OBSERVING ARCHITECTURAL ENGINEERING GRADUATE STUDENTS' DESIGN OPTIMIZATION BEHAVIORS USING EYE-TRACKING METHODS

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ABSTRACT

Parametric optimization techniques allow building designers to pursue multiple performance objectives, which can benefit the overall design. However, the strategies used by architecture and engineering graduate students when working with optimization tools are unclear, and ineffective computational design procedures may limit their success as future designers. In response, this research identifies several designerly behaviors of graduate students when responding to a conceptual building design optimization task. It uses eye-tracking, screen recording, and empirical methods to code their behaviors following the situated FBS framework. From these data streams, three different types of design iterations emerge: one by the designer alone, one by the optimizer alone, and one by the designer incorporating feedback from the optimizer. Based on the timing and frequency of these loops, student participants were characterized as completing partial, crude, or complete optimization cycles while developing their designs. This organization of optimization techniques establishes reoccurring strategies employed by developing designers, which can encourage future pedagogical approaches that empower students to incorporate complete optimization cycles while improving their designs. It can also be used in future research studies to establish clear links between types of design optimization behavior and design quality.

PRACTICAL APPLICATIONS

Increasingly, building designers use digital, optimization tools to explore and improve designs. This research identifies and categorizes several distinct design behaviors when using optimization tools that have not been previously recognized. Applying these categories to describe graduate student designer behavior allows educators to find opportunities for improving design education. While there is no set standard for how optimization tools should be used, different strategies range in the potential they create for simulation feedback to improve the design. Although all study participants were able to implement an optimization feature, they did not all fully integrate the feedback into their design decisions. From this research we observe that it is not enough to explain algorithms and show a student how to run an optimization tool, but these tools must be taught in the context of robust design approaches. Educators wishing to identify their students' design strategies can use the methods and language established in this paper to assess student comprehension of optimization techniques. Future work can apply the behaviors that investigate other dimensions of optimization in design, such as design quality and comparing categories of designers.

INTRODUCTION

As digital tools evolve, emerging computational strategies allow designers in the Architecture-Engineering-Construction (AEC) industry to address an increasing number of building performance criteria early in the design process. In particular, parametric design strategies, where a model is readily edited and explored by editable variables, enable AEC designers to rapidly consider numerous potential options while meeting disciplinary goals. Within parametric models, optimization techniques can systematically find the best options in terms of quantitative design goals such as energy use or structural efficiency (Felkner et al. 2013; Touloupaki and Theodosiou 2017). However, there is uncertainty about how to best apply optimization during design, especially for emerging interactive optimization approaches that let designers manage qualitative and quantitative goals simultaneously. Optimization can speed up certain design subtasks, and it can help find high-performance solutions within a design space that might be difficult to find otherwise (Mueller 2014). Yet it also requires a designer to formulate, analyze, and in some cases iterate a defined set of variables, objectives, and constraints, which may change the timeline or nature of activities in a typical design procedure.

While there is considerable established literature describing designer behavior in general, little is known about how diverse optimization tools influence design, particularly in the domain of architectural engineering education, as students gradually learn how to incorporate optimization. One source of potential confusion stems from the range of design tools that are described as employing optimization, especially in practice. On the one hand, some define “design optimization” very broadly as the process of systematically and quantitatively improving on a current solution, as in the case of building simulation (Heiselberg, et al. 2009; Nguyen et al. 2014; Liping et al. 2007). On the other end of the spectrum, some only use the term “optimization” to refer to numerical simulation and/or formal mathematical optimization (Attia 2012; Nocedal and Wright 2006), even in the context of building design. In the middle are heuristic techniques such as evolutionary algorithms that designers might implement alongside their own qualitative preferences, either *a priori, a posteriori* (Marler and Arora 2004), or interactively (Mueller and Ochsendorf 2015; Turrin et al. 2011; Touloupaki and Theodosiou 2017b). In all cases, the designer is left to establish their own sequence and timing for establishing the parametric variables and their relationships in the first place. If instructed to formulate their own design spaces and optimize a design, students might employ any of these approaches, with various degrees of completeness or effectiveness. Yet the characteristics of these ranging strategies have not been established.

In response, this research asks: what patterns of design behaviors do architecture and engineering graduate students employ while constructing and exploring a parametric model using optimization-based tools? Potential patterns include iterative decision loops involving the designer, an automated algorithm, or both, as well as their timing and frequency within a design session. Investigating how this group of designers, who are neither novices nor experts, utilize different optimization techniques can inform which strategies they employ with optimization tools. To investigate design in situ, a research study was conducted which asked participants to create a visually appealing atrium enclosure that addressed measurable concerns of daylighting, energy use, and structural performance. Eye-tracking data, screen recordings, and observational assessment were used together to apply the situated FBS framework (Gero and Kannengiesser 2004).

This framework allowed for identifying multidimensional steps in the design process, describing design session events, and discerning varying strategies among the participants. The student participants showed a range of behaviors in their use of optimization techniques —some spent considerable time formulating the problem and used optimization techniques near the end of the design session, while others adjusted the problem more frequently as they ran smaller iterative explorations. These diverse strategies are used to distinguish several distinct design iteration types and corresponding behaviors that are detailed in the results and discussion. In understanding the rich characteristics of designer strategies through qualitative methods, we can first discern these behaviors through deep analysis before future quantitative studies establish their prevalence among designer populations.

BACKGROUND

The AEC professions are continually tasked with providing high performing solutions, but the numerous considerations in building design rarely align. To manage potentially competing objectives, designers have incorporated computational exploration and optimization tools, which can account for multidisciplinary performance, to make more informed design decisions. While the feedback and guidance from these emerging design approaches can improve outcomes, designerly strategies for utilizing optimization in the context of design theory have yet to be thoroughly examined. In particular, the optimization patterns of intermediate designers, such as graduate level architecture and engineering students who have experience with design strategies but are still developing their optimization skills, are largely unknown.

Designerly Behaviors in the Design Process

To systematically characterize designer behavior when using optimization tools, and to determine how these tools potentially alter traditional processes, it is first necessary to ground the research in a conceptual framework for design behavior. Although design is a complex series of decisions, researchers have identified general characteristics of the design process (Cross 2011; Cross and Roozenburg 1992; Lawson 2006; Rowe 1987), which are used to recognize reoccurring design strategies. Most of these models establish a phase for problem definition, one for design development, and one for solution analysis, with opportunities for iteration throughout. However, these models are very broad in their scope.

Several researchers have considered characteristics of design behaviors when working collaboratively with computation tools (Haymaker et al. 2018), particularly in the medium of parametric modeling (Burry 2003; Oxman 2017; Stals et al. 2021; Tschetwertak et al. 2017). Literature shows that when a computer is used to support or make key decisions, there are different schemes by which to identify a designer's cognitive or computational decisions (Caetano et al. 2020, Oxman

2017; Yu et al. 2015a). In some cases, incorporating parametric modeling and rule-based digital software can improve the efficiency of design (Harding et al. 2012; Kalkan et al. 2018). However, other research has differentiated that parametric modeling is still the result of a tool and cannot replace the ingenuity of a human designer (Megahed 2015). In fact, precedent study observations show that in practice, parametric design focuses on more controlled, rule-based designs rather than a vast multitude of solutions (Wortmann and Tuncer 2017). This narrowing of potential designs based on designers' knowledge and intuition may also be evident in optimization strategies.

While these prior investigations of parametric design strategies inform aspects of this paper, we based our optimization-related study on the situated FBS framework (Gero and Kannengiesser 2004), which is an extension of the fundamental and widely applied FBS ontology (Gero 1990). Gero's original ontology has been used by many design disciplines to model, code, and analyze design behaviors (Howard et al. 2008; Kruchten 2005; Yan 1993). It models the design process by first assigning the characteristics of the desired artifact into three primary categories: function (the role of the artifact), behavior (how the artifact performs), and structure (the qualities of the artifact). The development of these characteristics is identified by eight types of fundamental design moves, which create a framework to define the design process. However, although the original FBS provided a clear foundation to describe a range of design tasks, it did not account for the influence of cognitive context on design.

