovery-driven research.

Case 2: Connecting Reflection & Informed Design

This study investigated students' improvements in design thinking in association with level and breadth of design reflectivity [43]. Understanding students' design thinking, particularly at the K-12 level is challenging. To tap into design thinking, we used a Conceptions of Design Test (CDT) [43] to assess student understanding of design through ranking and explaining the relative importance of a list of terms representing informed design (e.g., understand the problem, iteration, modeling). This performance-based test was given prior to starting the first Energy3D design challenge design activity and at the conclusion of the final design challenge. Assessing reflection presents an additional challenge. The electronic notes option in Energy3D provides one pathway for capturing students' reflections during their design process. For this study, all students were expected to write reflective notes while designing their net-zero houses and were prompted to "describe your design ideas and explain why you think they are good ideas." These electronic notes were examined and scored using a coding protocol based on existing literature that focuses on level and breadth/amount of reflectivity [43].

Integrating system-generated data with questionnaire data

Using statistical analysis, we sought to understand if a relationship exists between student reflectivity and their understanding of informed design. As such, this study provides an example of integrating data generated from Energy3D (the electronic notes) with data generated external to Energy3D (pre/post Conception of Design Test). A paired t-test was used to evaluate gains in informed design thinking and a one-way ANOVA was used to evaluate the relationship between student reflectivity and gains in informed design thinking.

The analysis showed gains in recognition of informed design. We found that highly and moderately reflective students had higher gains in informed design thinking compared to those with low reflectivity scores. However, the results did not indicate that students who demonstrated a higher level of reflectivity also became more informed designers. One possible explanation is that students in the study were beginning designers with limited experience. That we observed some gains in informed design thinking in relation to reflectivity suggests that Energy3D provides a learning experience that may help students develop awareness even though their reflexivity skills may lag behind. While reflection is an important component of designing and design learning, perhaps other behaviors are as essential. The path to informed design, it seems, cannot be predicted by reflection alone, indicating the need to better understand how other patterns of informed design interact.

Lessons learned

This study used more traditional forms of assessment (i.e. pre/post-tests and students responses/reflections) as opposed to log data. This case provided an innovative way to think about assessing reflection in terms of both breadth and depth. However, as we move toward using larger datasets, this method of coding reflections may prove too difficult from a scale-up perspective. In comparison, analyzing the Conception of Design Test is quite straightforward and could be automated. Looking at the relationship between reflection depth and reflection breadth might allow a macro-level view of reflectivity in the future.

By providing students with a reflection prompt, we had a more consistent quality of reflections than when students are not given any guidance other than to “think and reflect like an engineer” [44]. Even with guidance, we have observed that the quality of reflections can vary significantly from student to student.

We anticipate many future opportunities as we expand on this study leveraging the large learner data. First, the Conceptions of Design Test provides one vantage point for eliciting what students consider to be important in designing (and why). In the future we are exploring ways to triangulate this data with the process activity log files to investigate relationships between what students express as important to design and what behaviors they employ while designing. Similar to the first case, this will require finding ways to link the fine-grained process data and perhaps sequences of these actions to performance outcomes from the Conceptions of Design Test as well as reflectivity level to more fully characterize student design performance.

Case 3: Connecting Design Replays & Process Data

Although idea fluency plays an important role in design, it can be hard to identify in student design activities because we may not have access to the full realm of design possibilities a student considers before focusing on a smaller subset of options. Similar to the first case we presented, we used the design replays for this exploratory study but now in combination with the process data (the micro-grained activity logs) to examine if idea fluency is observable from watching the student design behaviors. The research goal was to determine if and how learning analytics can confirm the presence or absence of idea fluency [45].

As an exploratory study, we selected a subset of an existing large learner dataset (n=44). We reviewed three hours of design activity time for a class of eight (8) students, representing approximately 160 MB of Energy3D process data as design replays and the corresponding process data. A coding framework was iteratively developed for idea fluency as observed through watching Energy3D design replay files. The coding framework links levels of idea fluency to distinct design actions documented in the Energy3D log files such as building, modifying or adding walls, roofs, windows, solar panels, and trees.

Data visualizations linking system-generated process timelines with human observations

Two researchers coded for idea fluency and were able to distinguish a very idea fluent student from a student who generated considerably fewer ideas. By combining the design replays and the coding protocol, we were able to determine that idea fluency is directly observable through Energy3D. The most idea fluent student was observed building and modifying the windows and solar panels in order to achieve better solar performance of the building. This was observed in the design replays as she changed the size, shape and position of windows in order to have a higher functioning home with lower energy usage requirements. She also explored many positions and quantities of solar panels. In contrast, while the least idea fluent student in the sample did modify windows and solar panels in his design, he did not explore a wide range of options. The coding protocol allowed researchers to discuss student range of ideas numerically, as students' overall idea fluency scores could range from 0 to 2.

