

Curriculum Development and Education Research for Generative Design Thinking*

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Generative artificial intelligence (AI) algorithms have recently been applied to engineering design, particularly to explore design spaces which are too large for humans to feasibly comprehend. This paradigm shift from manual human-driven design to automated AI-driven design requires the designer to take a drastically different approach to design-objective space co-evolution during exploration following problem space definition. However, engineering curricula have not yet caught up to the recent rise of generative AI in design (i.e., Generative Design). This paper presents two sets of educational materials developed to teach Generative Design and reports their effectiveness in teaching undergraduate students. Study 1 investigated participant engineering design self-efficacy before and after completing a curriculum workbook developed to teach the fundamental concepts of human-driven and AI-driven design (using genetic algorithms) with CAD project-based learning activities to experience both design paradigms. Study 2 compared performance on a team design activity before (vs. after) students heard a lecture on AI-driven design and completed a topology optimization-based CAD activity. Studies 1 and 2 found beneficial effects of the curricula on students' engineering design self-efficacy and design artifact performance.

Keywords: design thinking; design cognition; engineering design; generative design; design education; self-efficacy

1. Introduction

Engineering designers have long sought to leverage cutting-edge technologies to apply their practice. Computer-aided design (CAD) software (e.g., Fusion, SolidWorks) became a key tool for both design practitioners and students during the second half of the 20th century, and the use of computational design tools (e.g., parametric schemas) to automate some previously manual design tasks has risen exponentially alongside developments in artificial intelligence (AI) research. In particular, a wide range of generative AI algorithms have seen increasing use in engineering design tasks, particularly for automated design space exploration to find the optimal solution via optimization-driven (e.g., genetic algorithms, topology optimization) or data-driven (variational autoencoders, generative adversarial networks) methods, which can be used to

generate solutions based on distributions either (respectively) predetermined or learned from data. More recently, the development of large language models (LLMs) which has greatly advanced generative AI to exceed previous AI capabilities has led to a massive increase in commercial use across various fields. For example, OpenAI's [1] LLM-based ChatGPT attempts to mimic and exceed human intelligence and logic during a conversation with the user.

The integration of generative AI into design drastically changes the traditional role and design thinking (i.e., the high-level cognitive approach) of the designer during exploration¹ by removing the opportunity for the human to drive the co-evolution of the design and objective spaces. This occurs as the human iteratively explores the design space via manually rearranging variable parameters to create artifacts and then evaluating the perfor-

¹ Design and Objective Space exploration following problem space definition. We acknowledge that [2] defines the design/solution space as each possible solution and each solution's performance. However, we distinguish between the Design Space (each possible design solution) and Objective Space (each solution's performance) to highlight the differences between human-driven TD and AI-driven GD [3].

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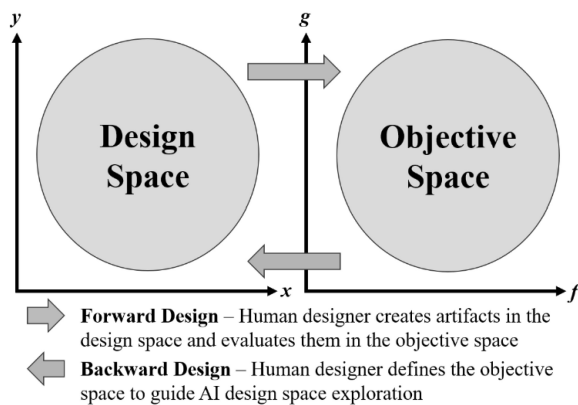


Fig. 1. Forward Design methodology in the Traditional Design (TD) paradigm vs. the Backward Design methodology in the Generative Design (GD) paradigm.

mance of these artifacts in the objective space [2]. We refer to this exploration methodology as Forward Design: exploration that flows from the design space to the objective space (Fig. 1). This occurs in Traditional Design (TD), a human-driven design paradigm which requires the designer to engage in what we call Traditional Design Thinking (TDT): the cognitive approach which underlies the Traditional Design process. This differs from the new Generative Design (GD) paradigm introduced by generative AI tools and the Generative Design Thinking (GDT) which accompanies AI tool use. The human designer in GD works “backwards” by first computationally defining the objective space via the variables ranges to consider, constraints to avoid, and one or more goals. An AI agent will then explore and exploit the design space as it iteratively optimizes solution performance towards the goal(s). In short, designers in TD employ Forward Design by exploring the design space and moving to the objective space, while in GD, the designer uses Backward Design by driving exploration from the objective space and collaborating with AI to exploit the design space [3].