In response, Gero and Kannengiesser (2004) present a revised method called the situated FBS framework (Figure 1), which considered an additional, recursive dimension of design: the conceptual environment. This new framework expanded the original 8 processes into three conceptual environments: an external world, an interpreted world, and an expected world. By dividing the FBS elements into each world and categorizing the processes as an action, interpretation, or focusing, the situated FBS framework provides a more extensive strategy by which to map the evolution of the design process. For example, within the synthesis, analysis, and evaluation processes, an expected behavior (Be^i) motivates the designer's idea for a structure (Se^i) (process 11), which the designer then represents that structure externally (Se) as a sketch or 3D model (process 12). Next, the designer considers whether the representation aligns with their idea (process 13). Simultaneously, that structure produces an associated behavior (process 14), which the designer can compare to the expected behavior (process 15). If considered adequate, the designer can proceed to documentation, or they may repeat the processes going as far back as reframing Functions (process 16).

With this framework, design researchers can incorporate more comprehensive modeling of iterative thinking and the regeneration of ideas. Even with these adjustments, the FBS ontology has been criticized for its ambiguity (Cascini et al. 2013; Dorst and Vermaas 2005) while others emphasize FBS's applicability (Galle 2009). Nevertheless, the FBS ontology has been used to model design in many disciplines (Gu et al. 2012; Uflacker and Zeier 2008), including parametric building design (Yu et al. 2015a). Its expanded version, the situated FBS framework, also presents several advantages for this study of optimization strategies. It provides an order by which to identify design events and organizes the relationships between the designer's ideas, the behavioral bounds of the design, and the realization of the design artifact. It also acknowledges the iterative loop between what the designer envisions and what manifests externally (shifting between the 3 worlds), which can occur in parametric, rule-based design exploration.

Parametric design tools have been shown to help designers produce unconventional solutions (Wortmann and Tuncer 2017; Yu and Gero 2015b), some of which may not have been originally conceived by the designer. The uniqueness of the designs and potential for innovation have been assessed by traditional methods for measuring creativity and shown that parametric thinking is a viable form of design (Lee at al. 2014). In addition, this method of idea generation prompts consideration of a designer's source for decision making. In Yu et al.'s study (2015), the researchers defined a subset of characteristics in the FBS ontology and classified the designer's decisions as either "design knowledge" or "rule algorithm" to differentiate the source of cognitive effort throughout the phases of the design session. We also identify subsets of decisions within the situated FBS framework in this paper to codify the participants' design process and identify design events unique to optimization. Differentiating between decisions focused on developing the artifact or developing the optimization approach is valuable in evaluating computational design behaviors, especially as the use of digital tools to solve complex building challenges becomes more pervasive.

Building Optimization as a Design Technique

As the performance needs of our built environment grow more stringent, it is increasingly difficult to address multiple design considerations across a range of professional specialties. Although achieving an effective, holistic design is advantageous, building performance criteria vary in units, scale, and importance, making them difficult to empirically compare and optimize (Brown and Mueller 2016a; Felkner et al. 2013). For example, the benefits of increasing natural daylight with more windows can compete with the goal of reducing energy consumption. Building optimization quickly becomes convoluted as there are many numerical and experiential criteria, such as spatial, structural, and mechanical objectives (Touloupaki and Theodosiou 2017). Furthermore, when AEC disciplines collaborate on optimization projects, it has been shown that an iterative process emerges between the designers and their optimization tools (Geyer and Beucke 2010).

Traditionally, designers relied on knowledge to find effective solutions, but computational tools allow designers to rapidly explore a range of solutions with quick performance feedback, enabling more efficient production of high-performance designs for architects and engineers (Brown et al. 2020b; Gerber and Lin 2014; Mueller and Ochsendorf 2015). However, some designers criticize digital design space exploration for its limitations in design thinking and potential design fixation compared to traditional sketching processes (Stones and Cassidy 2010). Nevertheless, optimization has been utilized by a variety of engineering disciplines with advantageous results (Touloupaki and Theodosiou 2017; Kollat and Reed 2007; Simpson and Martins 2011) and research has shown that the use of computational tools is a viable method for design in AEC (Mueller and Ochsendorf 2015; Turrin et al. 2011; Yang et al. 2015). In particular, the applicability of optimization in computer aided architectural design has been suggested early in the development of building computation simulation (Radford and Gero 1980). However, due to the emerging nature of optimization tools, the best practices for their use are still being defined. At this point, strategic optimization education can impact the effective implementation of such tools by graduate designers and is not unique to just optimization.

Student Designers Working in Digital Tools

It has been suggested that parametric design is advantageous to the development of a designer because it prompts the setting of constraints on a design task to find different solutions rather than focusing on one solution (Schnabel 2013). Yet students may be limited in their ability to fully execute a design since they are still developing as designers themselves and are still mastering design tools (Chase 2005). In addition, curriculum standards in building design education vary by discipline, and the influence of pedagogical systems on problem-solving strategies are somewhat unpredictable (Cross et al. 1994). Specific to optimization pedagogy, recently developed courses in architecture and engineering programs have introduced optimization to students with promising initial results (Brown and Bunt 2022; Oliveira et al. 2018; Pasternak and Kwiecinski 2015), but the learning outcomes of these courses are not standardized, and the tools and processes used vary by institution. Nevertheless, much of the emerging research that considers early-stage optimization tools focuses on student participants (Brown 2020a; Brown and Mueller 2016b; Gerber and Lin 2014; Mark 2012), so there is value in identifying specific sources of student limitations in design environments, particularly for optimization.

Considering this population, it has been shown that novice designers tend to use less sophisticated processes compared to experts (Atman et al. 2007; Deininger et al. 2017), which may hinder effective use of optimization methods. Intermediate designers, though, such as graduate-level architect and engineer students, represent a stage in education development in which designers possess a foundation for disciplinary design decisions and have experience working with design tools, but are still developing as effective problem solvers. Identifying graduate student designer strategies while they make decisions with optimization tools may help categorize effective behaviors, improving tools for design development, and enhance learning processes for graduate students as future experts. Accounting for the context of proliferating digital tools in AEC, this research focuses on optimization behavior in conceptual building design.

METHODS

This IRB approved study asked graduate-level architect and engineering design students to propose an optimized solution in response to a conceptual building design task. The multi-method research design employed eye-tracking, screen recordings, and interviews to capture different streams of data from the design sessions. Observational data analysis and artifact analysis techniques were used to qualitatively code the design segments within the situated FBS framework. Our analysis protocol was also employed to identify designerly events unique to optimization, relating reoccurring behaviors between designers to potentially effective optimization strategies.

Participants

The streams of observational and interview data were collected from a sample size of 10 architecture (5) and architectural engineering (5) graduate students at a research-intensive public university in the northeastern United States. This population is of special interest to understand the design practices of designers at an intermediate educational stage rather than those of novice undergraduates (who typically have not developed either design or engineering skillsets) or practitioners (who are fully expert in their designerly ways). While this sample size may seem small, each participant generates 3 hours of video screen capture data, eye-tracking data, and interview data, supporting a multi-stream qualitative study. This amount of data is quite large and rich considering the purpose of this study is to identify and characterize the types of optimization behaviors rather than conduct predictive or generalizable statistics. Participants included 6 women and 4 men. They were recruited by email announcement of the study to the architecture and architectural engineering department and were compensated with a $20 gift card. The participants completed a survey before beginning the design task and reported at least 1 year of experience (average 3.5 years) and a moderate level of confidence with the study's modelling tools, along with at least 1 year of experience in optimization. Amount of time spent in design practice among participants, which can occur before or during the pursuit of graduate degrees, ranged from 0-10 years. By studying graduate-level designers, we elicit a deep understanding of how the design learning process occurs as architects and engineers move past their novice design tendencies.

Design Session

All design sessions were conducted in a controlled research space equipped with a computer, eye-tracking hardware, and software. The research procedure is shown in Figure 2. After the participants were situated at the computer, they were briefed on the design task through a standard video introduction and their eye-tracking setup was calibrated for their sitting position. After watching the design task video, but before working in the digital space, the designers were provided with paper and pencils to take notes or sketch on paper for 5-10 minutes, which enabled them to create initial ideas separate from the model space. They then proceeded to work in the digital modeling tools to develop their design and produce optimized solutions. The designers were prompted to work for as long as they felt comfortable, resulting in sessions that lasted approximately 3 hours.