Challenges with linking observed design behavior (idea fluency) and process data (build, add, or modify a design element) was further investigated using statistical analysis. When students use Energy3D, design actions (process data) are captured in a JavaScript Object Notation (JSON) log file. We analyzed this process data for each individual student in the study by loading the log file into R statistical software as a data frame. The different actions (e.g. Build/Modify Windows) could then be organized into multiple time series diagrams (i.e., one per type of action) that show how many times an action occurred during a particular minute within the log file. Figure 3 represents this action count output for the (a) most and (b) least idea fluent students identified from the design replay analysis. The process data analysis confirms that these students are distinguishable by their process data, just as they were from the design replays.

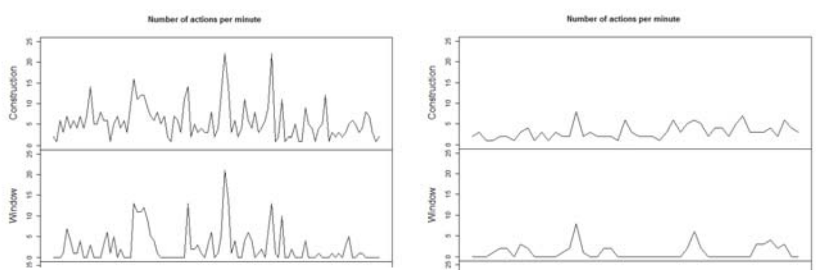

Fig. 3 (Right) Idea fluency as seen from the process data for most idea fluent student (Left) Idea fluency for least fluent students

Figure 3 allows a way to visualize a design process generated from the fine-grained log files for the most idea fluent student in the class for all possible construction activities (i.e. Build/Modify: Walls, Roof, Windows, Solar Panels and Tree) and for specific window for building or modification actions. Not only does the process data correspond with observations from the design replays, the graphs also offer a useful visual tool to graphically assess the extent to which students practice idea fluency. As such, we anticipate this approach will be fruitful for analyzing other kinds of informed design behaviors.

Lessons learned

In general, this case provides additional insights into using multi-modal data (i.e. design replays and process data) to understand design behavior, preliminary stages of quantifying design behavior (i.e. idea fluency), and generating data visualizations (i.e. graphs of process data counts) as intermediate representations for identifying and characterizing patterns. Coding the design replays for levels of idea fluency allowed us to quantify qualitative data, while visualizations of the process data allowed a qualitative perspective for the quantitative data. Through the case of two students, we demonstrated how micro-level process data could be used to validate macro-level observations made from viewing student design process through design replays. Together process data and design replays essentially tell the same story, and might be able to be used interchangeably. However, future work will need to investigate design behavior that might not be easily detected from observing the design process, and we will need to continue our growing understanding of ways to link fine-grained micro-level design data (distinct design actions) to macro-level design behaviors (informed designing) to combinations and sequences of macro-level design behaviors.

Summary and future work

Engineering design is a skill that is hard to measure, but it must be fairly assessed if it is to be taught in every K-12 classroom as required by the Next Generation Science Standards. The large learner data techniques we are developing through this project are likely to make an impact on the assessment of engineering design in K-12 contexts. In this paper, we offer three cases as pathways for thinking about the kinds of research that can be conducted with large learner data about how students design and for reflecting on lessons learned. By sharing these experiences we hope to contribute to crucial conversations on what it means to gather, analyze, interpret, and eventually use large learner data to guide improvements in how students design.

Challenges and opportunities

As shown in these three cases, we are using Energy3D to investigate (1) patterns of engineering design processes and how these relate to design performance including science and design learning outcomes, and (2) relationships between science and design inquiry. While we are finding that large learner data provides many opportunities, there are also many challenges. In some cases, we have developed and tested approaches to resolve challenges; however, the essence of these challenges remains as areas for ongoing development. These are summarized below in terms of navigating the complexities of multi-modal data, translating among different units of analysis and inquiry lenses, and generating intermediate visualizations.

