Optimization Strategies of Architecture and Engineering Graduate Students: Responding to Data During Design

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Abstract. Both architects and engineers increasingly use design optimization in the early stages, but it is unclear how designers' disciplinary background may influence their optimization strategies. In considering designs with multiple conflicting objectives, large datasets of options are often produced, which can be difficult to navigate. Architects and engineers may engage with optimization tools and their feedback differently based on their background, which can affect collaborative efforts and influence design outcomes. In this study, graduate architecture and engineering students with experience in optimization responded to a design task with both quantitative and qualitative goals. The task required participants to establish and explore their own parametric design variables, producing large datasets with numerical and visual feedback. Screen recordings of the design sessions were analyzed to characterize optimization events initiated by the designers, revealing when and how often they ran optimization routines and how they reviewed the optimization feedback. The study showed that the architecture students tended to use optimization later and iterate less than the engineering students, who relied on quantitative data more often to edit their design space and justify their decisions. Future efforts to incorporate design optimization into graduate education should be cognizant of these differences, especially in multi-disciplinary settings that encourage architects and engineers to mutually engage with data during collaborative design.

Keywords: Multi-objective optimization, 3D parametric design, disciplinary design strategies, design study.

1 Introduction

Although architects and engineers both contribute professional expertise in designing our built environment, they often use different tools, which can hinder cross-disciplinary considerations. However, optimization tools embedded in 3D modeling environments allow designers to consider many numeric and geometric objectives simultaneously, which can support integrated design decisions [1], [2]. The ability to interactively create, manipulate, and analyze datasets with multi-objective feedback is advantageous in navigating visual and performance implications. While considering these possible advantages, it should be acknowledged that architects and engineers may use these tools in different ways—interdisciplinary environments do not simply merge the professions. In their design training, architects and engineers engage with design data in different forms, ranging from open-ended analyses to strictly defined problems with clear parameters and constraints. Understanding how developing designers make decisions in data-rich digital environments, and particularly how architects and engineers might show different optimization strategies, is a first step in facilitating better collaboration between the disciplines when optimizing. While it has been shown that parametric design has distinct design thinking characteristics [3], [4], optimization approaches are still being explored in these environments [1], [5]–[7]. This research thus asks: **How does the disciplinary background of architecture and engineering design students relate to their optimization strategies during conceptual design?**

This paper presents an initial study which prompted architecture and engineering graduate students with experience in optimization to develop an atrium roof for a fictional university in the Southwestern United States. They were asked to account for daylight, solar radiation, and/or structural performance, along with the contextual appearance of their design. Participants developed a 3D parametric model for geometry and used optimization tools to account for the specified objectives. All variables were created by the designers, making them responsible for defining the structure of the optimization problem within an architectural design prompt. A survey of participants focused on educational experience. Screen recordings from the design sessions were collected and analyzed to capture significant events, assessing when and how frequently the designers navigate between performance feedback and design development. It was expected that while there would be recuring and similar behaviors exhibited by the designers, the focus of their optimization efforts would align with typical disciplinary characteristics, such as greater comfort with numerical feedback for engineers and more internalized decisions for the architects.

2 Background

2.1 Optimization in Building Design

Optimization, as a design strategy, enables the consideration of quantitative objectives such that designers make more informed decisions [5]. This approach is useful in building design as the requirements of our built environment become more numerous and complex [8], [9]. Many design goals for buildings are inversely related, such as daylight and energy conservation, where the use of more glass will increase daylight, but not provide an as efficient U-value compared to an insulated wall for thermal performance. Conflicting relationships between objectives can make finding optimal design solutions in the objective space challenging, particularly when the design goals become more numerous, as in full building design [6], [10].