2. Motivation

Engineering design has traditionally been driven by humans, but several factors suggest that the future of engineering will shift to include a more substantial focus on GD. Business profit motives are driven by an increasing demand for highly personalized products and services that must be quickly developed via AI capabilities, and increasingly complex design problems prompt the designer to consider a wider range of variables than is feasible for human cognition and thus are better suited for generative AI agents [4]. However, GD is a recent paradigm shift which has not yet been widely introduced into engineering design curricula; current students are

not yet being adequately prepared for their future professional roles. In a recent workshop organized by the authors, design educators and practitioners from 11 institutions discussed educational and research gaps in teaching GD/GDT [5]. A key takeaway was the need for curricula to teach undergraduate students GD via project-based learning (PBL), a prominent pedagogical approach for teaching engineering design. Therefore, the goals of this paper are to disseminate educational materials to teach GD, to create pathways for undergraduate engineering students to cultivate GDT, and to study the effectiveness of these materials. Specifically, we aim to address the following two research questions. First (RQ1), what effect does learning and practicing GD concepts have on student engineering design self-efficacy? Second (RQ2), what effect does learning and practicing GD concepts have on student performance on a design task?

The rest of the paper is organized by the following structure. In Section 3, we briefly review literature on PBL and self-efficacy, a crucial teaching outcome for preparing students to succeed in their academic and professional careers. Section 4 provides an overview of Sections 5 and 6, which describe the educational materials developed to teach GD and the human-subjects studies conducted to evaluate learning outcomes of undergraduate engineering students completing these materials. Directions for future studies are discussed before concluding in Section 7.

3. Literature Review

3.1 Project-Based Learning

The goal of design education is to develop students with little-to-no design experience into designers who can solve real-world design problems by providing them with the requisite knowledge, technical expertise, cognitive ability, and a sufficient cache of experience [6]. Imbuing designers with these skills from classroom instruction alone is difficult due to the high complexity of real-world engineering design problems which are often ill-defined and prompt the designer to iteratively work through different problem-solving stages, each of which requires a different skillset [7]. Early design education approaches which emphasized building theoretical knowledge over providing design experience were deemed insufficient by the industry as newly hired professional designers were found not ready for their jobs [8-9]. In response to industry concerns and the NSF’s call for education reform [10], educators have embraced project-based learning (PBL) as a pedagogical model for teaching engineering design which emulates professional design by prompting students to work collaboratively to

create solutions to authentic real-world design problems, e.g., those inspired by societal issues or chosen by an industry sponsor [7, 9, 11]. Specifically, research suggests that the key mechanisms underlying PBL are (1) prompting students to translate theory learned in the classroom into hands-on experience with design tools/hardware [7, 9, 12], and (2) working collaboratively [9].

In summary, PBL prepares students for professional design settings by offering them experience in actively and collaboratively solving authentic, multi-stage design problems. However, the addition of generative AI to the engineering design process shifts the role of the human designer. For instance, early research exploring the use of generative AI in engineering design shows that GD (compared to human-driven TD) prompts the designer to place greater emphasis on computationally defining the constraints and objective function(s) during early-stage design [13]. After off-loading the optimization of quantitative design goals to the generative AI agent, the human designer is then permitted to allocate additional resources towards considering qualitative design goals, e.g., aesthetics [14]. An updated role for the human designer in GD must be reflected in the curricula and PBL modules used to prepare student designers for their careers. However, to the researcher's knowledge, there have been no major collaborative efforts towards developing and testing PBL modules to teach GD which can be easily accessed and implemented by instructors.