Navigating the complexities of multi-modal data

The data generated through Energy3D contains data of different types (design replays, activity logs, electronic notes, process analytics, etc.) and streams (some data is generated within the system, some requires post-processing). This creates a rich and complex data set with many opportunities to integrate and triangulate among different data sources. As an example, the design replays affords zooming in and out, fast forwarding, and rewinding to locate a phenomenon of importance that can then be investigated through other data sources. Also, some of the data can be automatically analyzed; some requires manual coding but could be automated in the future. However, navigating such a complex dataset to make informed research design decisions can be its own challenge. What stream or combined streams of data can best provide the most direct evidence for a given research goal? How to combine streams that have different scales or units of analysis?

Translating among different units of analysis and inquiry lenses

A central theme in our on-going research is finding ways to map fine-grained activities captured in the Energy3D logs (e.g., Edit, Move, Add) to more coarse-grained design process activities (e.g., balancing trade-offs, reflection, idea fluency). This translation challenge has many elements. In part, it involves mapping across different units of analysis; in part, it involves mapping patterns that can emerge through data mining to patterns that have theoretical or practical value. As shown in these cases, certain kinds of data afford building bridges between different units of analysis and conceptual frameworks. Case 1 demonstrates how the electronic notes feature provided a bridge for connecting individual “moves” (activities in the log file) and reflections (comments documented in the electronic notes) to design process sequences (observed in design replays). Similarly, Case 3 demonstrated how process data could be used to validate observations of idea fluency in the design replays. Case 2 tells a different story of integrating process analytics with performance assessments. Other researchers have noted this difficulty in translating big data from students into actionable intelligence, and our research attempts to address these difficulties,

Generating intermediate visualization

Perhaps the critical importance of visualizations is no surprise; we know that visual representations can be powerful. The cases presented in this paper continue a history that illustrates the power of design process visualizations as both outcomes and intermediate tools for making meaning of design behaviors. Our research team has repeatedly experienced the many benefits of iteratively generating intermediate visualizations to aid pattern discovery and characterization, as well as collective sensemaking. This is providing an added push towards developing visual process analytic techniques, as illustrated in Case 3. In addition, we are learning how intermediate data visualizations are helping us traverse the challenges of multimodal data: visualizations generated from the micro level data offer a more macro level view more in line with existing research and frameworks for analyzing design behavior.

Using the affordances of human analysis as a pathway for scaling up big data analysis

Many of our studies rely on some element of human labor to establish links between micrograin design process actions and macro level patterns of design process behaviors (made up of many combinations of micrograin actions). This is not feasible at the scale of big data, yet we are finding useful ways to integrate learning analytics with human based qualitative analyses that could be scaleable. Case 3 illustrates how we combined labor-intensive human analysis with visualizations generated from Energy3D log files to test for observed variations of idea fluency. In other words, we used the affordances of human analysis to characterize macro-level observations that could then be tested with system generated micrograin design action representations. This appears to offer a pathway linking initial development of design patterns that meaningfully distinguish variations in design patterns (via human analysis) with log file generated patterns (via automated analysis).

Iterative and integrative co-development

Through these reflections we came to understand the iterative and integrative dimensions of large learner data research for the context of design cognition. Most lessons learned, from these three studies as well as the larger body of research connected with this project, are used as feedback to improve the Energy3D software. For example, we are developing ways to enable automatic assessment of solution quality, which has consequences for what features are logged in the system, how these can be easily extracted for analysis, and what kinds of quality assessment information might be provided to students as a formative feedback. As another example, our interest in the informed design behavior of balancing trade-offs (Case 1) has resulted in integrating cost calculations into the energy calculations so that students can more easily explore and grapple with trade-offs between cost and energy efficiency. Similarly, our interest in reflection (Case 1 and 2) has changed the ways reflection notes appear on the monitor as a prompt for students to write electronic notes more frequently and with greater detail and intent.

Our experiences also support the insights of Worsley and Blikstein [17] in how integrating learning analytics with human-based qualitative analysis may be necessary for situations that involve open-ended tasks such as engineering design. Each case in this paper illustrates integrating qualitative and quantitative perspectives as one mechanism for bridging the gap between different units of analyses. In some cases, qualitative approaches such as observing the design replays are used to inquire into elements in the log files; in others, quantitative approaches are used to inquire into qualitatively observed design patterns. Each case also illustrates integrating top-down and bottom-up approaches, which perhaps explains why these three cases are exploratory studies along two intersecting tracks: exploring features of a design phenomenon (e.g., reflection, science-design integration, idea fluency) and exploring what aspects of the system allow investigation or visualization of that phenomenon. The top-down approach starts with existing design cognition theories that are appropriate to the study, and then looks for ways to formulate these theories in forms computable from the Energy3D logs. Case 3 provides a useful example of this approach. The bottom-up approach starts with the Energy3D logs and attempts to reveal features in the data using design cognition and performances questions without necessarily being guided by a specific design theory. While the cases presented in this paper do not provide as much detail regarding this particular approach, our other research on visual process analytics provides examples of using data mining to visualize low-level data for researchers to recognize high-level patterns.