Though formal mathematical optimization seeks a single answer, in practice, multi-objective design optimization strategies often produce dense datasets in pursuit of finding "better" solutions [11], which can be difficult for designers to sort. Optimization tools employ a range of algorithms within specialized interfaces for user interaction, such as displaying a 3D model with plots of the design and objective spaces. Figure 1 shows an example of the relationship between 3D model space, variable design space, and optimization objective space. A designer develops the parametric model with variables, and the resulting geometry displays in the 3D space. At the same time, objective performance values are generated in an objective space. When an optimization process is used, the tool will rapidly iterate through the model, changing the values of variables to minimize the resulting objectives. In situations with no clear winner, a designer will need to edit their original design and rerun the optimization or select a design based on priorities or characteristics not captured in the model. Often, selecting a final design will rely on qualitative requirements, intuition, or preferences. Optimization tools can thus help designers make informed decisions while still allowing for design freedom. However, architects and engineers are trained differently, and thus may diverge on objectives, as well as how they engage with such tools.

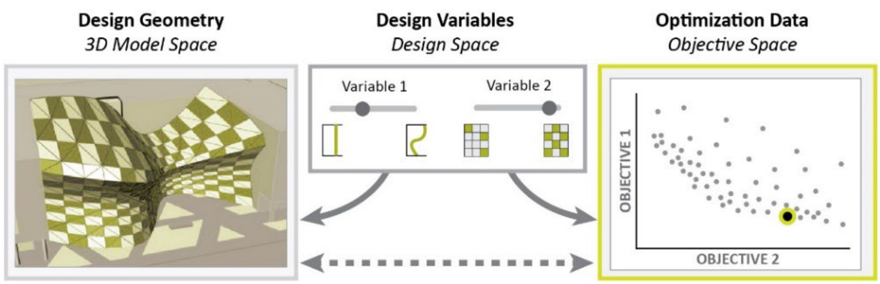

Fig 1. Navigating between the geometric and numeric feedback in the 3D modelling, optimization design process.

2.2 Differences in Architecture and Engineering Education

It has been shown that architects and engineers tend to design differently, with architects assuming partially defined problems and engineers pursuing well-defined problems [12]. This distinction in design strategy aligns with aspects of their design education. In contemporary architecture education, architects are trained to think spatially, often using 3D modeling tools in their first or second years of training, while there is still a call to improve visualization skills in engineering education [13]. The additional years of computer-space design experience can set architects apart from engineers as spatial design thinkers. Furthermore, parametric modeling has recently been incorporated in architecture education [14], [15] and some researchers have called for more parametric modeling in architecture practice [16]. However, research has shown that AEC students generally express a larger learning curve in becoming acquainted with 3D digital modeling tools than in learning the associated design concepts [17].

Engineering education characteristically emphasizes design decision making as well, though typically centered in the first-year engineering courses and senior design. It has been documented that engineering undergraduates typically struggle to negotiate authentic problem- and project-based design tasks without “right” answers, since traditional coursework often emphasizes arriving at a correct, tangible solution, following established problem-solving methods [18]. Focusing on a final solution is imperative in our built world where design decisions have monetary and life-safety consequences. However, there has been a shift towards project-based learning in engineering education as engineers also need to be adept communicators, team members, and lifelong learners [19], [20]. An additional complication is that architects and engineers can define the outcome of a “design” differently: in practice, engineering design can be represented by algorithms and codes, numerical simulations, spreadsheet outputs, and physical prototypes, in addition to spatial computer-aided designs.

The appropriate scoping of design tasks for education is critical, as design tasks with definitive solutions rarely allow for ambiguity of interpretation and can narrow thinking. Engineers with a low tolerance for ambiguity also create fewer novel ideas [21]. Similarly, solution-focused thinking can be a barrier for navigating optimization strategies because of conflicting qualitative and quantitative goals in building design. Selecting a “best” solution from optimized datasets relies on both informed performance feedback and the intuition of the designer.

With this background, optimization has been incorporated in the education of architects and engineers with initial positive results [22]–[24]. Researchers have looked at how designers make decisions in a parametric modelling space, recognizing the difference between choices made by the designer’s knowledge versus decisions made by algorithms [25], [26]. Because variables are incorporated into a parametric model, there is the potential for unexpected designs to emerge. Developing a well-built parametric model, with appropriate constraints but freedom of exploration, requires effective parametric strategies [27]. Moreover, what might motivate when a designer makes decisions based their own intuition or on the suggestion of an algorithm is difficult to distinguish, particularly in the application of optimization. Disciplinary training likely influences the way that optimization occurs in designerly domains, though this relationship is not yet explored. Observing how disciplinary background influences optimization strategies can inform how the professions approach complicated datasets created during the process. To consider these questions, this research used a design study which asked graduate architecture and engineering students with experience in optimization to respond to a building design task. Their behaviors with the optimization tools were then compared.