While Grasshopper in Rhinoceros was used as a consistent parametric modeling platform, the designers were able to choose their own optimization plugins, since the application of these tools is a part of authentic design behavior. In this study, the participants preferred using either Galapagos (Rutten 2013), presumably adding their own prioritization mechanism to manage multiple objectives or Design Space Exploration's Multi-Objective Optimization tool (Brown et al. 2020b) to find optimized solutions. Notably, both tools preview intermittent design iterations while running, such that designers can make visual assessments before the tool has completed its optimization loop. It is also worth noting that these chosen tools do not fully enable interactive human-in-the-loop optimization at the scale of design generations or internal dynamic data visualization, which are possible using newer or less common parametric tools, such as Stormcloud (Danhaive and Mueller 2015), Wallacei X, (Wallacei X 2018) and Stepper (Brown and Mueller 2018). Full documentation of design strategies with these tools would require future analysis.

The participants could repeatedly use their optimization tool in the session if they wished, but they were not explicitly prompted to do so. After settling on a final design, the designers were asked to submit 2-4 screenshots of their proposal and a written design statement to give to a fictional client. Immediately following submission of their deliverables, the researcher interviewed the participants using a semi-structured interview protocol, asking about their goals for their design, how they approached completing the design, and what they would do differently if they had more time. The interviews were used as cognitive proxies to contextually ensure that behaviors were correctly interpreted.

Design Task

The design task asked participants to develop a glass atrium infill for a fictional university client in Phoenix, Arizona. This site was chosen because of the region's hot and sunny summer climate, which is easily recognized or readily learned in an online search. A university setting was used for site context to prompt the need for visually exciting designs, and for its accessibility to the participants. The design task required the designers to address at least two of three provided objectives. The first objective is to maximize daylighting during the summer solstice (June 21) at noon. While building designs often consider daylight at multiple times throughout the year, full daylighting simulations can take hours or even days to run. Focusing on a significant instance in time is a common design strategy that eliminates wait times and reduces required computation power. The second goal is to minimize solar radiation. Within the task, reducing the surface area of the atrium will reduce solar radiation, as will substituting thicker glass or opaque panels with better u-values. The third objective is to minimize the elastic energy of the structure, as calculated by Karamba3D (Preisinger and Heimrath 2014). It is desirable to have a structure with less deflection because it will allow for smaller members to build. Reducing structural weight can also reduce costs. Optimizing a whole structural system is a complex task but asking the designers to focus on two of these three goals provides a conceivable and numeric goal for them to manage in the constraints of this conceptual design task.

The designers were given the design task through two introduction videos. In the first video, the fictional client showed four example atriums that the university admires. Although providing examples to the participants may bias their design solutions and prompt them to imitate what they are shown (Zalewski et al. 2017), clients often share their visions for a project during an authentic design process in practice. Providing participants with examples of atriums also frames the design task in terms of parametric thinking, which was the intended design environment of this study. However, before introducing the designers to the study's computational tool, participants were allowed to sketch or write out initial ideas, permitting them to first consider ideas not constrained to the computational environment.

Participants were also provided with a base file containing the site context, important points of reference, and pre-built scripts that calculate the objectives. The script required that the participants provide surfaces for the intended solid panels, surfaces for the glass panels, the structure represented as lines, and the structural support points. In this way, the designers could focus their efforts on working towards an optimized solution, and the study was given a consistent frame for simplified performance simulation between the designers. Moreover, this study focuses on optimization tactics, not on the designer's ability to assemble a structural analysis simulation.

Qualitative Coding and Characterization of Design Behaviors

During the design session, the participants' behaviors were captured by screen recording and tracking their eye gaze data using EyeWorks eye-tracking hardware (EyeTracking 2011). Eye tracking, combined with screen capture recordings, is a robust method to understand design behaviors because it offers the ability for researchers to not just capture outcomes, but also actions and patterns of behaviors paired with information about what the participant is looking at or turning their attention toward. These types of data are highly complex, with each minute of participant behavior resulting in hundreds if not thousands of potential data points for each participant generated over a ~3 hour design task.

The researchers also observed the design session to record times when the participant sketched or encountered difficulties with the tool, and to facilitate an immediate follow up interview about the participant's rationales for critical design decisions. The follow up interviews asked the designers to elaborate on their design decisions and what difficulties they encountered. They were also asked, if given more time, what would they do differently to further refine their design.

Data Analysis

To analyze the streams of data, various methods were employed. First, the video recordings were reviewed and activities that did not pertain to the design session were removed, such as saving and restarting the program. Second, the eye-tracking data were initially analyzed using digital tools to interpret broad patterns in participant behavior. Using additional software from EyeWorks, the eye gaze data was paired with two Regions of Interest (ROI) on the screen to identify if the participant looked in the parametric space (Grasshopper), the 3D modeling space (Rhino), or away from the screen altogether. These tools help interpret the digital information representing design behavior.

When working in these tools, a designer develops their model by programming geometry in the parametric space and viewing their model in the 3D modeling space. While these regions stay the same for each participant, the displays inside the regions are dynamic as participants rotate or zoom in on the design or pan across their script. Thus, a significant dwell time in an ROI shows either consideration of the design artifact or computational manipulations of the design. Figure 3 shows where the two ROI's are on the screen (the 3D modeling space and the parametric space), a preview of what may be displayed in the spaces, and a brief description of what occurs in the spaces. Eye tracking was thus required to accurately identify loops between Regions of Interest, which eventually helped define behaviors.

The output video files from the eye-tracking data were analyzed using observational qualitative data analysis processes, called "coding," honed for observational and time-resolved research to characterize design behaviors. These methods work abductively from existing frameworks for design cognition to accurately describe the breadth of behaviors observed (Mehta et al. 2020). A codebook describing the names and definitions of the design activities, which could be categorized, was developed through literature and piloted iteratively on the data in consensus with the other members of the research team and strongly grounded in design theory. After this iterative codebook was developed, a single researcher rewatched all the design sessions and notated the presence of every design behavior and their time stamps. The coding comprised of elements from the situated FBS framework in identifying the iterative process between Function, Behavior, and Structure in the context of the optimization environment. The typology of behaviors captured, aggregate percentages of behaviors captured over time, and the ordering in which behaviors occur through the duration of the design challenge are used to answer the research question related to patterns of design behaviors.

The interview transcripts were employed as an external validation method to ensure that the research team was interpreting behaviors accurately, particularly for critical decisions, but were not independently thematically analyzed for this study. Together, the multiple streams of qualitative data (screen recording, eye tracking, and interview transcripts) are used to inform the interpretation of the behaviors as they relate to architectural engineering design education.

Event codes

We determined 13 events of behavior that manifested across all ten participants. Figure 4 shows the coding of events in the situated FBS framework to the conceptual optimization process. The code also highlights several concrete events identified in this study, which define the behavioral structure of the individual sessions. The sessions were divided into two primary phases, "pre-modeling" and "modeling," which are determined by the placing of a first component in Grasshopper. Placing the first component is coded as a process 12 in which the designer manifests their idea for an artifact in the external world. In this study, the pre-modeling phase is mostly rapid formulation (processes 1-10), and although sketching in the Pre-modeling phase is also a process 12 since it allows the designer to externalize their ideas onto paper, the formulation processes are informally executed and not within the scope of this paper.

Synthesis events

We also captured the occurrence of "synthesis events" as a manifestation of the processes. Synthesis events include a process 11, which is envisioning solutions (Se^i) from formulated behavior (Be^i), and process 12, which is externalizing the solution. In this study, process 11 was an internal decision, so this step was not explicitly captured. However, synthesis process 12 accounts for many of the designer's actions and was divided into 4 categories to better describe the designer's externalized decisions. Most of the actions in the parametric space that create structure (Se) are when the designer places a static component, but there are other events which relate directly to the optimization process. Following precedent from Yu et al. (2015a), which divided Function, Behavior, and Structure into knowledge-based and rule-based cognitive decisions, this research identified 3 events within process 12 in this study: the introduction of a variable to the model, a return to sketching on paper, and the defining of solid and clear panels. Introducing a variable suggests the potential for that element to be influenced by optimization feedback. Notably, not all the variables created in each session were used in the optimization events, which turns them into parameters in formal optimization language. Overall, individual narratives concerning the use of variables inform each designers' process. The process 12 event of "returning to sketching" is also not always present in every session, but it is determined when a designer looks away from the screen and picks up their writing utensil. All designers created surfaces in their design and discerned between solid and glass panels. Until this event occurs, their design decisions are geometric and do not considered materiality, which is a Behavior aspect of the design.