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References

1. Bienkowski M, Feng M, Means B (2012) Enhancing teaching and learning through educational data mining and learning analytics: An issue brief. Washington, DC: Office of Educational Technology, U.S. Department of Education
2. Achieve (2013) The next generation science standards. Washington, DC: Achieve
3. Katehi L, Pearson G, Feder M (2009) Engineering in K-12 education: Understanding the status and improving the prospects. The National Academies Press. Washington, DC
4. Svihla V, Petrosino AJ (2008) Improving our understanding of K-12 engineering education. Paper presented at the The International Conference on Engineering Education
5. National Research Council (2010) Standards for K-12 engineering education? The National Academies Press. Washington, DC
6. Apedoe XS, Schunn CD (2013) Strategies for success: uncovering what makes students successful in design and learning. Instruct Sci 41(4):773-791
7. Hmelo CE, Holton DL, & Kolodner JL (2000) Designing to learn about complex systems. J Learning Sci 9(3):247-298
8. Kolodner JL (2002) Facilitating the learning of design practices: Lessons learned from an inquiry into science education. J of Indust Teacher Edu 39(3)
9. Mehalik MM, Doppelt Y, Schunn CD (2008) Middle-school science through design-based learning versus scripted inquiry: Better overall science concept learning and equity gap reduction. J Eng Ed 97(1):71-85
10. Vattam SS, Kolodner JL (2008) On foundations of technological support for addressing challenges facing design-based science learning. Pragmatics and Cognition 16(2):406-437
11. Cross N (2001) Design cognition: Results from protocol and other empirical studies of design activity. In C.M. Eastman, W.M. McCracken & W. Newstetter (eds.), Design Learning and Knowing: Cognition in Design Education. New York: Elsevier Press
12. Kan JWT, Gero JS (2009) Using the FBS ontology to capture semantic design information in design protocol studies, in J McDonnell and P Lloyd (eds), About: Designing. Analysing Design Meetings, CRC Press:213-229

13. Atman CJ, Bursic K (1998) Verbal protocol analysis as a method to document engineering student design processes. J Eng Ed 87(2):121-132
14. Atman CJ, Deibel K, Borgford-Parnell J (2009, August) The process of engineering design: A comparison of three pepresentations. Int Conf on Eng Design (ICED), Palo Alto, CA
15. Mentzer N, Becker K, Sutton M (2015) Engineering design thinking: High School Students' Performance and Knowledge. J Eng Ed 104(4):417-432
16. Goldschmidt G (2014) Linkography: Unfolding the design process. Cambridge, MA: MIT Press.
17. Purzer Ş (2011) The Relationship between team discourse, self-efficacy, and individual achievement: A sequential mixed-methods study. J Eng Ed 100(4):655-679
18. Purzer Ş, Fila ND (2013) Innovation process mapping protocol: An approach to assessing students' understanding of innovation as a process. ASEE Annual Conf & Expo
19. Costa R, Sobek DK (2004) How process affects performance: An analysis of student design productivity. ASME Int Design Eng Tech Conf and Computers and Info in Eng Conf, Salt Lake City, September 28-October 2
20. Dong A, Hill, AH, Agogino AM (2004) A document analysis for characterizing design team performance. ASME J of Mech Design 126(3):378-385
21. Crismond D. Hynes M, Danahy E (2010) The design compass: A computer tool for scaffolding students' metacognition and discussions about their engineering design process. Proceed Assoc for the Advancement of AI Spring Symposium
22. van Schaik J, Scanlan J, Keane A, Takeda K, Gorisse D (2011) Improving design rationale capture during embodiment design. Int Conf on Eng Design (ICED), Copenhagen, Denmark August 15-August 19
23. Sims-Knight JE, Upchurch RL, Pendergrass N, Meressi T, Fortier P, Tchimev P, VonderHeide R, Page M (2004) Using concept maps to assess design process knowledge. Proceedings of the 34th ASEE/IEEE Frontiers in Education Conf. Savannah, GA
24. Adams R, Fralick B (2010) Work in progress: A conceptions of design instrument as an assessment tool. Proceedings of the Annual ASEE/IEEE Frontiers in Education Conf, Washington DC, October, 2
25. Hsu M, Cardella ME, Purzer Ş (2014) Assessing design. In Ş. Purzer, ME Cardella, J Strobel (Ed.), Engineering in Pre-college settings: synthesizing research, policy, and practices (pp. 303-313). West Lafayette, IN: Purdue University Press
26. Atman CJ, Yasuhara K, Adams RS, Barker T, Turns, J, and Rhone E (2008) Breadth in problem scoping: A comparison of freshman and senior engineering students. Int J of Eng Ed 24(2):234-245
27. Adams RS, Beltz N, Mann L, Wilson, D (2010) Exploring student differences in formulating cross-disciplinary sustainability problems. Int J of Eng Ed 26(2):324-338