3 Methods

3.1 Study Setup

This study asked participants to respond to a conceptual design task with clear design goals using optimization techniques. The design interface provided numeric and visual feedback, while the optimization tool produced datasets with a range of possible solutions. In observing how the participants interacted with the tool and responded to feedback data, this study established patterns of behavior in relation to the disciplinary background and experience of participants.

Participant Recruitment, Background, and Selection. Participants were recruited from the graduate programs of the architecture and architectural engineering departments at a large university in the Northeastern United States. After expressing interest, potential participants completed an intake survey which collected data about educational background, previous professional work experience, parametric modeling skills, and their understanding of optimization. To qualify for inclusion, participants were required to have completed coursework in multidisciplinary building design and have at least 6 months of experience with parametric modeling and optimization. These prerequisites established their ability to adequately respond to the study task. However, the participants were graduate students and not yet experts in their field, which was taken into consideration when developing complexity in the design task and managing for design fatigue. The study was approved by the Institutional Review Board and participants were financially compensated for their time after completing their design session.

Ten total participants (five from architecture and five from architectural engineering) were included in the study. Although this number does not establish statistical significance, the goal is to identify behavioral differences as an initial investigation into optimization techniques. Each participant represents a dense collection of data with 3+ hours of recorded files per person. This work follows methods evident in qualitative research to establish a framework for studies with more participants in the future.

Design Session. To begin, participants watched a video brief which explained the design task and introduced the provided base file with site context. The video ensured that participants received a standard level of detail along with illustrations to demonstrate context. Participants were allowed to take notes or sketch while watching the video. They could return to their paper and pencil tools at any point in the session.

Next, participants were situated in front of a workstation that was pre-loaded with unobtrusive eye-tracking software and hardware (i.e., no headgear), which was then calibrated to each participant. The researcher sat to the side and observed a mirrored computer screen to not intrude on the participants' space. The researcher collected memos during this time, making notes about design choices, behaviors, and sketching. Although the researcher answered participant questions about the study's instructions, the researcher did not provide feedback on the designs or optimization strategies. Once the participants were satisfied with a design, they wrote a design statement justifying their final solution and submitted 3-5 screenshots of their design to the researcher. Figure 2 shows the study events and data that was collected to compare behaviors based on disciplinary background experiences.

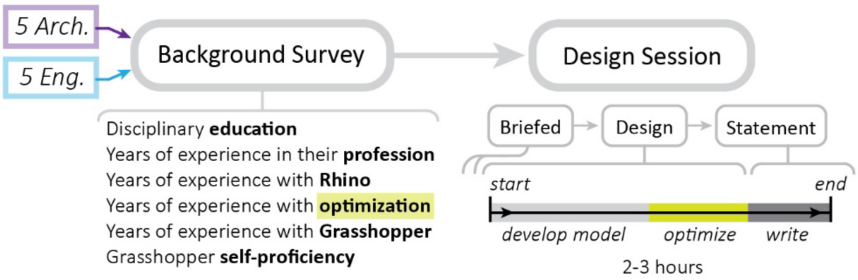

Fig 2. The study sequence, including a background survey, design session, and data collection.

Design Task and Tools. Participants were asked to develop an atrium roof for a fictional university in the hot climate of Arizona. The site was chosen for its generally known sunny conditions, which can also be readily found online. The participants were shown site context and instructed to address two of three optional performance criteria: maximizing daylight, minimizing solar radiation, and maximizing structural performance. Their designs also had to consider contextual appearance.