Pre-analysis and analysis events

Other definitive events in this study are when participants first plug elements into the objective value generators and when they first activate their optimization tool. Shifting to the generator signifies a transition from relying on design knowledge to preparing for optimization feedback. The designers may return to design knowledge after interacting with the objective generator, but this is an event unique to the optimization process, and the timing of its occurrence in the session informs how integral the designers see optimization in their final solution. To meet the requirements of the objective generators, they may also have to restructure part of their model, relying on a mixture of design knowledge and parametric knowledge.

A further indicator is when the designer starts preparing the optimization tool to optimize the design. This is not always an efficient process, particularly for the student designers, as the planning for optimization sometimes prompts re-evaluation of design variables. Once the optimization tool is run, a series of analysis, evaluation, and synthesis processes (13, 14, 15, and 12) occur between the designer and optimization tool from which the designer can make a design decision.

Evaluation and documentation events

Before proceeding to documentation, a designer will verify if the behavior of the design meets the expected behavior. In early conceptual design development, this process is largely driven by the optimization tool, which minimizes the objective values. However, the designer may consider the results manually and decide to repeat earlier processes or proceed to documentation. In some cases, a designer may follow process 16, which is an opportunity to change the function of the design by changing which of the two objectives they wish to pursue. This process did not occur in this study's design sessions.

The final event defined in this study is the shift to documentation. This is defined as when the designer opens the writing document and begins to compose their design statement or take screenshots of their final design. In some cases, the designers refine the representation of their design in preparation for documentation, such as applying color to the different panels.

Evaluation of Designer Behavior

Coding and identifying these processes allowed the design team to compare reoccurring behaviors, design focus, and significant events. In following the situated FBS framework, a series of repeated actions are identified in the conceptual design optimization sessions. While Gero and Kannengiesser acknowledged types of design "Reformulations," this research identifies iterations performed by the designer, by the optimizer, and by the designer and the optimizer together, shown in Figure 5. Prior to running the optimization tool, the designers ran through process 11, 12, and 13, in a series of iterative loops. These loops were identified by the designers' dwell time in the Grasshopper canvas and the modeling space, as recorded by the eye-tracking tool.

Appropriate dwell times are often determined by the task context (Carter and Luke 2020) and are difficult to standardize (Hessels et al. 2016). While eye tracking has been used in many areas, its application in 3D architectural modeling tools is less common. Dwell times that are measured in milliseconds tend to correspond to small Areas of Interest, like a button on a webpage. However, this research uses Regions of Interest that correspond to how participants consider the design versus manipulating the design script. Both activities likely require dwell times in the small number of seconds, which have also been considered in relation to programming activities (Jbara and Feitelson 2017). Frequency of looking at the regions is significant, as iterative loops were identified at the resolution that patterns emerged for the design sessions. Based on researcher experience with the design tools and iteratively testing different timeframes, the sessions were divided into 0-4 seconds, 4-12 seconds, and 12+ seconds. Glancing in the model ROI for less than 4 seconds was determined to be a "check" that the Grasshopper command was doing the intended purpose, rather than a responsive assessment of the design associated with a process 13. Looking at either region for longer than 12 seconds indicated that the designer was focusing on component assembly in Grasshopper (ROI2) or reflecting on the representation of their model (ROI 1). An Iteration Loop A (IA) was determined when the designer looked back and forth between Grasshopper and the modeling space at least once, for 4-12 seconds in each region. IA loops can be counted, providing a metric by which to compare the designers' iterative behaviors.

The second Iteration loop is performed by the optimization tool, Iteration Loop B (IB), starting from process 14 to 15, 11, and 12. It runs through these rapidly and iteratively until stopping back at Bi. Notably, the optimization tool does not perform process 13, as it cannot consider if the external structure aligns with the designer's interpreted structure. After running the optimizer, the designer may continue to move through synthesis, analysis, and evaluation processes based on abstract goals, or move directly onto documentation. If they respond to the optimization feedback and make adjustments, then that is considered an Iteration Loop C (IC). This iterative process is similar to the interactive behavior identified by Geyer et al. (2010) as a designer works back and forth between design modeling and optimization.

These iteration loops allowed us to identify how early the designers ran their optimization tool in the session, what processes they followed after reviewing the results, and if they repeated the optimization. IA loops were identified automatically based on relationships in the eye-tracking data. Although IB and IC loops contain defined actions, not open to interpretation or variation of researcher perspective, they did require manual recordings of when a certain component was placed, connected, or manipulated in the screen recordings. A member of the research team reviewed the sessions twice to verify that the processes were accurately identified. The occurrence of the iteration loops, types of Structure moves, and optimization events produce narratives that enable comparison between participants.

RESULTS

Based on the coding structure, simplified session time plots are shown in Figure 6. The sessions are divided into Pre-modeling and Modeling phases. The beginning of the Modeling phase is marked with "0 minutes." The horizontal line in each diagram is the session timeline from beginning to end. Along the timeline, the IA (Designers) loops are plotted, showing their occurrence and duration. Similarly, below the timeline, iteration types IB (Optimizers) and IC (Designer with optimizer) are shown with blocks, indicating when and for how long each loop lasted. Above the timeline, significant events within the optimization process are also labeled according to their triggers in the previous section. Plugging their design into the objective value generator ("obj.") represents an active, cognitive engagement with the design objectives. Later in each session, the opening of an optimization tool and preparing to run it ("prep optimizer") is considered the beginning of the optimization process. At the end of each timeline, the time spent documenting the design is shown as a thicker gray band.

The sessions are organized by three categories of optimization behavior, as determined by re-occurring characteristics. A "Complete Optimization Cycle" is when the participant completed at least one full IC iteration and there is evidence of informed edits to their design, such as the presence of an IA iteration after optimizing or a substantial amount of time spent considering results. A "Coarse Optimization Cycle" is when the designers completed at least one IC iteration, but the cycles did not influence any notable changes in the design. The third cycle, a "Partial Optimization Cycle," is when the designer did not complete a full IC iteration, meaning they did not consider the best performing suggestions from the optimization tool. Although the cycle categories do not indicate the quality of design idea or the efficacy of resulting design performance, they do organize a system by which to understand optimization techniques and discuss nuances between behaviors. The next three sections describe in detail representative participants for each type of cycle.

Complete Optimization Cycle

The Complete Optimization Cycle participants closely followed an expected optimization process in which a designer integrates behavioral (process 14 and 15) considerations in the development of their design and completes at least one full designer-optimizer (IC) iteration, with observable edits to their design, before documenting their project. Figure 7 shows detailed session time plots of Participants 01 and 03, who exhibited characteristics of the Complete Cycle. In these detailed session time plots, creation of a new variable is indicated by a circle, and a participant returning to sketching by picking up their writing utensil is shown by a triangle. The figure also shows when the designers defined the difference between solid and glass panels in their model (S^p) along with notable instances within the eye gaze fixations.

The enlarged portion of the Eye Gaze Fixation plot for Participant 01 shows three examples of IA iteration. The designer looked back and forth between the model space and parametric space for at least 4-12 second clusters, suggesting a loop of design edits, which was confirmed by researcher observation. As the sessions progress and the designers focus more on preparing for the optimization process, the occurrences of IA loops become less frequent. However, each designer also completed an IA loop between optimization runs, suggesting that an informed change was made to the design before running the final optimization loop. Several smaller differences are apparent, however. Participant 01 returned to sketching after placing a component and before developing their model, while Participant 03 immediately started to create variables. Also, as indicated by the early square notations in the IB zone, Participant 03 used a direct form-finding tool to achieve an optimized structural shape first rather than use "structure" as an objective in a parametric optimization run. This is a distinct form of optimization based on setting optimality criteria and seeking those criteria directly, but it is only possible in a parametric environment designed specifically for this purpose. It was thus coded for summary statistics as an optimization loop but represented differently from an IB loop.

Coarse Optimization Cycle

Figure 8 shows the detailed time plots two designers who exhibited a "Coarse Optimization Cycle." It includes Participants 05 and 06, who completed IC loops but did not use optimization strategies thoroughly and thus presented subtle differences in their sessions. The IC loops of these sessions are very brief compared to Participants 01 and 03. Although the brevity of an IB loop will depend on the robustness of the chosen tool and the simplicity of a design, time spent considering the optimized options (process 15) can reflect the sophistication of the optimization run or the intent of the designer. These two participants ran several IB loops in a short time because the design options were not as diverse as they envisioned, but they did not know how to manipulate the variables to produce optimization results that aligned with their vision. Participant 05 did not engage in optimization events until late in their session and realized the structure of their model's code was not compatible with the requirements of objective generators. The participant rebuilt part of the model and lost some of the qualities from their original design. The detail from Participant 05's time plot in Figure 8 shows their focus on Grasshopper space as they manipulated code.

