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A Computer-Aided Design Based Research Platform for Design Thinking Studies

Design thinking is often hidden and implicit, so empirical approach based on experiments and data-driven methods has been the primary way of doing such research. In support of empirical studies, design behavioral data which reflects design thinking becomes crucial, especially with the recent advances in data mining and machine learning techniques. In this paper, a research platform that supports data-driven design thinking studies is introduced based on a computer-aided design (CAD) software for solar energy systems, ENERGY3D, developed by the team. We demonstrate several key features of ENERGY3D including a fine-grained design process logger, embedded design experiment and tutorials, and interactive CAD interfaces and dashboard. These features make ENERGY3D a capable testbed for a variety of research related to engineering design thinking and design theory, such as search strategies, design decision-making, artificial intelligent (AI) in design, and design cognition. Using a case study on an energy-plus home design challenge, we demonstrate how such a platform enables a complete research cycle of studying designers" sequential decision-making behaviors based on fine-grained design action data and unsupervised clustering methods. The results validate the utility of ENERGY3D as a research platform and testbed in supporting future design thinking studies and provide domain-specific insights into new ways of integrating clustering methods and design process models (e.g., the function–behavior–structure model) for automatically clustering sequential design behaviors. [DOI: 10.1115/1.4044395]

Keywords: sequential design decision, design thinking, computer-aided design, unsupervised learning, data clustering, design process, solar energy systems design

1 Research Background and Paper Overview

1.1 Engineering Design and Design Thinking. Design is a purposeful activity that aims to meet a set of requirements for an artifact [1,2]. It typically involves *defining* problems and *solving* them [3]. The former stage usually transforms design from ill-defined problems to well-defined ones, from which both design variables and constraints can be identified, and the design space is determined. This step often requires design ideation, conceptualization, and requirement analysis. The later stage relies on different strategies of searching to find the most appropriate solutions within the identified design space. In both stages, design heavily relies on a designer's knowledge consisting of not only explicit knowledge that can be obtained from encoded information, such as text and drawings, but also tacit knowledge that is difficult to visualize and mainly accumulated from experience [4]. In addition, designers are bounded rational due to human's limited information-processing capability [5]. In this process, engineering design thinking (EDT), as shown in Fig. 1, plays an important role in bridging design knowledge and design problems, given the bounded rationality of designers, to guide designers' operations to navigate through the design space in a stepwise but iterative manner (also known as sequential decision-making), in order to achieve the design objective. According to Dym et al. [6], EDT is a complex process of inquiry and learning that designers perform in a systems context, making decisions as they proceed, and often working collaboratively.

1.2 The Significance and Challenges. A deeper understanding on designers' thinking and decision-making is critical to the discovery of generalized design processes and heuristics that can, in turn, be used to facilitate design process and enhance design automation. This is particularly useful to the development of computational design methods. For example, evidence has shown that human beings are quite successful in heuristically solving design problems with large solutions space and often nonconvex objectives. Recent studies [7,8] also show that human search displays a different pattern compared with computational algorithms. Therefore, integrating human intelligence into current computational design frameworks can initiate a new paradigm of human intelligence computational design.

However, the challenges of studying EDT naturally follow because thinking often resides tacitly inside the mind of designers and is difficult to make it explicit [9]. Therefore, empirical study and data-driven approaches are common pathways to study EDT. Existing literature has demonstrated the use of various types of

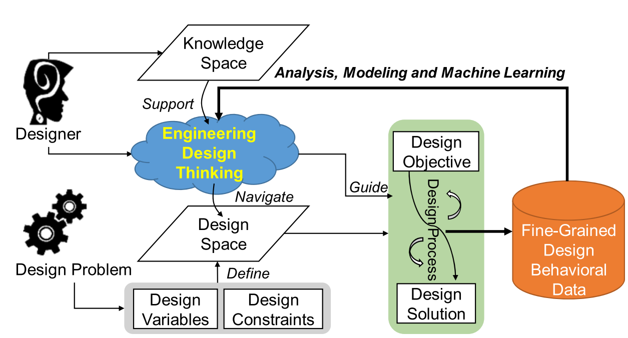

Fig. 1 Engineering design process and design thinking

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data (e.g., texts, drawings, and videos) for design thinking studies, such as design knowledge acquisition [10], design creativity assessment [11–13], and search patterns [14]. Sha et al. [15] also demonstrated the effectiveness of using behavioral data for studying designers' sequential decision-making strategies under competition. Even if extensive research has been conducted in this field, significant challenges remain. For example, design problems are often complex and must be decomposed into subtasks. Therefore, system thinking plays a critical role in organizing and iterating through tasks *across different design stages*. The essence of system thinking and its role in EDT are rarely studied due to the lack of research platform that supports the collection of quality behavioral data in a complete system design cycle (see Sec. 2.2 for details). The insights drawn from those studies cannot be easily transferred to practical engineering design context. In addition, current research pays little attention to the temporal granularity of the behavioral data; yet, this is critical to probe into the dynamics of EDT. Valuable information that could reflect design strategies might have been overlooked if data are only collected after large time intervals.

To address these challenges, this paper introduces a new research platform based on the computer-aided design (CAD) software, ENERGY3D [25]. ENERGY3D is originally developed by Xie (one of the team members of this project) for CAD of solar energy systems. But it has been recently adapted, and unique features (e.g., built-in experiment modules) have been added to transform it to a research platform and testbed for EDT studies and data-intensive design research. See more detailed discussion in Sec. 3.

1.3 Overview of the Paper.

The *primary objective* of this study is to develop a research platform based on ENERGY3D in support of fine-grained data-driven research of designers' thinking and decision-making. With a case study on automatically clustering designers' sequential decision-making behaviors, we demonstrate how this new platform enables a complete research cycle in studying EDT and facilitates the development of an integrated approach to automatically clustering designers' sequential design behaviors.

The *contribution of this work* lies in three aspects: (1) the identification of a set of data requirements that is critical to the validity of EDT research; (2) a new open-source research platform that facilitates researchers to conduct design experiments and collect high-quality design behavioral data in support of EDT studies; and (3) an integrated approach based on three unsupervised learning and clustering methods (i.e., K-means clustering, hierarchical agglomerative clustering (HAC), and network-based clustering) for automatic clustering of sequential design behaviors.

The remainder of the paper is organized as follows. Section 2 presents state-of-the-art research on EDT and data collection methods. In this section, we also summarize the major differences between the proposed platform and existing ones and present the data requirements for EDT studies. In Sec. 3, we introduce the ENERGY3D-based research platform and its unique features for EDT studies. In Sec. 4, a case study on clustering designers' sequential design behaviors based on such a research platform is presented. Section 5 concludes the paper with closing insights, broader impacts, and our future work. An earlier version with preliminary results on the case study was presented at the ASME 2018 Computers and Information in Engineering Conference in Quebec City, Canada [26].

2 Background and Literature Review

In this section, we first present a review of existing literature on EDT studies. Then, we give a particular emphasis on the studies based on CAD software and nonintrusive data logging because these topics are relevant to the proposed research platform. At the end, we provide a summary of the typical data collection methods in these studies, from which we identify the limitations of current research and present our view on a set of new data requirements that shall be considered in the EDT studies.