Participants used Grasshopper, a 3D parametric tool, to develop the geometry of their design in Rhinoceros, a 3D digital environment. Optimization was conducted using plugins built for Grasshopper. These tools are established environments for design optimization, being used in past research [28]. Although participants could use any available optimization tool, the participants chose Galapagos [29], Design Space Exploration [30], or Octopus [31]. They were provided a file with existing site context and a script with pre-built quick calculations for the objectives, as opposed to more detailed simulations. Daylight and solar radiation calculations accounted for area, materials, and geometry of the surface panels. Structural performance was measured by reducing elastic energy using the structural analysis plugin Karamba 3D [32]. Figure 3 shows a sample of the environment interface with the provided site context and parametric canvas with the objective generators.

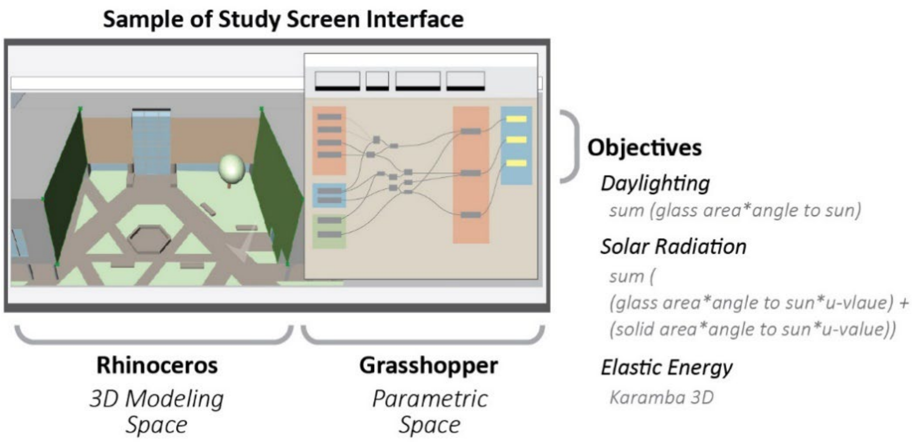

Fig 3. Sample interface with the model space, parametric space, and objective calculations.

3.2 Data Collection and Evaluation

The following three data streams were collected to answer the research question:

Background Survey and Analysis. The survey collected data about participants' educational background and experience with the study tools, which is used to compare participant experience and training to designerly behavior when engaging with optimization. A summary of background characteristics is given in the results.

Screen Recordings and Analysis of Observational Screen Capture Data Analysis Methods. Screens were recorded using screen capture software from Eyetracking, Inc. The screen capture hardware and software were non-intrusive, meaning they are not wearable and do not interfere with a participant's natural behavioral tendencies and processes. To analyze the recorded screen capture data from the N = 10 participants, methods consistent with observational qualitative analysis using content analysis methods [33] were employed, relying on a modification of an *a priori* framework of design behaviors informed from the FBS literature [34]. This was then honed to describe the significant observable design events that are captured via screen recording. The coding schema was discussed with the broader research team and validated in early rounds of analysis to ensure that it was comprehensive to define and verify behaviors in the parametric space, such as the placement of the first component in the parametric model space and interaction with the optimization tools. The coding scheme and definitions are presented below:

(1) Activate Objective Feedback: Plugging geometry into the objective generators indicated a shift from focusing on visual model development to model performance. The importance of defining numerical objectives and appropriately incorporating them into design decisions has been established in previous assessments of optimization [35].

(2) Preparing Optimizer: Opening the optimization tool and beginning to adjust its settings signified a shift in participants attention from their own design decisions to engaging feedback from the optimization tool. All participants performed this act.

(3) Run Optimizer: Running an automated optimization process showed that the participant began generating data for observation. Early and numerous optimization runs indicated an integrated, iterative process compared to plugging a model into the objective generators and running fewer automated processes later in the design session.

(4) Review Results: Viewing either a data visualization in the tool or cycling through designs it produced indicated the beginning of this action. While some participants only glanced at the results, others considered the options for an extended period of time.

To analyze the data, the researcher watched the recordings while qualitatively "coding" the design behaviors occurring over time through descriptive content analysis methods using a post-positivist paradigm [33]. The occurrences of significant events were plotted on session timelines like the one shown in Fig 4.