3.2 Engineering Design Self-Efficacy

A key learning outcome for design educators is to build student self-efficacy. Self-efficacy is a psychological concept which refers to one's judgement of their ability to accomplish a task [15]; high self-efficacy is accompanied by increased motivation for doing a task and confidence that one's efforts will achieve their goal(s). A student's self-efficacy plays a key role in both influencing how well they learn new ideas/skills during their academic career, and in determining the success of their future professional careers [16, 17]. Bandura's seminal Self-Efficacy Theory [15, 18] describes four sources for self-efficacy on a task: (1) mastery experiences (previous attempts at a task and analysis on success/failure), (2) vicarious experiences (observation of others achieving a task), (3) verbal or social persuasion (being convinced that one has the ability to achieve a task), and (4) physiological and affective states (how one interprets and responds to task-related stress).

One also possesses a task-specific self-concept for their efficacy in any given task [16]. Research exploring engineering design self-efficacy (EDSE) has mainly focused on developing instruments to

measure the concept and related important sub-constructs, e.g., motivation, a crucial factor for determining if one will attempt/complete a task, or anxiety, which may potentially keep one from attempting tasks or hinder their performance when trying due to fear of failure [16, 19–20] and then testing improvements in student self-efficacy after an intervention, which typically takes the form of a semester-long design course emphasizing PBL modules [19–26]. Another line of research has focused on confirming the hypothesis that higher self-efficacy is related to higher performance on a design task, e.g., via correlational studies [27] or quasi-experimental methods to analyze differences in the quality/performance of designs submitted by students [28] or student teams [29] to design prompts. Specifically, these studies suggest that higher EDSE is related to more effective resource management during team design tasks [29], likely by increasing motivation to achieve one's goals and persistence while doing so [27, 28] and increasing their usage of cognitive strategies [27].

Finally, it has repeatedly been shown that student engagement with university makerspaces is related to higher self-efficacy [30–34]. Makerspaces are DIY machine shops which allow students to practice design via collaborative projects by providing access to professional design equipment, e.g., paid software, advanced hardware, and rapid prototyping methods like 3D printing and laser cutting [30]. Research on university makerspaces (which are usually located within engineering departments [31]) suggests that student participation in makerspace design projects can build self-efficacy through each of the sources in Bandura's [15, 18] theory: by providing students with mastery experiences as they design, have vicarious experiences of seeing others design, experience social persuasion via collaborative projects, and experience the physiological states associated with success/failure in design [31, 32]. Two key takeaways from the studies listed in Table 1 are (1) providing students with the chance to build mastery, vicarious, and collaborative experiences with the associated physiological states through engineering design projects (e.g., in the classroom or in makerspaces) will enhance their EDSE, and (2) higher EDSE is related to higher performance in design tasks.

Self-efficacy in conducting engineering design is a crucial learning outcome for educators to consider for several reasons. For instance, design is considered by many to be the central engineering task [7, 35] and an essential skill for engineering program graduates to possess [36]. Additionally, rapid development of design technologies requires professional designers to be capable of lifelong learning [17, 37].

Table 1. Publications investigating task-specific self-efficacy in engineering design [16, 19–34]

Author(s), Year [Reference]	Developed Instrument	Intervention(s)	Examined Design Performance	Examined Makerspaces
Carberry, Lee and Ohland, 2010 [16]	Yes	NA	No	No
Seth, Tangorra and Ibrahim, 2015 [19]	Yes	Design course	No	No
Kittur, Olayemi, Harvey and Taffe, 2024 [20]	Yes	Design course	No	No
Michael, Booth and Doyle, 2012 [22]	No	Design course	No	No
Jones, Campbell and Villanueva, 2019 [24]	No	Design course	No	No
Major and Kirn, 2016 [25]	No	Design course	No	No
Gray, Saterbak, Santillan, Rizk and Sperling, 2020 [26]	No	Design course	No	No
Nolte, Berdanier, Menold and McComb, 2020 [23]	No	Exam-based vs. PBL-based design course	No	No
Sung, Ding, Jing, Sereviene, Bulseco and Xie, 2024 [21]	No	AI teaching assistant	No	No
Avsec and Szewczyk-Zakrzewska, 2018 [28]	No	NA	Yes	No
Tsenn, McAdams and Linsey, 2013 [27]	No	NA	Yes	No
Menold and Jablokow, 2019 [29]	No	NA	Yes	No
Morocz, Levy, Forest, Nagel, Newstetter, Talley and Linsey, 2016 [30]	No	NA	No	Yes
Hilton, Talley, Smith, Nagel and Linsey, 2020 [31]	No	NA	No	Yes
Hilton, Tomko, Murphy, Nagel and Linsey, 2018 [32]	No	NA	No	Yes
Tomko, Nagel, Aleman, Newstetter and Linsey, 2017 [33]	No	NA	No	Yes
Mahmud, Sawchuk, Hulton, Nagel and Linsey, 2021 [34]	No	NA	No	Yes