2.1 Existing Research on Engineering Design Thinking.

Existing literature on EDT can be primarily categorized into the following three directions.[2] A more comprehensive review of state-of-the-art research on designer thinking is provided in Ref. [27].

- *Protocol studies*: Protocol analysis relies on observation and can be categorized into in vivo studies (e.g., the think-aloud method [28]) and in vitro studies (e.g., interviews with designer [29]). The observational data need to be transcribed, segmented, and coded, and then post-analyses can be performed to generate insights into design thinking. Typical topics of the study include design creativity [13,24,30,31] and fixation [32–34], example modality [11,35,36], the role of sketches [37–40], and differences of thinking patterns between experts and novices [41–44]. Since the coding scheme is a critical step, extensive research is carried out in evaluating different coding methods (e.g., the function-behavior-structure (FBS) scheme [45,46]) and sketch coding methods (e.g., the C-sketch method [47]).
- *Controlled experiment*: Controlled lab experiments are very effective for validating the causality between factors of interest and design outcomes. As experimental settings need to be well designed beforehand, controlled experiments often offer greater intrinsic validity [27]. The results are often generalizable and extensible [48]. Typical subjects of study in this area include the effects of design cost [7,15] and designers' expertise [49–52] on design outcomes, team effects in design [12,53,54], analogical reasoning [55,56], and provocative stimuli [57,58]. Recently, the design field has a trend of using gamified design scenarios [15,59–63] to study design behaviors and thinking.
- *Simulation trials*: Recently, research has been pursued to "replay" designer thinking, particularly the sequential decision-making, using computer simulations. For example, McComb et al. study designers' sequential learning abilities using Markov chain [14,64] and simulated annealing [16,54,65]. Gero and Peng [66] also use Markov chain to study the behaviors of a constructive memory agent. Sexton and Ren [8] leverage human searching capability to fine-tune the parameters in Bayesian optimization for enhanced performance. Panchal et al. [7] integrate Gaussian Process model and game theory to study designers' strategies in sequential decision-making under competition.

2.2 Design Thinking Studies Using Computer-Aided Design Software and Nonintrusive Data Logging.

Nonintrusive data logging is a method that automatically logs designers' actions in real time as they use an interactive simulation or design environment without interrupting their design process. On the one hand, this can be realized by commercial CAD software, which often has an explicit data schema for logging designers' actions and relevant metadata, e.g., timestamps, and structures of design artifacts, e.g., geometry hierarchy, in generic data storage formats such as XML. Data captured through these platforms can be processed and sometimes analyzed computationally to accelerate research. For example, Jin and Ishino [19] proposed a data mining framework, DAKA, which can extract designers' design activity and knowledge from CAD event data. Gopsill et al. [20] used CAD as a sensor to collect design action logs and studied micro design patterns, which showed the implications of operations, such as "deletion" and "reversing," in design iteration. Sen et al. [23] presented a nonintrusive protocol study with the aid of a software on measuring information content when designers perform free-hand sketching

[2]Brain-mapping techniques, mainly the electroencephalogram and the functional magnetic resonance imaging, have been adopted to investigate the neurological basis of design thinking. These studies are particularly interested in understanding how cognitive functions are supported by different brain areas. However, this research stream is not comparable with our research and hence is not summarized.

Table 1 Representative research platforms for EDT studies based on the literature review

Reference	Design problem	Design platform/ software	Data format	System or component design	Design information data	Built-in experiment materials
McComb et al., 2015 [16]	Truss design	Self-developed and closed source	Not reported	System—configuration design	Not reported	External tutorial; no built-in materials
Yu et al., 2016 [17]	Desalination system/sea water reverse osmosis	Self-developed and closed source	Not reported	System—parametric design	Design parameter values; timestamp	External tutorial; no built-in materials
Egan et al., 2015 [18]	Myosin design	Self-developed and closed source	Not reported	System—parametric design	Text; Design parameter values	External tutorial; no built-in materials
McComb et al. 2017 [14]	Truss design and home cooling system	Self-developed and closed source	Not reported	System—configuration design	Design actions	No built-in materials
Jin and Ishino, 2006 [19]	Car front door	Commercial and open source	Not reported	Component design	CAD drawing commands	No built-in materials
Gopsill et al., 2016 [20]	Pulley	Commercial and open source	Not reported	Component design	CAD drawing commands	No built-in materials
Ritchie et al., 2008 [21]	Cable organization system	Commercial and closed source	Yes (XML)	Component design	Design actions in virtual reality	No built-in materials
Sha et al., 2015 [15]	Function minimize	Self-developed and closed source	Not reported	Component or System—parametric design	Design parameter values	No built-in materials
Sivanathan et al., 2015 [22]	Bracket support	Commercial and open source	Yes (XML)	Component design	Design actions and video	No built-in materials
Sen et al., 2017 [23]	Burger maker	Commercial and closed source	Yes (Excel)	System—conceptual design	Design sketches; timestamp	No built-in materials
Toh and Miller, 2014 [11]	Milk froth device	No software platform	Not reported	System—conceptual design	Sketches	No built-in materials
Gero et al., 2018 [24]	Wheelchair assist device	No software platform	Not reported	System—conceptual design	Sketches and video	No built-in materials
This paper (ENERGY3D)	Solar energy systems	CAD-based platform	Yes (JSON)	System—multiple design stages	Design actions, design config., text, artifact, etc.	Built-in experiment materials

of design concepts. On the other hand, many researchers have developed their own applets for data collection. For example, in order to explore design heuristics and sequential design patterns, McComb et al. [64] collect design behavioral data with two configuration design experiments with the aid of self-developed applets for truss design and cooling systems design. Sha et al. [15] developed an economic decision game applet based on z-Tree and studied the effects of design cost on designers' sequential decision-making under competition.

In addition, logged data may be processed in real time to offer designers immediate feedback or suggestions for advancing their design process [67,68]. Sivanathan et al. [22] extend the data logging method to what they call ubiquitous multimodal capture that incorporates CAD logging, keyboard and mouse logging, eye tracking, screen and environment video, galvanic skin resistance, electroencephalogram, and electrocardiogram. They demonstrate the feasibility of this collection scheme through case examples of bracket design and collaborative design review. While ubiquitous multimodal capture collects extensive data from a designer, it comes at the cost of being disruptive for the designer and expensive to implement.

In summary, CAD-based nonintrusive data collection method offers a great opportunity to EDT research. However, many self-develop applets have limited functionalities and only address a particular design phase, e.g., conceptual design. In addition, commercial CAD software is a tool and not designed for research purpose per se. The data collected from such software are typically drawing or sketch commands (e.g., circle, extruding) and are not able to produce a continuous flow of research data in a complete design process. Yet, design has a life cycle and contains many design stages, such as concept generation, preliminary design, embodiment design, engineering analysis, and design validation. Many facets of EDT due to the systems design essences (often require systems thinking) can be hardly assessed. Therefore, the insights obtained from the research based on those platforms are difficult to draw generic insights. The data collected from the self-developed applet is also ill structured without using standard data structure and schema. This creates burdens for data processing and sometimes causes missing data, which inevitably hinders the major effort at the core of research. More importantly, these applets are often in closed form and not accessible from public, which causes barriers in repeating and reproducing the research findings for cross-validation. In Table 1, we summarize the representative research platforms used in design literature. While existing work sets standards and guidelines for many ongoing research projects, our proposed research platform addresses the above limitations and, therefore, well complements the existing ones, and thus provides an alternative engineering system design testbed where many new and developed approaches for EDT studies can be investigated and tested. In the following section, we introduce the unique features of the proposed research platform and show how those features complement current platforms and how they can ease the research cycle of design thinking studies.