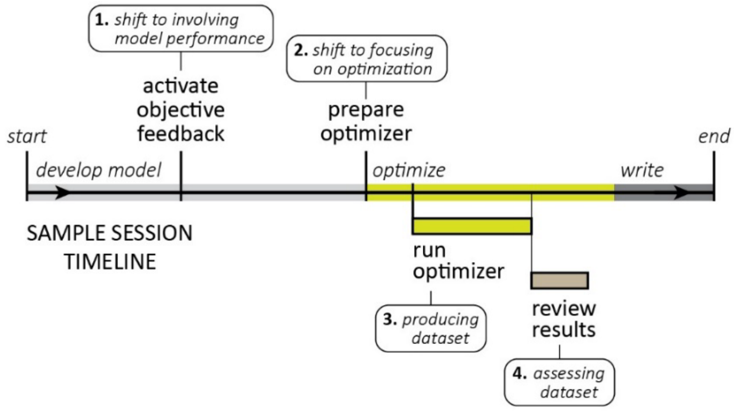

Fig 4. A sample session timeline labeling the key events identified in each session.

Design statements. The participants also submitted a 150-250 word design statement, written to the fictional client, that presented the suggested solution. There were no explicit requirements of the design statement, and thus they varied in content. Thematic analysis methods were employed to characterize the dominant themes in the written design prompts, using an emergent coding scheme to understand the patterns, again relying on conventional qualitative content analysis methods, this time employing an emergent coding approach [33]. Four primary topics were noted in the statements: (1) the potential *users*, such as students; (2) the participant's *design vision*, which could be as explicit as "I wanted the roof to look like a tree" or abstract as in wanting the space to be well shaded; (3) stating which of the three *objectives* were considered; and (4) referring to *optimization* or improving design performance. Comprehensively, the characteristics of the design statement were compared to the design behaviors and educational background of the participants to draw initial observations about the difference between architecture and engineering students when optimizing.

4 Results and Discussion

This study's primary research question asked, **how do the disciplinary background of architecture and engineering design students relate to their optimization strategies during conceptual design?** To create an authentic design challenge, the study's design task allowed the participants to develop their own geometries with variables that they defined. This unrestricted parametric space prompted solutions of different quality and parametric range. Although evaluation of the final designs falls outside the scope of this research, the range of design spaces developed by four of the participants are presented in Figure 5. While some participants built models with greater geometric variation, others focused on controlling smaller changes in the design space. The emphasis of this work, however, responds to the research question and considers differences of the designers' design strategies, not their final designs.

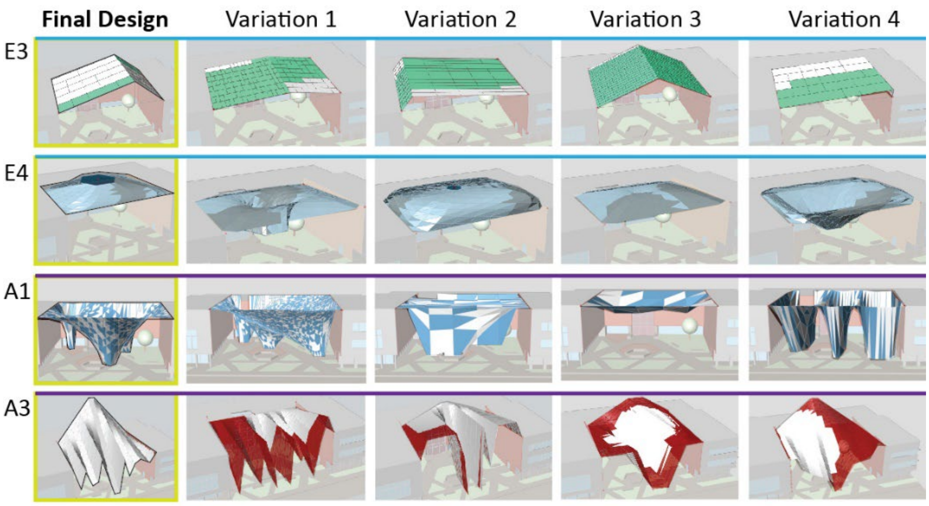

Fig 5 Sample of two engineers' and two architects' designs, showing their final design and two of the variations of their parametric model.