While other sessions show sparse IA iterations as participants adjusted code, Participant 06's time plot shows a density of IA iterations before preparing the optimization tool. This behavior suggests that, for Participant 06 to correctly activate the objective generators, they had to change their design and repeatedly view the results in the model space. The absence of this behavior in the other sessions suggests that this designer's solution developed in response to the guided requirements of the study, not exclusively by their own vision for the project. This dependency on prompted Grasshopper coding may reflect less experience with parametric and optimization design techniques. Although this participant could wield optimization tools, issues with self-driven design performance may arise if they were to employ optimization techniques in future, professional projects where design efficacy and efficiency are imperative.

Partial Optimization Cycle

Figure 9 shows the plots for Participants 02 and 04, who did not complete an IC loop during the study. This characteristic is considered a "Partial Optimization Cycle." Although most of the designers responded to the optimization tool's feedback, Participant 04 started writing their final design statement before completing their first optimization run. This suggests that either the variables affecting the participant's design were not dependent on the optimization feedback, or that the participant did not consider their optimization routine to have possible benefits for informing a final design decision. However, a lack of IC iterations does not always mean that optimization techniques were not used to improve the design. In Participant 02's first two optimization runs, they watched the tool generate a range of possible designs while it ran. After briefly seeing that the possible solutions were not as varied as they hoped, the designer stopped the optimizer's automated process and edited their design variables to create more variations of possible solutions. This was an informed action as part of a process 13 (considering the physical structure of the design), but not a process 15, and therefore not an IC iteration. Nevertheless, the optimization tool was integrated into the participant's design strategy.

Optimization Characteristics

Figure 10 summarizes the optimization characteristics for six representative sessions that were analyzed in more detail. The figure shows what percentage of the session had transpired before the participant engaged with the objectives' components and when they started to prepare the optimization tool. The participants began using the objective components at between 43-75% of the timeline, suggesting a transition from developing the structure of the model to considering the behaviors of their model. After plugging their designs into the objective generators, participants began to optimize at different times as well. While Participant 03 started to optimize as early as halfway through the session, Participant 05 did not start optimizing until near the end of their session. Figure 10 also indicates which of the two objectives the participants focused on in their optimization sequences. Finally, it states how many IA, IB, and IC iterations that the participants performed and how many variables were used in their final IB run. The parenthetical number (5) for Participant 03's IB loops shows the number of direct form-finding runs employed.

The number of variables used in the final optimization output varies by participant. Participant 05 had the most variables, which may explain why they spent so much time generating code before beginning to optimize, but Participant 04 had a similar delay with fewer variables. Although all designers created variables (parametric sliders) early in their design, only Participants 01 and 06 used all of these sliders in their optimization process. In some cases, variables were only used by the designer to consider design variations outside of the optimization framework.

DISCUSSION

To summarize, several design patterns emerge from the results. Three iterative loops were identified from applying the situated FBS ontology to differentiate iterations from the designer, the optimization tool, and from the designer and optimization tool together. These loops can show when a designer relies on their own design knowledge to make decisions or when they use optimization feedback to inform their design. The occurrence of these loops defined the three categories of design strategies based on their presence, timing, and repetition.

This research shows that the graduate student designers use optimization with varying degrees of intent. While some used optimization feedback to understand the extents of their parametric model (like Participant 02) or inform changes to their design (like Participant 01 and 03), others did not fully integrate optimization into their design strategies. This behavior is evident in sessions that did not make edits between optimization IB iterations (like Participant 05) or did not complete an IC iteration (like Participant 04). Participant 04 showed a partial use of optimization tools, and their behaviors suggest that their vision for their design was not responsive to optimization feedback, since their documentation was started before the optimizer completed its assessment. Not using optimization feedback in this case may reflect design fatigue within the context of the study, as their session lasted longer than the other participants'. From observing their parametric model, though, their optimization variables controlled only subtle changes to the model, suggesting that optimization as an influencer in design was not part of their strategy. Only partial or no use of optimization feedback in student designers may indicate a lack of experience or comfort with optimization tools, or it may simply show a preference for other design approaches.

Although the participants tended to create many variables (or parametric sliders) early in their design session, not all variables were included in the optimizer's process. Many of the variables were used to explore design options manually rather than as part of their performance-driven investigation, but they could also have been used to set a parameter or constraint that did not change during optimization. While previous research has discerned schemes for processing parametric design behavior (Oxman 2017; Yu et al. 2016) and identified an iterative loop between design decisions and optimization (Geyer and Beucke 2010), the findings from this experiment confirm the presence of these loops while developing a parametric script during design. This paper thus adds to existing knowledge by showing how early and frequently students modify their model structure in response to an optimization cycle.

Implications for Design Pedagogy

In categorizing the sessions by optimization behaviors, we establish an initial method to identify the characteristics of graduate student designers, which can inform future curricular development and even student assessment if measured directly. Students with experience using optimization tools do not always fully incorporate them into their decision-making process in a way that leverages optimization's strengths. If the goal of having optimization in the curriculum is to empower students to include such automated or interactive optimization runs to improve design outcomes, then additional emphasis must be placed on contextualizing optimization for design. This could include formal teaching of strategies for variable selection and parametric problem definition, visual interpretation of results, and how to use optimization iteratively to arrive at a satisfying result. Particular topics of emphasis may differ across the disciplines in the study, as the goals of optimization in an architecture studio or graduate engineering course are likely different.

In addition, when considering how much of the design session the participants spent optimizing, the results suggest that incorporating objective feedback earlier in the design session aligns with more IC designer-optimizer iterations. The designers who started preparing for the objective feedback sooner in the sessions ran more optimization iterations. While getting to the optimization process sooner provides more opportunities for design improvement, it does not ensure quality of design expression. However, in optimization education, emphasizing the early and integrated use of optimization for student designers can at least prompt more engagement with the approach.

Finally, this study noted that when given the choice, most participants selected either the default evolutionary solver native to the software itself or a multi-objective optimization tool that uses an evolutionary process to generate approximations of the Pareto front for further consideration. If instructors seek to encourage students to use faster gradient-based algorithms, interactive tools, or other methods beyond evolutionary algorithms, more emphasis on these alternative methods is likely needed. These tool preferences may also have occurred for practical reasons, such as ease of access or use, rather than because students thought they would achieve the best results, but this would have to be determined through future study.

Limitations

As with any study, there are some limitations to the findings. Although there were only ten participants, the data generated from this project is insightfully rich in ways that have not been presented in the AEC design literature before by using deep multimethod qualitative and time-resolved observational research methods. Our data set from ten participants represents approximately thirty hours of in situ observational data employing multiple strands of time-resolved data, offering a unique depth of insight useful to design theorists and educators. Further, the goal of the study was to identify designerly behavior during optimization in intermediate-level designers to promote theory-informed transferability of the research findings, not to understand how predictively generalizable these patterns occur across larger populations. We leave this to future work. The advantages and affordances of using deep qualitative methods will always be balanced with a pragmatic tradeoff of sample size, as has been well-established in the qualitative research methods literature. We meet the requirements of qualitative research methodologies by grounding our work in theory, establishing theoretical and pragmatic validity (Welther et al. 2017) through our use of and interpretation of results through FBS design theory, and are satisfied with our codebook in that we reached saturation such that no new themes emerged during analysis (Creswell and Creswell 2017; Saldana 2015).

Other limitations to this study include that the design task focuses on a conceptual design challenge, which does not capture all possible strategies that may be used when developing a full project. However, optimization strategies are often used to explore solutions at early phases of design to investigate concepts of interest. Studying a design challenge with a narrow activity scope rather than a comprehensive design process creates many advantages for data collection, but may also diminish its authenticity. In addition, since students were able to select their own tools, this study does not cover behaviors across the full range of optimization possibilities, including more emerging interactive optimization strategies. Finally, this study does not assess design quality directly, so it assumes that full incorporation of optimization into design simply gives the best future opportunity for high-quality designs. Several of these limitations are left for future work.