3 The Research Platform

In this section, we introduce our research platform for EDT studies based on ENERGY3D and discuss the key features that make it a suitable and powerful tool in supporting EDT research. Before demonstrating the details, we first summarize our view on the data requirements that shall be met for EDT research in order to address the limitations of existing methods identified in Sec. 2.2.

3.1 Data Requirements for Engineering Design Thinking Research.

To successfully execute the proposed research and achieve the objective, the data are critical and specific requirements

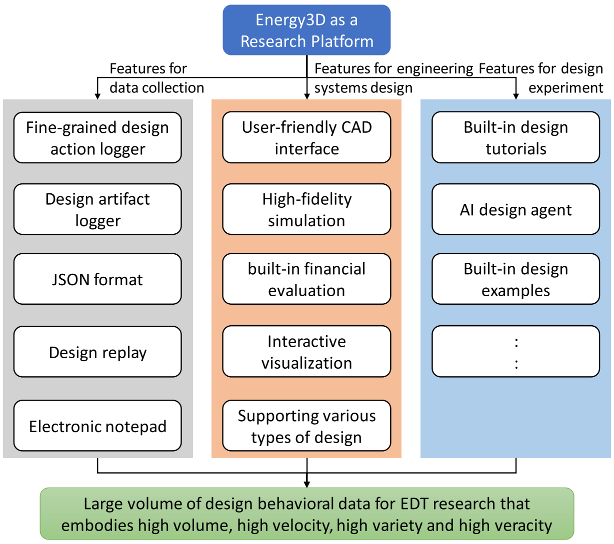

Fig. 2 Unique features of ENERGY3D in supporting engineering design thinking research

deserve careful attention. We identified five requirements based on our literature review performed in Sec. 2.

(1) *Intrastage and interstage design iteration.* Design iteration does not only occur within each stage but also between stages [69]. For example, designers often utilize science simulation to refine their designs in concepts generation [70]. The decisions made during such an iteration play a vital role in assuring a successful design. A tool that supports the collection of design process data and design actions in both intrastage and interstage iterations is needed.

(2) *High fidelity*. In a design process, ad hoc decisions are often made. Unnoticeable actions could be nontrivial information reflecting useful decision-making strategies. It would be ideal if every single movement of designers can be recorded. The data should be a collective memory of the complete output and all iterations in design.

(3) *Nonintrusive*. Intrusive data collection (e.g., interviews) is time consuming, and thus restricts research scale [60,71]. Such a process could easily add cognitive load to designers, thus possibly contributing biases toward the observed behaviors [72]. These limitations can diminish the validity of the data.

(4) *Rational behavior*. Most decision theories assume rational behaviors, but designers have bounded rationality [73]. When collecting design behavioral data, designers' irrationality should be accounted for and decision-supporting tools (e.g., simulations) shall be leveraged to inform rational decisions to improve the quality of design data.

(5) *Multiple forms*. The data should be a combination of operational, textual, and even video data to support the cross-validation of research approaches or methodologies.

3.2 Using ENERGY3D as a Research Platform for Engineering Design Thinking Studies. With the aim of meeting these requirements, we introduce a new research platform based on ENERGY3D, a computer-aided design software developed by Xie [25], one of our team members. It was developed as a tool for solar energy systems design and analysis as well as for K-12 education research. To make it applicable to support engineering design research, specific features such as built-in experimentation, tutorial and templates, new computational modules, and additional data collection methods have been added. In summary, as a platform for design research, ENERGY3D has unique features in three aspects (Fig. 2).

3.2.1 Features for Data Collection. First, ENERGY3D can continuously and automatically log and sort every user action and design snapshots (computer models, *not* images[3]) in a fine-grained resolution. These data represent the smallest transformation possible on a design object that changes how it looks or performs. That means the design process and even the design artifact can be entirely *reconstructed without losing any important details*. Therefore, it works as a "sensor" of design behaviors so as to capture the design processes in detail and in a nonintrusive manner, i.e., designers are not aware of the data collection and can concentrate on their design activities without any hindrance to their design thinking.

Second, ENERGY3D logs the data in JavaScript Object Notation (JSON) format. JSON is a generic machine-readable data storage format that relies on two common data structures, arrays, and key-value pairs, to encode a variety of data schemas. In ENERGY3D, each logged action contains the action itself, e.g., adding a wall, and metadata about the time and date when the action was taken. Central design attributes associated with each action are recorded as well, such as the size of a window or the results of an energy simulation. Such a standard data format makes it possible to translate any design activity, logic, or strategy into computer code and vice versa. JSON data can be readily processed by most programming languages and statistical platforms like R, making it convenient for researchers to analyze the data with their preferred toolset. Standardization and automation make the design research cost-effective and scalable.

Third, ENERGY3D stores a rich blend of both qualitative and quantitative data. In the JSON file, textual design actions are stored as qualitative data and values of design parameters are stored as quantitative data. For qualitative data, ENERGY3D has an electronic notepad. During a design, designers can write down important ideas, findings, and thought processes. The collection of these data is particularly beneficial to research on systems design thinking where both quantitative and qualitative skills are required [74].

Fourth, in addition to CAD modeling, ENERGY3D has built-in modules of engineering analysis, scientific simulation, and financial evaluation that realize a seamless design environment. This ensures the collection of design data during intrastage and interstage iterations, for example, how designers make decisions with economic considerations, i.e., design with rationality. These data are important for the study on designers' thinking in complex systems design and the role of system thinking in engineering design.

3.2.2 Features for Engineering Systems Design. The interface of ENERGY3D is intuitive to operate [75]. ENERGY3D encompasses several predesigned components (i.e., doors, window, solar panel, etc.) that ease the design difficulty such as drawing components from scratch. This ensures that participants can focus on the design process and employ design thinking instead of time-consuming drawing process. In addition, easy operation will help shorten participants' learning curve, which often influences the validity of behavioral data in design research.

It is worth noting that simulations in ENERGY3D are very accurate and trustworthy as it provides real-world design configuration and materials [76]. For example, the building simulation engine is calibrated with DOE's BESTEST benchmarks. This feature ensures authentic and high-fidelity design practice. Moreover, during simulations, ENERGY3D graphically illustrates the results through interactive visualization and animation, which allows designers to easily and efficiently get formative and immediate feedback. This is critical to their rational decision-making and exploration of design space in engineering systems design.

ENERGY3D supports various solar energy system designs (see Fig. 3). Design can be conducted in various contexts with different

[3]ENERGY3D has a design replay feature. The design artifacts are saved as ENERGY3D files and later can be used for replaying the entire design process. This allows researchers to check designers' design processes in detail and will help validate against mined design knowledge and strategies from the log data.