From the results of all participants, three influential dimensions of data emerge: 1) years of experience and confidence in the study's tools, 2) patterns in the participants' design sessions, and 3) characteristics of the designers' final design statements. Collectively, these data suggest disciplinary strategies that increase or limit the inclusion of optimization feedback in design, which, when utilized effectively, can positively influence overall design performance. As a result, introducing design students to both qualitative and quantitative design goals throughout their education may equip them to more wholistically incorporate dataset feedback and optimization suggestions in their design decisions.

4.1 Participant Background

The participants' background information is summarized in Figure 6. The Grasshopper self-proficiency is illustrated by a scale of 0 to 5. The architects had considerably more experience with Rhino, and some more experience with Grasshopper, but all reported experience levels were considered adequate to authentically respond to the design task. The architects also had greater professional experience, with participant A1 reporting the greatest number of years. The distinction between participants' years with optimization were closer. This aligns with expectations from disciplinary backgrounds since architects are trained early in their education to use 3D modeling tools. Their expressed confidence with Grasshopper also reflects a comfort with the design tool, perhaps as a result of their design training. To consider the influence of these experiences, the background differences were included in the context of the design session behaviors.

	Years of Experience				Grasshopper
	Professional	Rhino	Optimization	Grasshopper	Self-proficiency
Engineering Graduate Students					
E1	1	1	1	3	●●●●○
E2	1	1	3	3	●●●○○
E3	0	1	1	1	●○○○○
E4	0	3	2	3	●●●●●
E5	1	1	1	1	●●○○○
Architecture Graduate Students					
A1	10	3	2	3	●●●●●
A2	4	5	2	5	●●●●●
A3	1	7	2	7	●●●●○
A4	2	7	4	5	●●●●●
A5	6	5	3	5	●●●●○

Fig 6 Background information on the graduate student participants

4.2 Session Sequences

The design sessions were plotted to detail important events in the sequence. The results from the engineering graduate participants are presented in Figure 7 and the architecture graduate participants in Figure 8. The timeline labels when the participants plugged their model into the objective calculators (measured as a percentage of the session), when they started to prepare the optimization tool, and how long the session lasted. It also shows when the designer ran an optimization tool (indicated in yellow-green) and for how long they reviewed the results, if at all (indicated in brown). E2 and A2 did not review the datasets. Along the right side of the figure, the participants number of optimization runs, years of experience with the 3D modeling tool, and self-provided proficiency with Grasshopper are provided.

Disciplinary differences in design sessions. The architecture students seemed to engage less significantly with the feedback data from optimization compared to the engineers and from the session plots, they ran the optimization tool a fewer number of times than the engineers. The architects also tended to wait until later in the design session to engage with the numeric feedback of the optimization tool, with the exception of Participant A1, who plugged their model into the objective algorithms earlier than all of the other participants. This designer also spent the longest amount of time considering the results of the optimization tool compared to the other participants. A primary difference between this participant compared to the others is years of professional experience, as was presented in Figure 8, where Participant A1 worked at least 4 more years in their disciplinary professional setting than the other participants. Although the architecture students tended to include optimization later in their process compared to the engineering students, years of work experience and maturity of a designer can influence optimization strategy, incorporating algorithmic thinking early in an optimization, conceptual design task. Additional research should be conducted to better determine the relationship between professional experience and optimization strategies.