CONCLUSIONS

This paper presented the findings from a study which considered the designerly behaviors of graduate student designers in architecture and architectural engineering when responding to a building design optimization task. The study used eye-tracking and screen recording methods to record data and coded the designerly behaviors following the situated FBS framework. Three types of design iteration loops were used to characterize partial, coarse, and complete optimization cycles by participants. These findings from this study, while of interest to education and design cognition researchers in advancing foundational theory, also offer significant opportunities to modify and augment graduate-level design curricula in architectural engineering and related fields. As the categories of cycles suggest, while the students understood how to run the optimization tools, not all were prepared to use the performance feedback in their own designs. While graduate-level education may show students how to use the optimization tools, students need to know how to integrate the tools in design projects as well. In much of architectural engineering education curricula, digital design tools are often taught secondary to design concepts, which is appropriate for certain applications, but incorporating digital tools in graduate-level education can better prepare student designers to use the tools effectively rather than as an afterthought.

In addition, the use of observational methods in an authentic design challenge offers insight on common issues, obstacles, or ineffective design strategies often employed that may be missed in typical "expert vs novice" studies. The impact of this work lies in the preparation of a future workforce that is computationally agile in their future careers, helping them use simulation feedback to design buildings that are more energy-efficient, low carbon, safe, and durable.

In future work, it is necessary to consider how the categories of optimization behavior proposed here relate to other variables in the optimization design process, as well as to the quality of design outcomes. For example, future behavioral studies that evaluate the quality of designs produced can indicate which optimization-based processes are more effective and should thus be taught to student designers. The methods for observing optimization behavior presented in this paper provide a scheme by which to continue to examine designers' optimization strategies. They can be adjusted to accommodate the discovery of new techniques and tools using quantitative methods. Nevertheless, this study observed several clear patterns in design optimization behavior, showing that earlier and iterative incorporation of optimization runs by graduate student designers can lead to more critical engagement with the feedback they provide.

DATA AVAILABILITY STATEMENT

Some or all data, models, or code generated or used during the study are proprietary or confidential in nature and may only be provided with restrictions (eye-tracking files, screen recordings, researcher notes).

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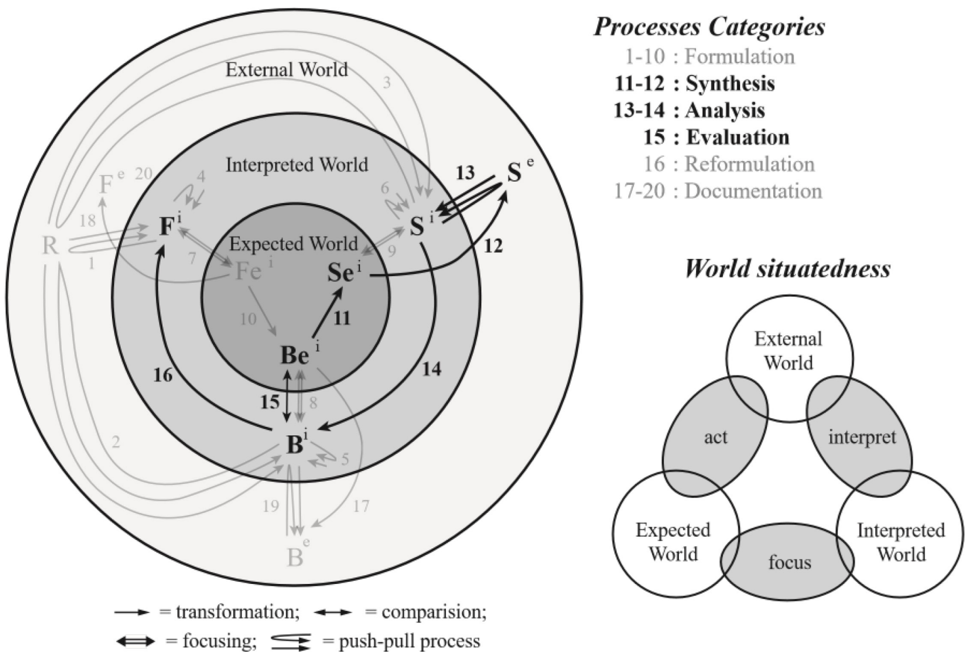


Fig. 1. The situated FBS framework with emphasis on the processes focused on in this paper, and the situatedness and interaction of three worlds, after Gero and Kannenglesser (2004).

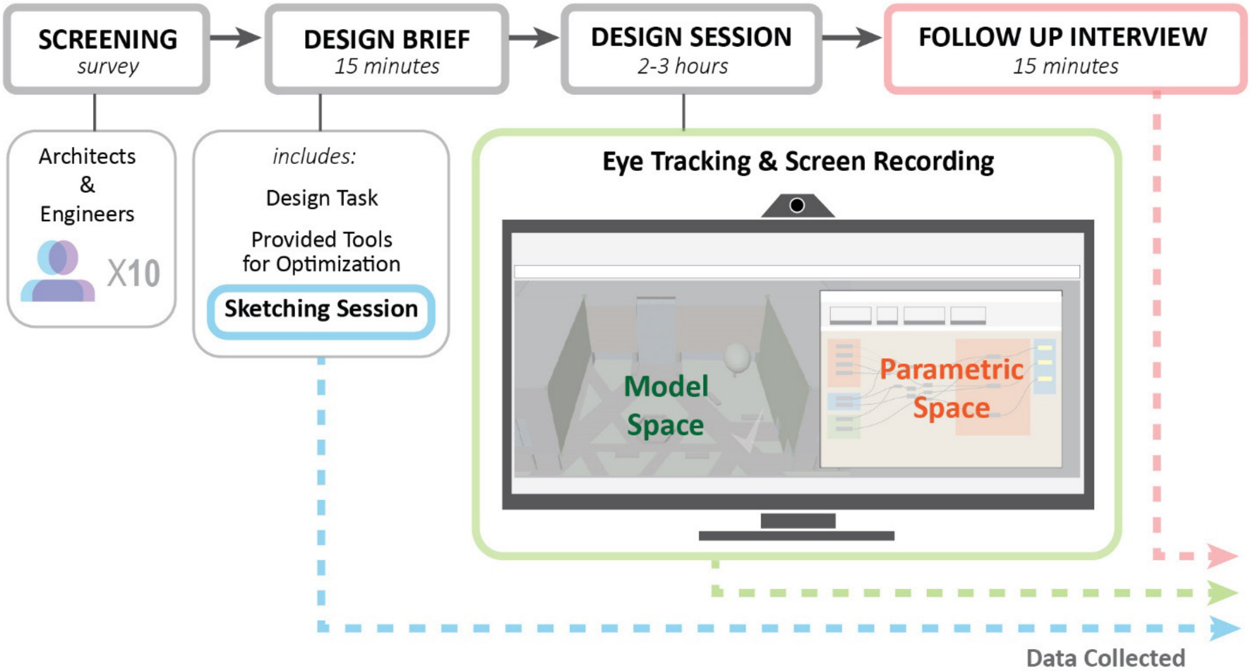


Fig. 2. Summary of the events in a design session, showing the data that was collected, and a preview of the digital design interface.