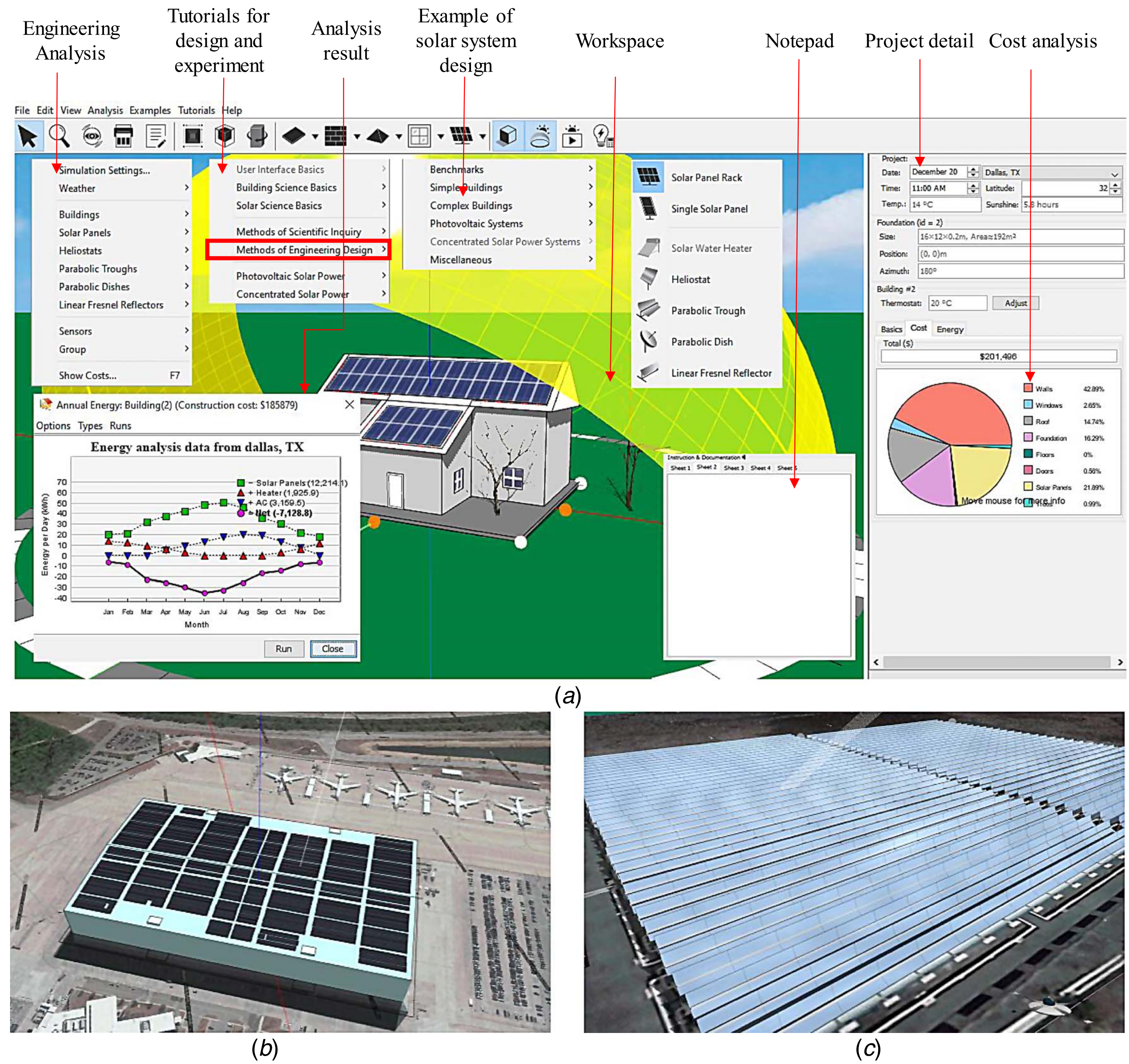

Fig. 3 Energy3D supports various solar systems design: (*a*) the user interface of ENERGY3D, (*b*) a rooftop photovoltaic system for Boeing's South Carolina factory, and (*c*) parabolic troughs in Hawaii

options of solar harvesting devices, including solar panel, heliostat, and parabolic trough, and different solar panel brands. With these capabilities, researchers can create different experiments covering a wide range of design scenarios in different levels of design complexity, such as single component design, geometric design, layout design, material design, and architectural design.

3.2.3 Features for Human Subject Experiments in Design Research. To facilitate experiments for design research, ENERGY3D contains many built-in tutorials for designers to get acquainted with the domain knowledge of solar science, building science, and engineering design. These tutorials can be used as pre-session before experiment in order to account for the variation of learning curves among participants. In addition to these tutorials, a set of design experiments have also been made publicly available through the authors' websites [77,78]. The researchers can easily adapt these examples to create new ones for their own research purpose and data collection.

With all the above features in three aspects, as shown in Fig. 2, ENERGY3D can support the collection of a large volume of fine-grained design behavioral data, which is essential to big data mining and machine learning of EDT. Such fine-grained data possess all four characteristics of big data [79]: (1) High volume: A large amount of design process data will be generated. (2) High velocity: One of the characteristics of big data is velocity, which means how fast the data are collected. ENERGY3D collects, processes, and visualizes data in real time at the scale of seconds. Such an improvement on the continuity of the behavioral data can help improve the understanding of the flow of design thinking. (3) High variety: The data encompasses multiple forms involving design actions, parameters, analyses, and simulations. (4) High veracity: The data are comprehensive to ensure fair and trustworthy assessments of designer performance. These big data have the potential to yield direct, measurable evidence of design thinking at a statistically significant level. This is fundamentally different from existing studies [19,20,67,68] using CAD logs that contain merely drawing commands. Xie et al.'s prior work [80–82] has shown that the data collected from ENERGY3D are capable of measuring the level of engagement, revealing gender differences, and distinguishing the iterative and noniterative cycles in design.

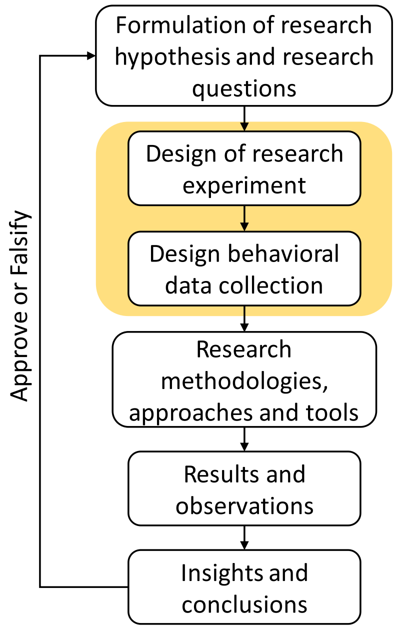

Fig. 4 A typical cycle for data-driven engineering design thinking research

With ENERGY3D as the platform, we follow a typical scientific research cycle as shown in Fig. 4 to conduct EDT research. As indicated in the figure, steps of research experiment and data collection are critical links in this cycle, yet their rigor and validity have received little attention. As introduced above, those unique features of ENERGY3D will provide researchers with strong support.

4 Automatically Clustering Sequential Design Behaviors: A Case Study

In this section, we demonstrate a case study using ENERGY3D as the research platform where each of the research steps in Fig. 4 is followed. First, we present our research problem and the research question we investigated in this particular study. Then, we discuss how ENERGY3D is used to set up the experiment for design behavioral data collection. In this study, we develop an approach based on unsupervised learning-based approach that integrates the Markov chain model to automatically cluster designers' sequential design behaviors. Finally, on the basis of results, we answer the question and conclude the case study.