Despite this importance, the effect of off-loading design exploration on a generative AI agent on engineering design self-efficacy has not yet been explored. The small pool of studies which have investigated the relationships between self-efficacy and generative AI usage suggest that cognitively outsourcing tasks to AI may either help or harm user self-efficacy. For instance, a recent study [38] found that using generative AI to assist programming enhanced learning and self-efficacy if the user did not heavily rely on the AI agent.

Through the lens of Bandura's model [15, 18], cognitively outsourcing design space exploration to a generative AI agent would affect how a designer builds mastery experiences and experiences physiological states for success/failure for design. GD could enhance self-efficacy via helping the designer succeed in their goal to create high-performing artifacts. Alternatively, off-loading previously human-driven tasks on an AI agent may block one from gathering mastery experiences and experiencing the physiological states related to success that they may have otherwise earned. Given the rise of generative AI in engineering design and the importance of self-efficacy in determining future tool use [39], it is essential for researchers to investigate how generative AI-aided design exploration affects EDSE.

4. Generative Design Curricula Overview

To address the need for preparing engineering students to use generative AI in design and investigate the unexplored relationship between teaching GD and engineering design self-efficacy, the goals of this paper are to present two sets of educational materials and share the results from their classroom implementation. The first curriculum was developed, pilot tested, and implemented by the authors at the University of Texas at Austin, the University of Illinois Urbana-Champaign, and the Institute for Future Intelligence. The second curriculum was developed and implemented by the authors at Utah Tech University. Both curricula utilized PBL to build student self-efficacy via two of Bandura's sources [15, 18]: mastery experiences and the related physiological states in engineering design concepts. Additionally, both curricula taught students human-driven manual multi-objective engineering design before having them solve the same problem using generative AI. However, the curricula taught different GD approaches: via genetic algorithms in the UT-Austin (titled *Educating Designers for Generative Engineering*, or EDGE) curriculum, and via topology optimization in the Utah Tech curriculum. The present paper examines curricula for teaching GD using different algo-

1 rhythms to emphasize the need for developing materials to teach students multiple GD approaches. Sections 5 and 6 feature descriptions of each curriculum and the results of analyses conducted on data collected from human subjects completing the materials.

5. Study/Curricula 1: Educating Designers for Generative Engineering (EDGE)

This section contains a description of the *Educating Designers for Generative Engineering* (EDGE) curriculum and an overview of the human-subjects data collected using these materials. Section 5.1 outlines the study procedure (5.1.1), participant demographics (5.1.2), and the educational materials given to students (5.1.3 and 5.1.4). Section 5.2 describes the Engineering Design Self-Efficacy Scale [16], the dependent variable used to gauge student learning across four EDSE sub-constructs: *confidence*, *motivation*, *perceived success*, and *anxiety*. Sections 5.3 and 5.4 report and discuss the results and limitations of the experimental study.