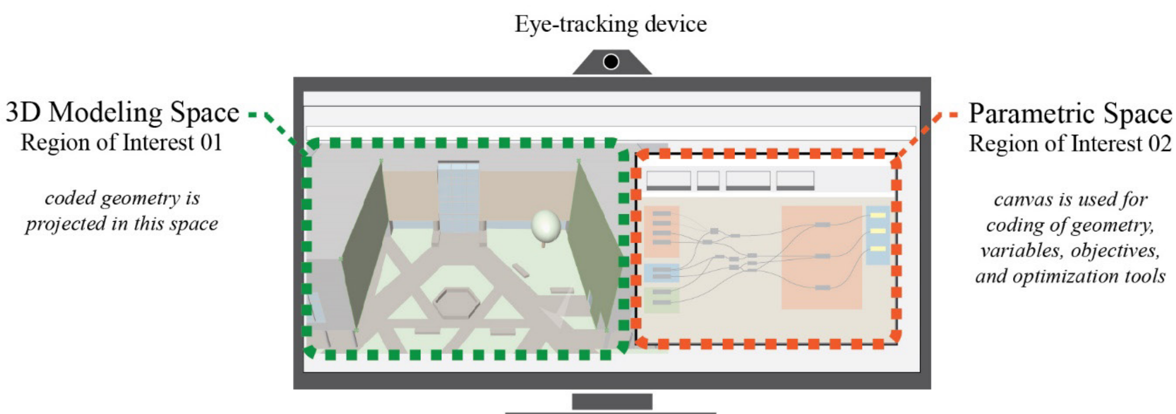
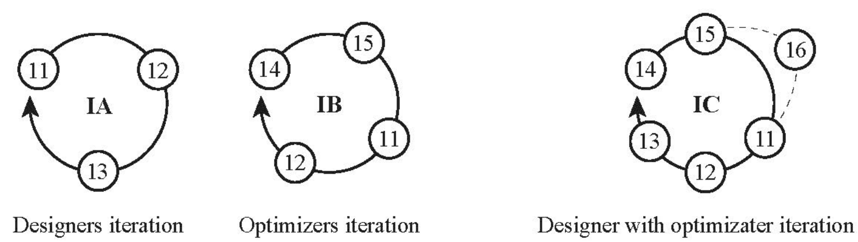


Fig 3. The two Regions of Interest (ROI) on the screen and descriptions of the regions

Process Group	Process	Discription	Events
Formulation	1-10	Internalizing design task; developing Be^i and Se^i	Pre-modeling process
Split Pre-modeling phase and Modeling phase			Placing first component
Synthesis	11	Envisioning solution from Be^i to Se^i	Event happens internally
	12	Externalizing envisioned Se to external S^e	Developing design in grasshopper*
		$S^e \rightarrow S^V$	Introducing a variable
		$S^e \rightarrow S^S$	Sketching again
		$S^e \rightarrow S^P$	Defining solid and glass panels
			Plug in elements to objectives
Analysis	13	Considering if external S^e aligns with Se	Reviewing design in model space**
	14	The resulting B^i from S^i sdf	running optimization tool
Evaluation	15	Interpreting if B^i meets Be^i	Reviewing optimization results
	16	Changing F^i based on B^i	Changing which objectives they pursue
Documentation	12		Editing representation of design
	17-20	Shifting from expected and intepreted into external	Writing about design

*Defined by looking in the Grasshopper canvas
**Defined by looking in model space for more than 0.5 seconds

Fig. 4. The coded behaviors in this study from the situated FBS framework.



Designer's iterationOptimizer's iteration Designer with optimizer iteration

Fig. 5. Identified iteration loops.

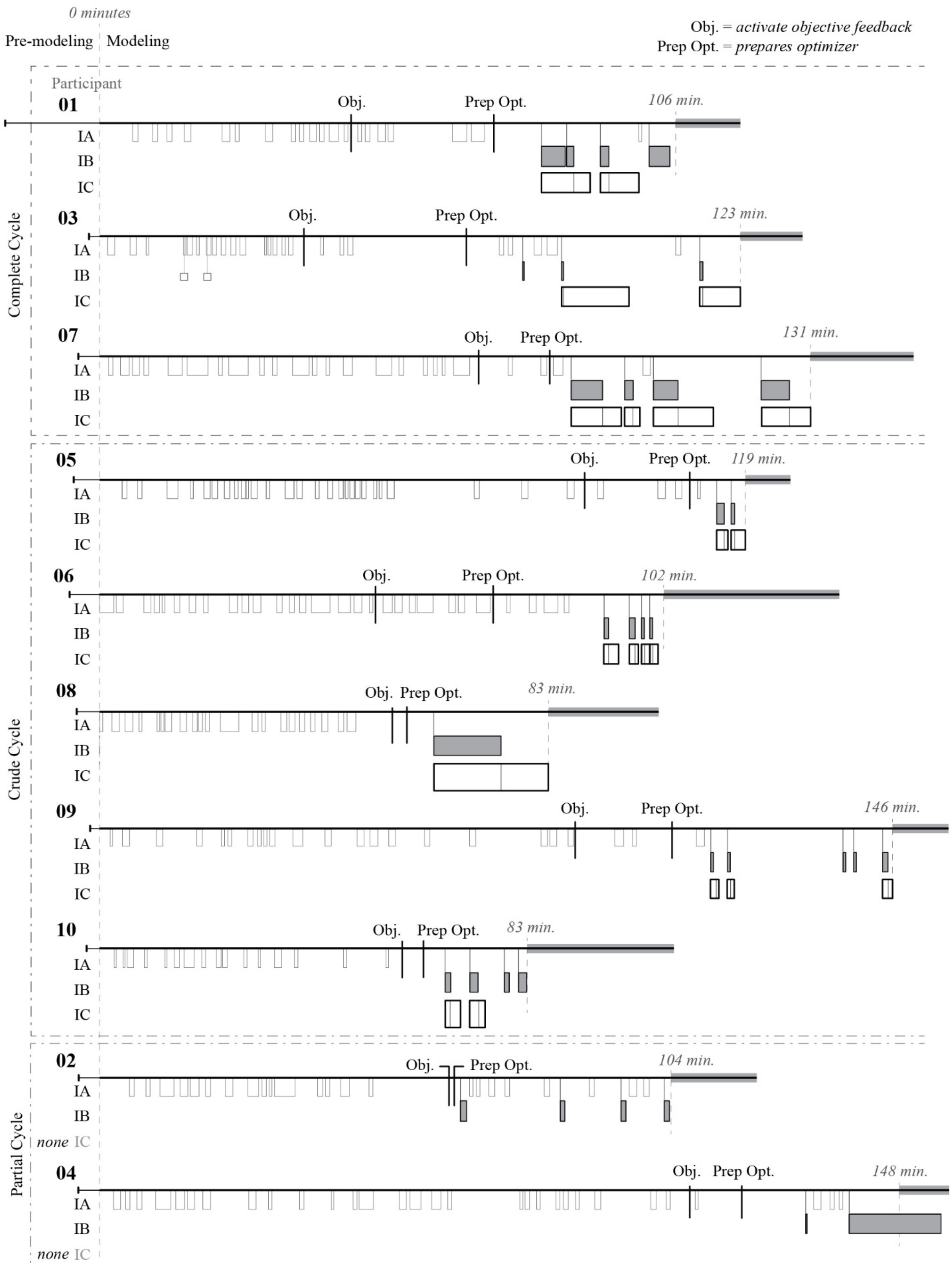


Fig. 6. Design session behavior time plots for all participants.

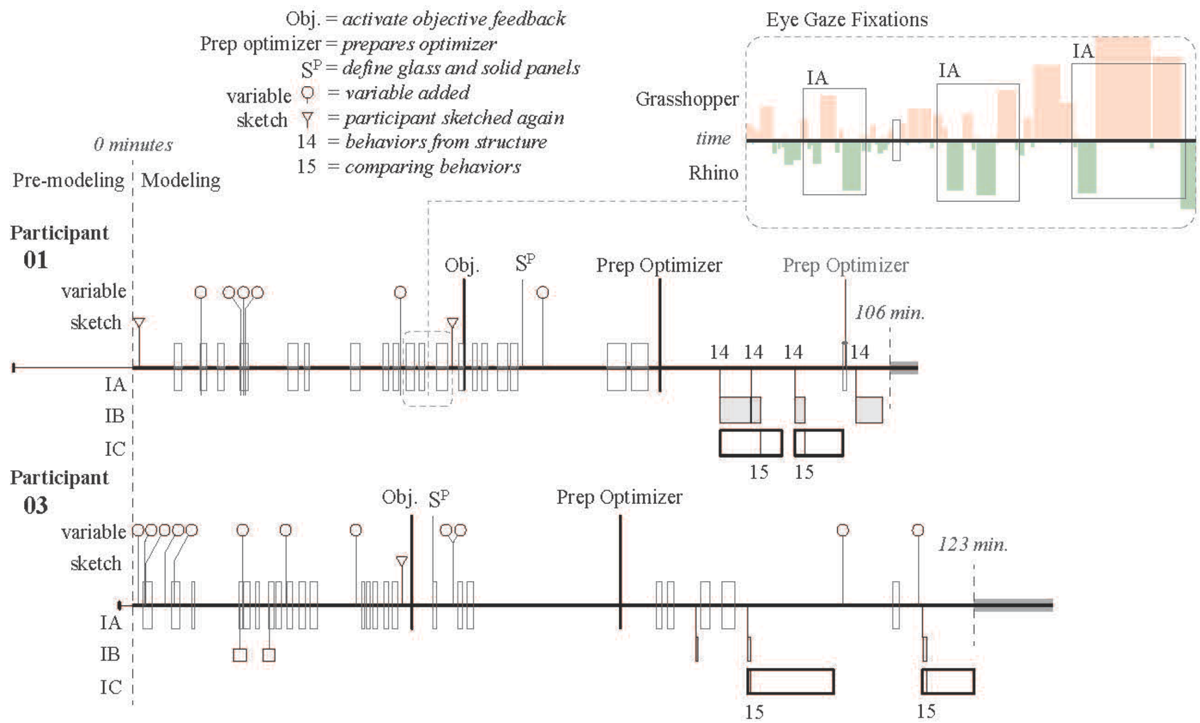


Fig. 7. Complete Optimization Cycle sessions with detailed time plots from Participants 01 and 03.