4.1 The Research Problem and the Research Question. Engineering system design is a decision-making process where a series of interrelated operations are determined by designers. During a design task, designers sequentially make decisions in order to explore the design space and iteratively improve their designs' quality. Therefore, sequential decision-making is an important factor in achieving quality design outcomes. In-depth understanding of sequential behaviors, especially their design patterns, help to uncover useful design heuristics to improve existing algorithms of computational design, design automation, and advance artificial intelligent (AI) in engineering design

However, modeling design decision-making is scientifically challenging because human decisions are the result of a mental process that is hidden, implicit, and sometimes tacit [9]. Such a challenge is even more complex in a system design context that consists of a large number of coupling design variables. To address the challenge, we adopt a data-driven approach and use unsupervised clustering methods to mine designers' sequential design patterns. This case study is motivated by answering the following research question: *What are the sequential design behavioral patterns that most designers would follow in systems design?* To answer the research question, a human subject experiment is conducted, and sequential design behavioral data are collected based on the research platform, ENERGY3D. In the following sections, we present this case study in detail.

4.2 Design Experiment and Data Collection Using ENERGY3D. In this section, we first give a brief description of the design problem. Next, we introduce our experiment procedure and the sequential design action data collected.

4.2.1 The Design Problem. The design problem in this case study is to build a solarized energy-plus home for a client in Dallas. See an illustrative example in Fig. 5. The design objective is to maximize the annual net energy (ANE). The budget for the house is \$200,000. The house should have a minimum height of 2.5 m, and the roof must be pitched. The building needs to have at least four windows and one door. The solar panel must be placed on the roof. The other constraints are shown in Table 2.

This design is a system design problem that involves many components (e.g., windows, roof, solar panel), many design variables (e.g., the number of solar panels, the cell efficiency of solar panel), and complex coupling relations among the variables. Therefore, the design space is very large. This is why the requirements and the constraints are developed to reduce designers' action space to a manageable level.

During the design process, designers make trade-off decisions. For example, there is no restriction on the area of the house. But if the area is too small, designers will not be able to place enough solar panel on the roof. As a result, the ANE will be insignificant. On the other hand, if the area is too large, the cost may exceed the budget. So, designers follow their own strategies during the design process to sequentially make decisions, guiding the exploration and exploitation of the design space so as to improve the ANE as much as possible.

Fig. 5 An energy-plus home design from one of the participants

Table 2 The requirements of the energy-plus home design project

	Items	Requirements
Build height	Story	1
	Height of wall	≥2.5 m
Roof	Roof style	Pitched
Window	Number of windows	≥4
	Size of window	≥1.44 m^2
Door	Number of doors	≥1
	Size of door (width × height)	≥1.2 m × 2 m
Solar panel	Distance between edge/ridge and solar panel	≥0 m

4.2.2 The Experiment Procedure and Data Collection. A human subject experiment was conducted where in a total of 38 students from the University of Arkansas participated. The participants were indexed based on which session they were in and which laptop they used; thus, A02 means that the participant was in session A and sits in laptop #2.

Each session consists of two phases: pre-session and in-session. The pre-session is 30 min[4] for participants to practice ENERGY3D with the built-in design tutorials. The pre-session is designed to account for the learning curves of humans. The data generated in the pre-session are not used for analysis. At the end of the pre-session, the participants are guided to transition to the in-session stage. The in-session stage lasts about 1.5 h. The design statement and the design requirements are provided at the beginning of this session, and a record sheet is provided for participants to record the ANE and cost whenever they iterate their designs.

Many of the ENERGY3D features, especially the CAD design features and the design experiment features, allow designers to explore the design space effectively and efficiently. For example, the graphical representation of construction cost and ANE analysis helps them to interpret their underlying trade-off. Moreover, the interactive visualization shows heat flux and sun path, which aid designers in making effective decisions on the location of solar panels and the orientation of the buildings.

Monetary rewards are provided at the end of the session to incentivize the participants to search the design space as much as they can. The participants are rewarded based on the amount of time they spend as well as the quality of their final designs, which are quantified by the ANE value and the construction cost. In this study, we are able to collect the design behavioral data using ENERGY3D at a fine-grained level. For example, the design artifact logger collects 220 intermediate ENERGY3D files and the design action logger collects 1500 line of actions per participant on average. This ensures a sufficient amount of data for later statistical analysis and data analytics. The JSON file includes entries in the following format: timestamps, design action, and its corresponding parameters and/or analysis values, such as the coordinate of an object and/or ANE output. An example of the data entries is shown below:

- *“Timestamp”: “2017-11-14 12:51:27,” “File”: “EnergyPlus Home.ng3,” “Add Rack”: \(”Type”: “Rack,” “Building”: 2, “ID”: 23, “Coordinates”: [\(“x”: −28.863, “y”: −49.8, “z”: 20.799)*].
- *“Timestamp”: “2019-02-22 09:07:44,” “File”: “EnergyPlus Home.ng3,” “Edit Window”: \(”Type”: “Window,” “Building”: 1, “ID”: 66, “Coordinates”: [\(“x”: −33.647, “y”: −3.783, “z”: 19)*].

4.3 The Research Approach. A general approach to automatically clustering sequential design behaviors is presented in Fig. 6. From the raw design in JSON format, 115 unique design actions are identified based on the data from 38 participants.[5] Analysis of such a high-dimension action space would yield results hard to interpret. In order to reduce the dimensionality and to better understand designers' sequential design thinking, the FBS-based process model is adopted to transform the action space into a design process space that consists of seven design process stages.

The FBS is constructed with three classes of ontological variables: function, behavior, and structure. Later, two additional variables are added for better representation of the design process: requirements and descriptions. Based on the five FBS ontological variables, a design process can be characterized by eight process stages: *formulation*, *analysis*, *evaluation*, *synthesis*, *documentation*,

[4]Our pilot study has shown that participants are able to master the operations of ENERGY3D for the energy-plus home design project in 30 min with the aid of the tutorial.

[5]In this study, only design actions, e.g., “Add Rack” and “Edit Wall” are considered for analysis. Trivial actions that do not affect the design quality, such as “Camera” and “Edit human” are ignored.

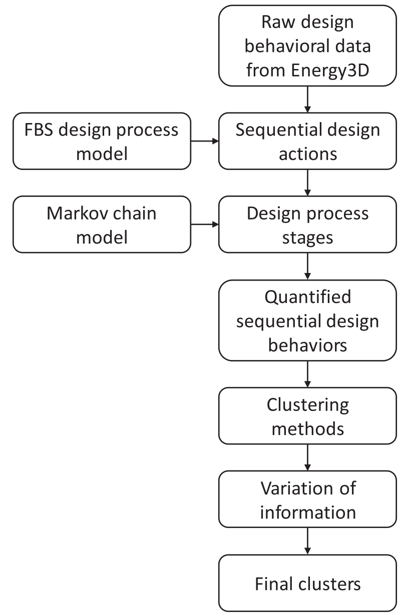

Fig. 6 Overview of the approach to automatically clustering sequential design behaviors

and *reformulation* 1, 2, and 3. Definition and interpretation of each design process stage are listed in Table 3. According to the FBS model, a coding scheme is established (third column of Table 3) to transcribe different types of design actions to the corresponding design process stages (see details in Ref. [26] about how each type of design actions corresponds to the design process stages in the FBS model).