5.1 Methods

5.1.1 Experimental Design and Procedure

Study 1 used a repeated measures (within-subjects) design to examine changes in participant engineering design self-efficacy after they completed the EDGE curriculum. Our hypotheses were that participants would show increased engineering design self-efficacy (*confidence*, *motivation*, and *perceived success*) and decreased *anxiety* after engaging with the curriculum material and completing the project-based learning activities. The study was described as an opportunity to learn and practice additional design concepts not covered in their classes due to the recency of generative AI-enabled design. All study activities were completed virtually, without researcher/instructor supervision, and on each participant's chosen schedule. Each participant began the study by reading and signing the informed consent form which detailed all study activities. They then completed the pre-test survey consisting of one short answer question to gauge their knowledge of how generative AI may be applied in the engineering design process, and the Engineering Design Self-Efficacy Scale [16]. Participants were then sent the Project Statement that included a list of study deliverables, links to all study materials, step-by-step instructions on how to complete the activities and upload the deliverables, and the deadline. After finishing the curriculum, each participant was asked to complete the post-test survey (identical to the pre-test survey) and subsequently received compensation. Participants were given a

month to submit the study deliverables and spent five to six hours completing the full set of curriculum materials.

5.1.2 Participants

A total of 5 undergraduate mechanical engineering students (1 female, 4 male; mean age = 25.6, SD age = 9.1) from 3 different North American universities completed the full curriculum. Participants were recruited from both lower and upper-level engineering courses at 3 locations (2 four-year universities and 1 community college). All students above age 18 were eligible to participate. One participant was a freshman, one was a senior, and the rest were sophomores. All participants had previous experience in CAD, though none considered themselves proficient. Three participants had previous experience with Aladdin (CAD software used in Study 1). Participants were given the choice between either course extra credit or a \$50 Amazon gift card for completing the full study, which contained 12 sets of practice activities and took around 5 hours. The results of Study 1 must be considered in the context of the low sample size (see Section 5.4). Multi-institutional data collection efforts are ongoing to address this issue.

5.1.3 Curriculum Structure and Lectures

The EDGE workbook [40] was developed to teach the fundamental concepts of different approaches to design and their respective types of design thinking via online text/video lectures and CAD activities (materials were previously pilot tested via a multi-case study of think-aloud data) [41]. Participants learn the progression of three design paradigms and respective design thinking approaches: traditional design/traditional design thinking (TD/TDT), parametric design/parametric design thinking (PD/PDT), and finally, generative design/generative design thinking (GD/GDT). Each paradigm is the focus of one chapter, and each chapter is divided into four sections based on an abstract and domain-general four-step design process model (Problem Definition, Exploration, Evaluation, and Iteration; based on [42]). Participants are also guided through solar farm design CAD activities in Aladdin and asked to provide solar energy solutions to problem statements developed to prompt application of the concepts they read/watched in the curriculum text/lectures.

The curriculum was designed for undergraduate students with varying levels of experience with engineering design concepts and/or CAD, but little knowledge of generative design. The *Preface* and *Chapter 1* cover basic engineering design concepts at an introductory level and are accessible to freshman students with little design experience.

Participants were provided with instructional materials for the CAD platform they used throughout the curriculum, and the researchers/instructors were available to answer questions via email. Additionally, higher classification students or those with more experience may be unfamiliar with the generative design concepts in *Chapter 3* which have not yet been incorporated into standard university curricula.

The curriculum begins with a short preface which briefly describes Forward and Backward Design for design-objective space co-evolution to provide the context for defining, comparing, and contrasting the TD, PD, and GD paradigms. The first chapter introduces TD as a typical manual, human-driven design process where the designer begins by defining the problem space before driving exploration from the design to the objective space (i.e., Forward Design) [2, 43]. The key theme of this chapter is that human-driven design exploration heavily depends on the previous experiences, knowledge, and cognitive processes of the designer [44]. The central role of the human designer in TD is emphasized to frame the drastic role change that occurs when AI is added to the design process. The second chapter guides the reader through the same generic design process using the PD paradigm. The emphasis of this chapter is the use of computational tools (specifically, a parametric schema) to automate some aspects of human-driven design space exploration which were previously completed manually. The final chapter focuses on the paradigm shift from TD/PD to GD which was enabled by generative AI-based approaches for design space exploration.