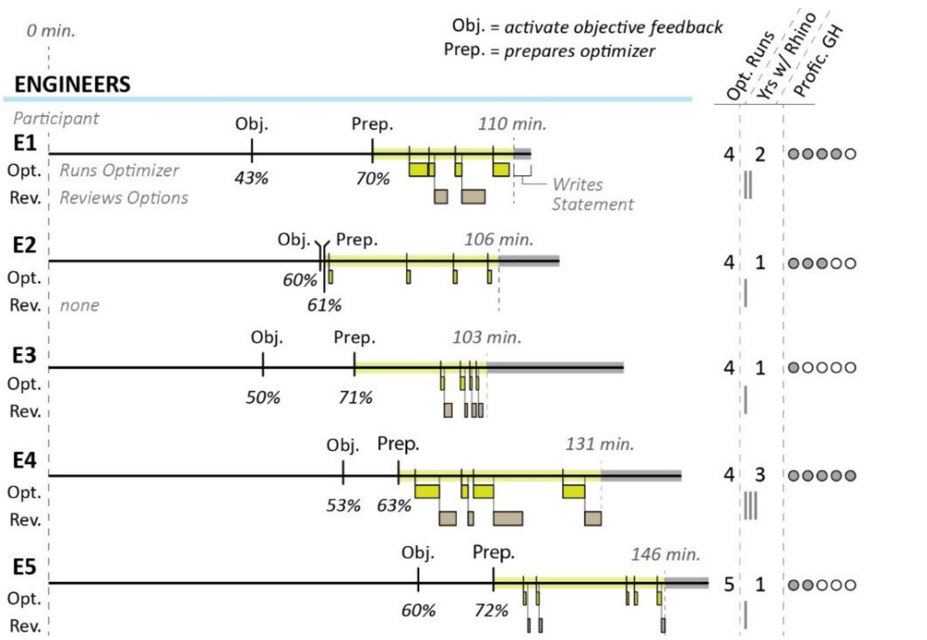

Fig 7. Session plots for the engineering participants, showing key events in their design process.

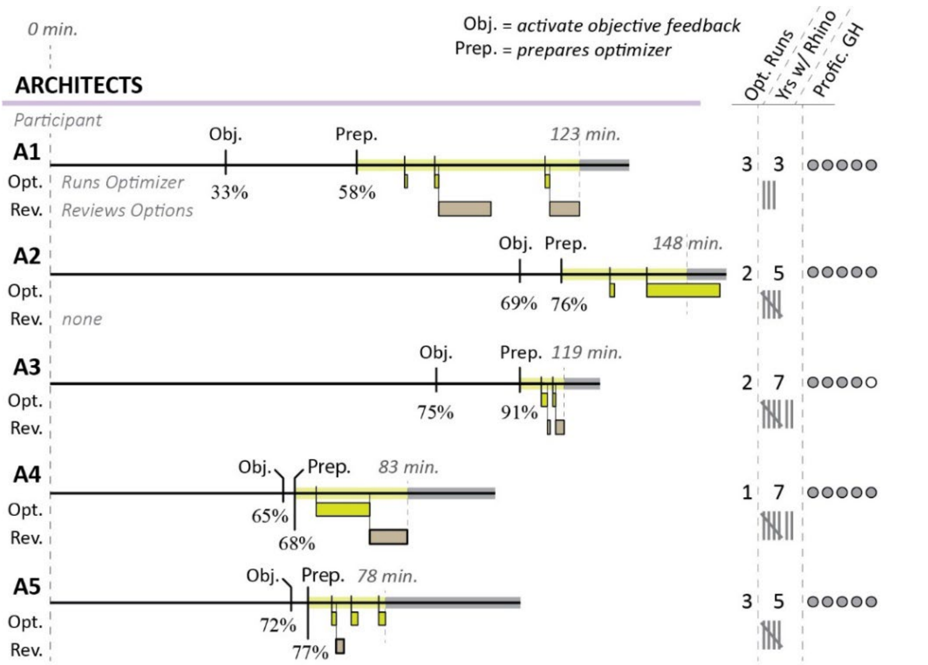

Fig 8. Session plots for the architecture participants, showing key events in their design process.

4.3 Design Statements

Figure 9 summarizes the mentions of design topics within the participants' statements, emphasizing when the topics were mentioned most with a yellow-green box.

	Statement Mentions			
	Users	Design Vision	Objectives	Optimization
Engineers	2	3	$\boxed{5}$	2
Architects	2	$\boxed{5}$	3	$\boxed{4}$

Fig 9. The mentions of design topics within the participants final design statements.