With the FBS-based transcription, the sequence of how the design space is explored (design action space) can be therefore mapped to a design process (design thinking space). Then, the first-order Markov chain model [83] is adopted to quantitatively characterize the sequential design process of each participant into a transition probability matrix. An entry (π_{ij}) of this matrix defines the probability that design process i transitions to j, which is calculated by $\pi_{ij} = n_{ij}/n_i$, where n_{ij} is the number of times design process j is followed by process i, and n_i is the total counts of the design process i occurs during the entire design. An example of the transition probability matrix of the first-order Markov Chain for participant C14 is shown in Fig. 7. The max

Table 3 The FBS model and the proposed coding scheme for design actions

Design process	Definition and interpretation	Types of design action
Formulation	Generate Function from Requirement and from Function to Expected Behavior.	Add any components
Analysis	The process generated from Structure.	Analysis of annual net energy
Synthesis	Generate and tune Structure based on the Expected Behavior.	Edit any components
Evaluation	The comparison between the Expected Behavior and the behavior enabled by the actual Structure.	Cost analysis
Reformulation 1	The transition from one Structure to a different Structure.	Remove structure
Reformulation 2	The transitions from Structure to Expected Behavior.	Remove solar device
Reformulation 3	The transition from Structure to Function.	Remove other components

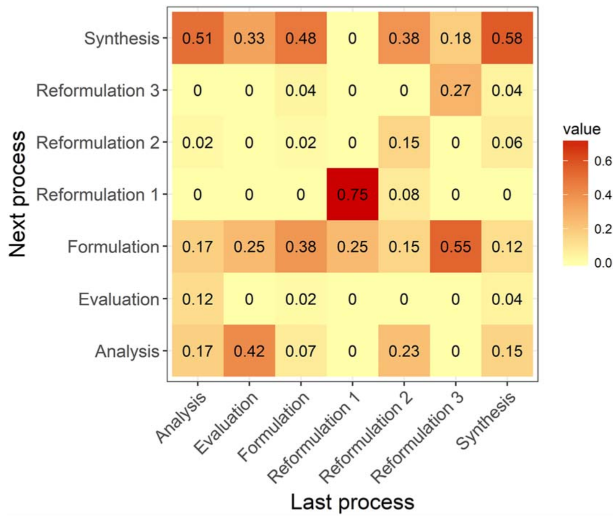

Fig. 7 Transition matrix of the first-order Markov chain for participant C14

probability is 0.75, indicating that the most occurred design pattern for this designer is *Reformulation 1* → *Reformulation 1*. This implies that the designer C14 was involved in removing structure (wall, window) significantly more frequently than other transitions. The value zero means that the designer never made that transition in his/her design. For example, the value from *synthesis* to *reformulation 1* is zero. This indicates that after editing or changing the parameters of any structural components (such as walls), this designer never removed those components.

Once the quantified design behavior, i.e., the 7×7 transition probability matrix, is obtained, it can be converted to a 49×1 vector. For n designers, a new $49 \times n$ matrix will be formed; thus, different clustering methods can be applied to these n designers to group those with similar sequential behavioral patterns. In this study, we apply three different clustering methods: K-means clustering [84], HAC [84], and network-based clustering [85]. These clustering methods are selected as representatives from three different clustering categories, i.e., hard clustering, flat clustering, and network clustering [86], which covers most commonly used clustering methods. K-means clustering works on Euclidean distance between data points and partitions dataset into K separate, nonoverlapping clusters such that the total within-cluster variation, summed over all the clusters, is minimum [84]. Since K-means requires the number of clusters as input, a separate algorithm (e.g., elbow plot method [87]) is often needed to determine the optimal number of clusters. The number of clusters obtained from the elbow plot method is used to guide the implementation of the other two clustering methods for fair comparison. Different from K-means, HAC produces a tree-based representation of the data, called dendrogram, from which a researcher can "cut" it into the desired number of clusters.

In Ref. [26], we developed a network-based clustering approach based on network community detection techniques [85]. In this method, a similarity network of designers is first constructed, in which nodes represent designers and links represent the distance between designers. In this study, two common distance metrics, residual sum of squares (RSS) [88] and cosine similarity (CS) [88], are adopted. In order to retain the strong similarities, a threshold value is selected to binarize the similarity network. Once the network is ready, different network community detection algorithms can be applied. We utilize the most popular and robust method [89], i.e., modularity maximization algorithm [90], to partition the network into different communities. Since the algorithm will automatically cluster the network into an optimized number of clusters, no predetermined number of clusters are needed. To enable the comparison between the three clustering methods, we trial and error the threshold value of similarities (i.e., the RSS and the CS values) until the number of clusters in the network matches the one obtained from the K-means elbow plot. Figure 8 illustrates the whole process and the connection between the network-based and K-means clustering methods.

Since different clustering methods could produce different clustering results, a verification approach is needed. In this study, a method based on the metric of *variation of information* (VI) [91] is developed for the verification and generation of the final clusters. VI measures the information lost and gained when it changes from one cluster to another. The lower the VI value is, the better is the partial agreement between two clusters. After obtaining the VI values for each pair of the clustering methods, the methods that have significantly large partial agreement can be identified, and the designers who have been always grouped together regardless of the clustering methods can be found, and therefore similar behavioral patterns can be mined from the data. In the following sections, we apply our approach to cluster designers' sequential decision-making behaviors in the solar energy system design project presented in Sec. 4.2.1. It is worth noting that each step shown in Fig. 6 can be programmed and seamlessly connected to turn the approach into an automatic clustering tool.

4.4 Clustering Analysis Results and Discussion. With the first-order Markov chain model introduced above, all the 38 participants' transition probability matrices are obtained and can be converted to a 49×38 matrix on which different clustering methods are applied. The optimum numbers of clustering are 4, 5, and 6, which are obtained from the elbow plot method. In this study, we evaluate the performance of all the different clustering methods (i.e., K-means, HAC, network-based clustering with RSS, and network-based clustering with CS) at each of these cluster numbers. In total, we come up with 12 different ways of doing the clustering analysis.