28. Baker RSJD, Corbett AT, Aleven V (2008) More accurate student modeling through contextual estimation of slip and guess probabilities in bayesian knowledge tracing. 9th Int Conf on Intelligent Tutoring Systems, Montréal, Canada
29. Crismond DP, Adams RS (2012) The informed design teaching and learning matrix. J Eng Ed 101(4):738-797
30. Xie C, Zhang H, Nourian S, Pallant A Bailey S (2014) A study of the instructional sensitivity of CAD logs based on time series analysis. Int J Eng Ed 30(4):760–778
31. U.S. Department of Education (2010) National Educational Technology Plan 2010: Transforming American Education: Learning Powered by Technology. Washington DC: Office of Educational Technology, U.S. Department of Education
32. Clarke-Midura J, Dede C, Norton J (2011). Next generation assessments for measuring complex learning in science: Rennie center for education research & policy
33. Sao Pedro MA, Baker R, Gobert J, Montalvo O, Nakama A (2012) Using machine-learned detectors of systematic inquiry behavior to predict gains in inquiry skills. User nodeling and user-adapted interaction
34. Horwitz P (2011) Interactive technology for formative assessment: How we got jere and what comes next. In P. E. Noyce & D. T. Hickey (Eds.), New Frontiers in Formative Assessment. Cambridge, Massachusetts: Harvard Education Press
35. McElhaney KW, Linn MC (2011) Investigations of a complex, realistic task: Intentional, unsystematic, and exhaustive experimenters. J Res Sci Teaching 48(7):745-770
36. Lewis T (2006) Design and inquiry: Bases for an accommodation between science and technology education in the curriculum? J Res Sci Teaching 43(3):255-281
37. Worsley M, Blikstein P (2014) Analyzing engineering design through the lens of computation. Jof Learning Analytics1(2):151–186
38. Socha D, Gornil A, Watler S, Adams RS, Tenenberg J, Roth WM (2016) Exploratory analysis of large ethnographic datasets. Proceedings of a workshop on Developing a Research Agenda for Human-Centered Data Science as part of the annual Computer Supported Cooperative Work conference, San Francisco, February
39. Xie C, Zhang H, Nourian S, Pallant A, Hazzard, E (2014). A time series analysis method for assessing engineering design processes using a CAD tool. Int J Eng Ed 30(1):218–230.
40. IBM (2012) What is big data? Retrieved May 1st, 2013, from http://www-01.ibm.com/software/data/bigdata/
41. Purzer Ş, Goldstein, MH, Adams, RS, Xie, C, Nourian, S (2015) An exploratory study of informed engineering design behaviors associated with scientific explanations. Int J STEM Ed 2(1):1-12
42. Valkenburg R (1998) The reflective practice of design teams. Design Studies 19(3):249–271

43. Goldstein MH, Purzer Ş, Adams RS, Xie C (July 2015) Exploring the relationship between student reflectivity and their understanding of informed design. Presented at Research in Engineering Education Symposium (REES), Dublin, Ireland
44. Goldstein MH, Purzer Ş, Zielinski M, Adams RS (June 2015) High school students' ability to balance benefits & tradeoffs while engineering green buildings. 122nd American Society for Engineering Education Annual Conference and Exposition, Seattle, WA
45. Goldstein MH, Purzer Ş, Vieira Meji C, Zielinski MK, Douglas KA (October 2015) Assessing idea fluency through the student design process. Conference Proceedings: Frontiers in Education (FIE) Annual Conference, El Paso, TX
46. Madhavan K, Richey MC (2015) Problems in big data analytics in learning. J Eng Ed 105(1):6-14