Disciplinary differences in design statements. As was expected from the hypothesis, the architecture participants consistently referred to a design vision, stating what they imagined for the design, while the engineers all stated their quantitative objective goals. However, not all participants mentioned the users of the atrium space or referred to optimization in their statements. Despite the engineers incorporating optimization feedback earlier in their design sessions compared to the architects, they were not as explicit in mentioning optimization. Meanwhile, the architects, who engaged with optimization feedback later in their design sessions, mentioned the study's focus of optimization more consistently. From their disciplinary education in design studios, they may be more practiced at reflecting a design task's requirements, despite the spread of project-based learning in engineering [18]. Alternatively, architects may be less formal in their use of the term "optimize." While engineers may view optimization and dataset processing as an inherent aspect of design and not important to mention to the client, the architects may have viewed optimization and dataset parsing as an influence on their design process, despite incorporating it less.

4.4 Implications for Disciplinary Education and Approaches to Optimization Feedback

Disciplinary background clearly related to different patterns in optimization behavior, but professional years of experience or greater comfort with the tools may have also played a role. During the design sessions, the more professionally experienced architects spent more time designing without optimization feedback for a greater percentage of time, rather than on optimization feedback. Alternatively, the engineers incorporated optimization feedback data into their design process more often. However, when writing about their final design, the architects mentioned optimization more consistently than the engineers. Other details of the design statements supported expected characteristics of the profession, such as the engineers stating their chosen objectives while the architects described their design visions.

With these results, it may be that participants' disciplinary training influenced their preparedness to navigate large datasets produced by optimization, but not recognize the role of optimization on their final design. While the engineers relied on optimization feedback iteratively to develop their design, they did not all include it in their statement. In contrast, the architects consider optimization later, often after large geometric decisions were already set, yet they mention optimization more readily. Although architecture pedagogies tend to approach design decisions conceptually, rather than requiring numerical feedback, there may be advantages to incorporating quantitative approaches to design in the context of optimization. As quantitative metrics can increasingly be simulated and optimized, preparing architecture designers to navigate dataset feedback as a part of their education may be valuable. Figure 10 shows a summary of these relationships.

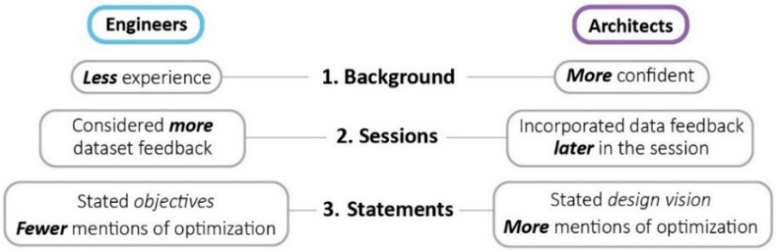

Fig 10. Summary of the results, emphasizing the different characteristics of the disciplinary backgrounds, design sessions, and design statements.

4.5 Study Limitations

To elicit authentic design behavior from the participants, the design task tried to provide an approachable scenario with challenging goals and accessible expectations. However, limiting the design space to the framework of the computer programs may have affected the designers' natural design process. Working within the constraints of cognitive fatigue was also central to the quality of data collection for this study. As has been noted previously, studying design behavior inherently impacts dimensions of the process, but this alone does not discredit the research, as the data must be considered within its context [36]. Additionally, this study did not assess the overall quality of the final designs and leaves the dimension of design efficacy for future investigations. Based on the participant background qualifications to participate in the study, it was established that the designers could develop an adequately performing solution in response to the design task. Future work intends to investigate design efficacy, but it is valuable to first establish differences in optimization behavior.

5 Conclusion

This study considered the optimization strategies of architecture and engineering graduate student designers compared to their disciplinary background when responding to a conceptual building design task that produced large datasets of solutions. Although the architecture students incorporated optimization and dataset feedback later in their design process and with less frequency compared to the engineering students, this was not true for one architecture student who had more at least 4 more years of professional work experience compared to the other participants. It may be that both disciplinary background and experience influence optimization behaviors. These initial findings may help instructors approach optimization curriculum with attention to the students' disciplinary processes. It lays a groundwork for understanding design behavior when students construct and use different performance feedback tools in combination with optimization tools. This work also establishes methods for investigation large datasets produced by optimization that can be applied to future investigations of optimization efficacy of both design students and design professionals.

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