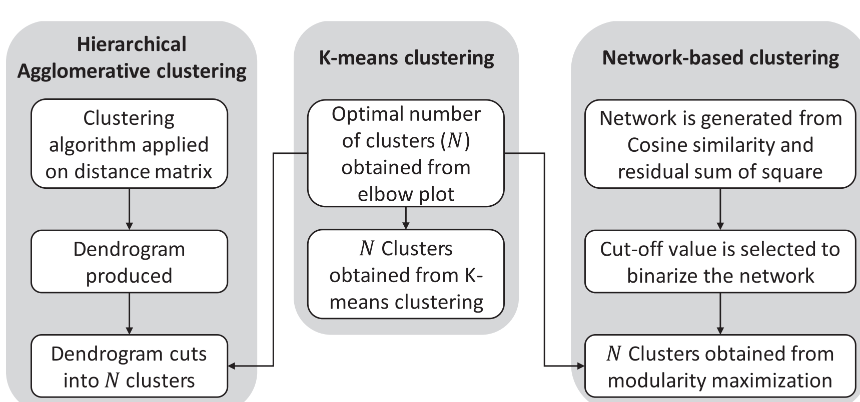

Fig. 8 Cluster analysis using three different unsupervised clustering methods

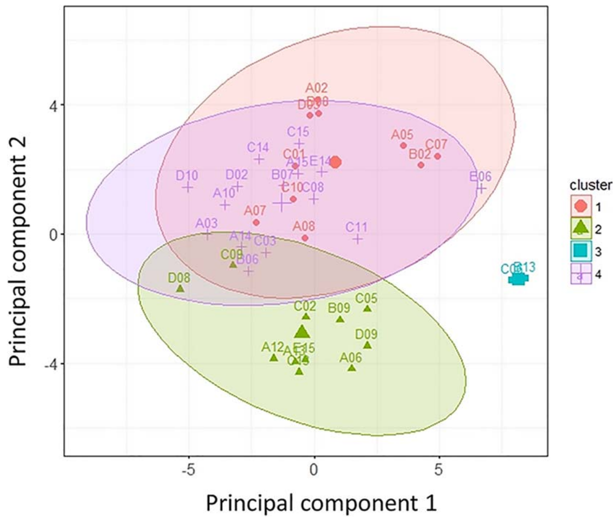

Fig. 9 K-means clustering of four groups plotted in two principal dimensions

Figure 9 represents the K-means clustering result with four clusters. The clusters are indicated by four different symbols (1, 2, 3, and 4). The number of designers in each cluster is 15, 11, 10, and 2, respectively. The plot shows the data points in two principal dimensions. From the figure, it is observed that designers B13 and C06 in cluster 3 are situated far from the other clusters in the Euclidean space. It is inferred that their sequential behaviors are quite different from the other designers.

HAC method clusters the designers by forming a dendrogram, as shown in Fig. 10. The height of the dendrogram indicates the designers' behavior similarity. To get four clusters, the dendrogram is cut at the height of 2.1. The resulting clusters contain 15, 14, 9, and 2 members, respectively. Figure 8 indicates that designers A12 and D08 have at the lowest height than any other pairs on the dendrogram. Therefore, they share the most similarity in sequential behaviors. Like K-means-4 clustering, HAC-4 clustering proves the similarity between B13 and C06. While in K-means-4 clustering, A10 and A14 are in the same group, and they are located at two different groups in the HAC-4 clustering. This reveals the inconsistency between different clustering methods.

For the network-based clustering, we calculate the RSS and CS similarities between each pair of designers using the vectors obtained from the transition probability matrix. This process

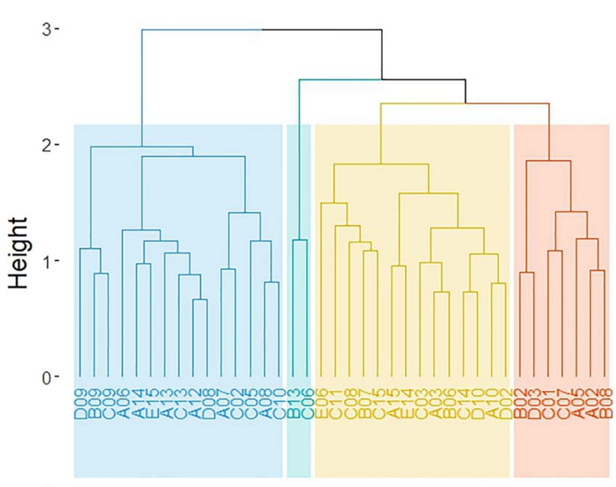

Fig. 10 Dendrogram produced by hierarchical agglomerative algorithm

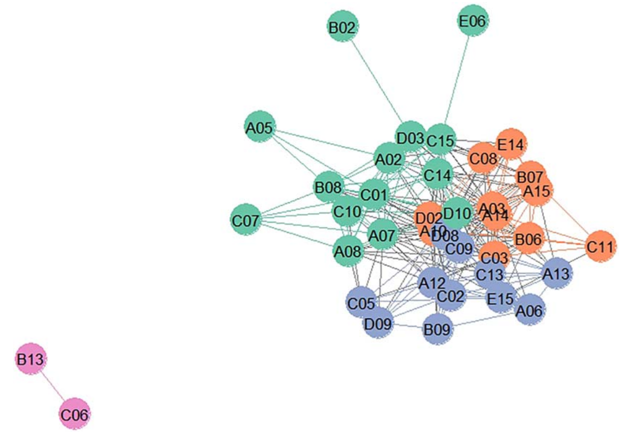

Fig. 11 The network-based clustering using residual sum of square similarity

produces two 38×38 similarity matrices from which the RSS-based network and the CS-based network can be obtained, respectively. To obtain the desired number of clusters (i.e., 4, 5, and 6 determined by the elbow plot method), we trial and error the RSS and CS values together with the modularity maximization algorithm to determine the threshold. The results suggest that the values 1.24, 1.23, and 1.22 of RSS similarity are able to yield 4, 5, and 6 clusters, respectively, for the RSS-based network. In the CS-based network, it is found that the values of 0.7, 0.75, and 0.77 are the threshold values of producing the desired number of clusters 4, 5, and 6.

Figure 11 shows the result of RSS-based network clustered in four groups each of which consists of 14, 11, 11, and 2 members, respectively. But in this method, the clustering results are different from K-means-4 and HAC-4. For example, E06 and E14 belong to the same group in K-means-4 and HAC-4, but in RSS-4, they are in separate groups. But results from different methods do have consistency. For example, B13 and C06 have been always grouped together in all three methods. Following the same approach of generating RSS-based network clustering, clusters can also be generated using the CS-based network clustering method, which shows both similarities and dissimilarities as well. For example, B13 and C06 are clustered together in K-means-4, HAC-4, and RSS-4 methods, but are separated in CS-6 method.

Since clustering results are not always consistent from different clustering methods, the VI-based metric (introduced in Sec. 4.3) is adopted to measure the mutual agreement between any pair of clustering methods so as to find the one that yields the largest agreement with all the other methods. The VI values are summarized in Table 4. By analyzing the distribution of VI values shown in the table, the threshold of 0.7 (corresponding to the top 25% quantile) is selected as the cutoff to filter out the clustering methods that have less consistent results. During this process, we are able to (a) find the most efficient clustering method and its corresponding number of clusters, and (b) find the designers that have always been clustered together so as to identify their sequential behavioral patterns. Here, the efficiency of a clustering method is defined in Eq. (1),

$$\text{Efficiency} = \sum_{i=1}^{k} f(VI_i) \tag{1}$$

where $f(VI_i = 1)$ if $VI_i \leq 0.7$, and 0 otherwise. $i = 1, 2, \ldots, k$ is the number of clustering methods used in this case study, i.e., $k = 12$.