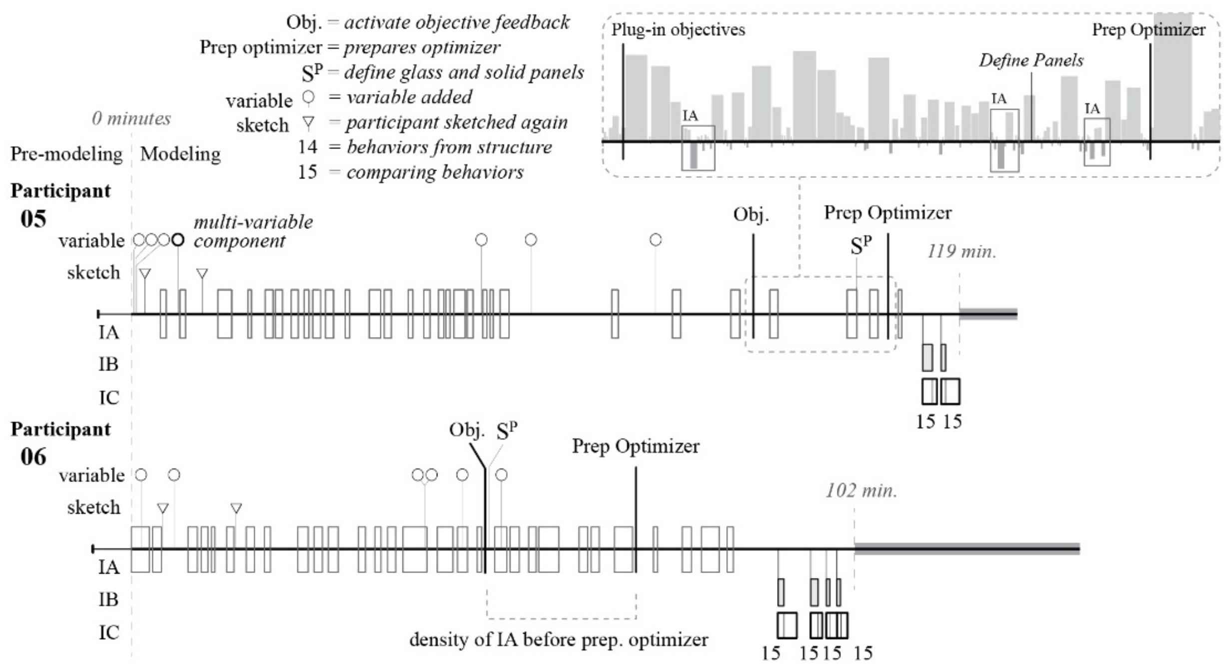


Fig. 8. Coarse Optimization Cycle sessions with detailed time plots from Participants 05 and 06.

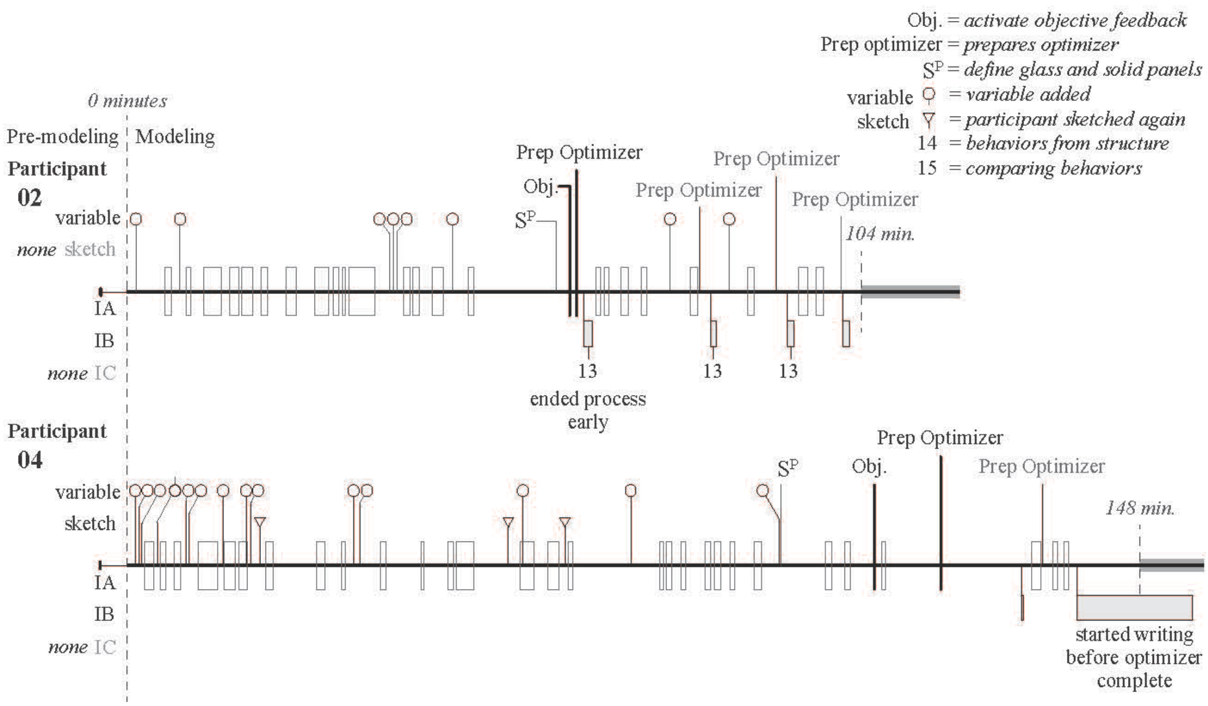


Fig. 9. Partial Optimization Cycle sessions with detailed time plots from Participants 02 and 04.

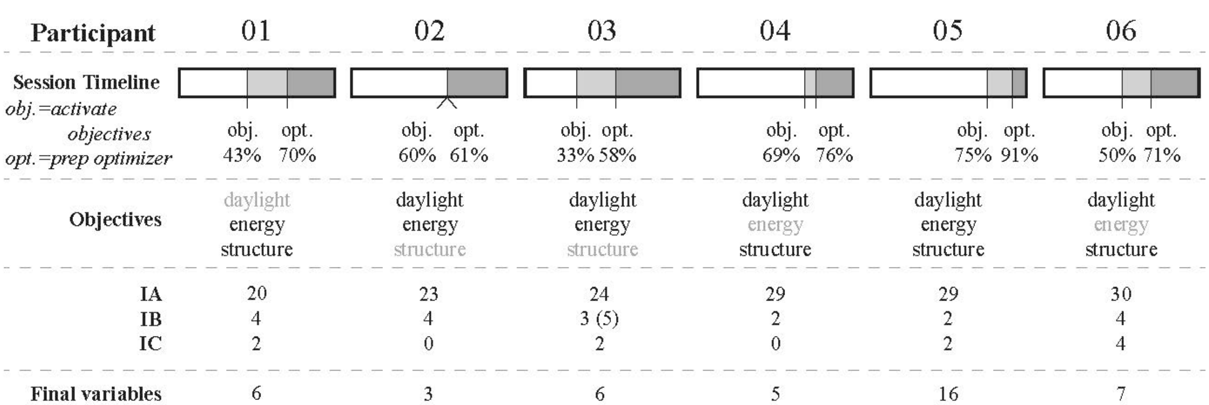


Fig. 10. A summary of characteristics from the optimization portion of the detailed sessions analyzed in Figures 7-9.