It is observed that K-means-4 clustering has the largest number of times in having greater partial agreement with other clustering methods. Therefore, K-means-4 clustering is the most efficient method among all the three methods in consideration. In Table 4,

Table 4 Variation of information between each pair of the clustering methods

	KM-4	KM-5	KM-6	HAC-4	HAC-5	HAC-6	RSS-4	RSS-5	RSS-6	CS-4	CS-5	CS-6
KM-4	—	—	—	0.55	0.69	0.71	0.45	1.20	0.95	0.76	0.27	0.31
KM-5	—	—	—	0.89	0.82	0.75	0.79	0.85	0.59	0.92	0.60	0.63
KM-6	—	—	—	1.25	1.17	1.11	0.99	0.74	0.89	0.86	0.94	0.96
HAC-4	0.55	0.89	1.25	—	—	—	0.98	1.47	1.13	1.25	0.70	0.73
HAC-5	0.69	0.82	1.17	—	—	—	1.12	1.39	1.05	1.39	0.82	0.86
HAC-6	0.71	0.75	1.11	—	—	—	1.14	1.33	0.84	1.41	0.76	0.79
RSS-4	0.45	0.79	0.99	0.98	1.12	1.14	—	—	—	0.95	0.85	1.33
RSS-5	1.20	0.85	0.74	0.47	1.39	1.33	—	—	—	0.65	1.42	0.67
RSS-6	0.95	0.59	0.89	0.13	1.05	0.84	—	—	—	0.68	1.42	0.71
CS-4	0.76	0.92	0.86	1.25	1.39	1.41	0.95	0.65	0.68	—	—	—
CS-5	0.27	0.60	0.94	0.70	0.82	0.76	0.82	1.42	1.42	—	—	—
CS-6	0.31	0.63	0.96	0.73	0.86	0.79	1.33	0.67	0.71	—	—	—
Efficiency	5	3	0	2	1	0	1	2	2	2	3	3

Note: The VI between the same clustering methods but different cluster numbers (e.g., K-means-4 versus K-means-5) is not worth comparing, and thus, the corresponding VI are not available and denoted as "—."

Table 5 Clustering results of design sequences irrespective of the clustering methods

A02, A05, B08, C01, C07
A03, A15, B07, C08, D02, D10, E14
A06, A12, A13, C13, D08, E15
A07, A08, C10
B06, C11
B09, D09

those VI values that are below 0.7 are highlighted in gray. By checking the occurrence of the VI values being below the threshold 0.7, we put K-means (4, 5), HAC (4, 5), RSS (4, 5, 6), and CS (5, 6) in consideration to identify the designers who have been always clustered together irrespective of the methods being used (see the results in Table 5). It is worth noting that each row of designers is grouped together without any labeling or prior knowledge.

4.5 Insights and Conclusions. With the clustering results, we revisit the research question we aim to answer in this case study: *What are the most frequent sequential design behavioral patterns that most designers would follow in systems design?* By analyzing these clusters, it is found that the highest transition probability for every designer in one group is similar for most of the cases. These behaviors are listed and discussed below.

- *Synthesis* → *Synthesis*

This transition between design stages is the most frequently occurred pattern. For example, the highest transition of all the designers of the third group (A06, A12, A13, C13, D08, and E15) is *Synthesis* → *Synthesis*. Also, the fifth group (B11, C06) uses this pattern very often. It indicates that the designers of these groups kept modifying the parameters of the components. The possible reason for this design pattern is that designers in the experiment were trying their best to exploit the design space by sequentially changing and tuning the design parameters. Such a behavioral phenomenon could be the reflection of the reward mechanism used in the experiment.

- *Reformulation* → Formulation

This is another pattern that has been shown frequently in many designers' data. We found that the highest transition probability of the second group (A03, A15, B07, C08, D02, D10, and E14) is *Reformulation 2* → *Formulation*. This pattern indicates that designers in this group spent a significant amount of time removing solar panels and adding them again. It may be due to the reason that they were trying to adjust the solar panel on the roof to a perfect condition. Also, the last group (B09, D09) followed the *Reformulation 3* → *Formulation* design pattern often. This implies that designers in this group spent most of the time adjusting the house structure by frequently removing the existing roof or others components and adding it again.

As a summary for this case study, with the data collected through ENERGY3D, we develop a general framework that can accommodate various clustering methods for identifying design behavioral patterns. Successful identification of similar behaviors and their design patterns has significant benefits in discovering efficient design heuristics and guiding team-based design. For example, useful design process stage frequencies and design patterns that lead to better design outcomes can be identified by correlating design quality with different behavioral groups. Also, in team-based design, to maximize the working efficiency, similar/dissimilar designers could be paired up to improve the communication and/or diversity within a group.

5 Closing Remark and Future Work

With the growing trend of leveraging data analytics and machine learning approaches in engineering design research, there is a need to create a research platform that enables the sharing of benchmark problems and testbeds and ensures the quality of datasets for valid, repeatable and reproducible research. In this paper, we identify the challenges in data-driven engineering design thinking studies and propose five important data requirements for design-driven EDT studies that must be satisfied in the first place in order to support the scientific rigor. Toward addressing these challenges and requirements, the authors take a few modest steps in this direction by creating and distributing a research platform using ENERGY3D—a computer-aided energy systems design software. We demonstrate the key features of ENERGY3D in three aspects: (1) features for data collection, (2) features for engineering systems design, and (3) features for human subject experiments. The blending of these features can effectively help researchers obtain datasets that satisfy those critical data requirements and exhibit the 4 V features of big data, thus making ENERGY3D a competitive candidate platform for the data-driven EDT research.

Through a case study on clustering human sequential design behaviors, this paper demonstrates the capability of ENERGY3D as a research platform to support a typical research process of answering research questions that are of interest. We show how the design action logger, the design artifact logger, and various CAD features and modeling interfaces work together to facilitate design activities in experiments and the collection of design behavioral data in a non-intrusive manner. The design examples created from this study have been made publicly available online [78] as a testbed for other researchers to adapt and test for their own research purposes.

Despite many strengths of ENERGY3D, the authors respect certain limitations that this platform may have if it is not properly used for design research, especially in the study of design thinking. For example, the majority of the data collected from ENERGY3D is in the format of design operations/actions in a CAD environment, but not the data that directly describe designers' mental process. While certain behavioral patterns do reflect design thinking, essentially the actions that a person takes do not necessarily indicate what that person thinks. Experiment shall be systematically designed, and additional forms of data need to be collected in support of the verification and validation so that valid conclusions can be drawn from the analysis of the fine-grained design activity data. In addition, currently, ENERGY3D does not support team design through a web-based interface. Several web-based features, e.g., the peer-to-peer or client–server communication could be enabled for designers to communicate and exchange information for a large system design project. These feature can support the research on design behaviors in team-based design. Moreover, ENERGY3D is developed mainly for solar energy system design, so the type of design activities that can be studied and the capability of studying the effect of domain knowledge on design behaviors are limited.

Our future work will be geared toward addressing these limitations. For example, one important feature we recently added to ENERGY3D is a built-in AI design agent. This feature can support the study of human decision-making behaviors in the presence of AI design assistant and human–AI interactions. For example, one question we are working on is to investigate how AI assistant can help designers handle design uncertainties by augmenting their information-processing skills, thus better informing their design decision-making. In addition, Xie has developed an auxiliary tool of ENERGY3D especially for aiding design behavioral research, called Visual Process Analytics [92]. With this tool, researchers can directly analyze their collected behavioral data in JSON to generate quick insights into the data. Based on the case study, we are also working to embed the clustering algorithms into ENERGY3D that will be beneficial to support team formation and collaboration. Such a feature can facilitate potential research on team-based design.

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