Participants learned Backward Design: design-objective space co-evolution which is driven by the human defining the objective space and off-loading design space exploitation to AI. The curriculum's recurring emphasis is on how the role and design thinking of the human designer changes with the use of different methodologies (Forward vs. Backward Design) and tools (manual vs. parametric vs. generative).

5.1.4 Aladdin and Curriculum Activities

Participants completed CAD project-based learning activities at the end of most sections and in the Open-Ended Design Problem. Activities were developed and administered in Aladdin (Fig. 2) [45], an open-source, web-based computer-aided design (CAD) platform which allows users to design solar energy structures (e.g., houses, solar farms) using traditional, parametric, or generative AI-based methods (specifically, genetic algorithms) and evaluate their simulated real-world performance. Aladdin also enables researchers/educators to develop pre-set CAD models for project-based learning modules to give students. Additionally, a fine-grained sequential log of each user action is collected which allows researchers/educators to analyze student design process behavior.

The activities at the end of each section prompted participants to work through the concepts they had just learned in the context of solar farm design. The researchers developed a CAD template of a local solar farm for participants to redesign with solar panels in Aladdin; the identical template was used for each of the curriculum section CAD activities.

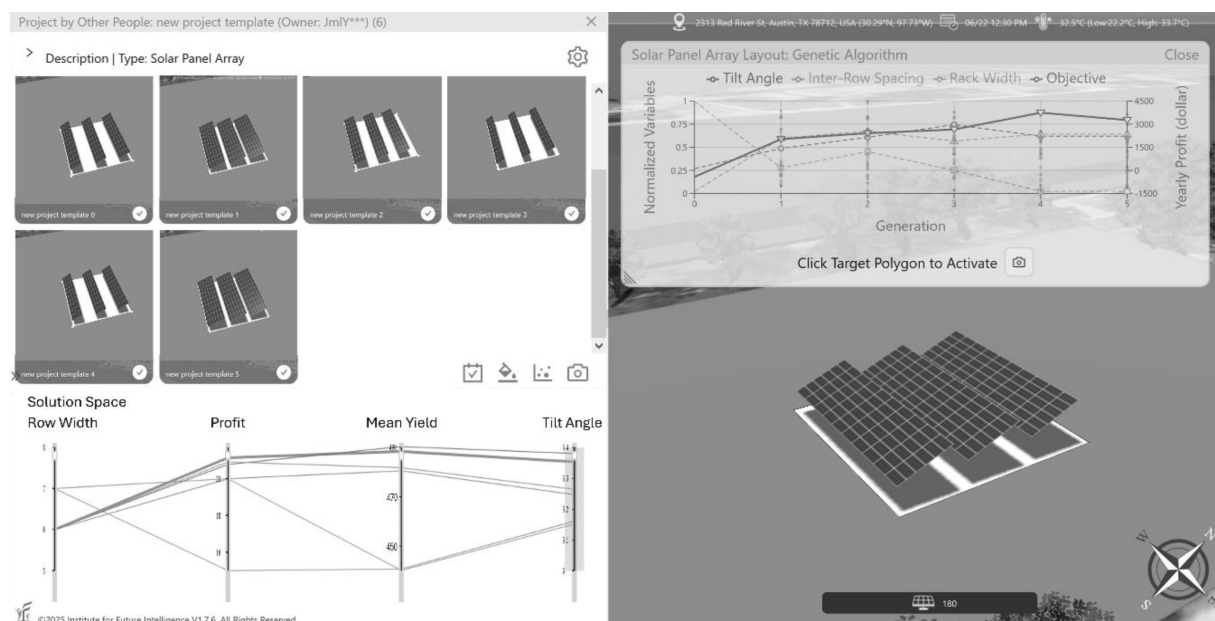


Fig. 2. Aladdin allows the user to compare the parameters and performance of multiple AI-generated designs in the Design Gallery.

The activities prompted participants to explore how solar panel widths, tilt angles, and row spacing affected solar farm annual profit and/or energy output.

Participants also completed the Open-Ended Design Problem (OEDP) at the end of the curriculum. The OEDP Project Statement instructed the reader to submit as many designs as they can for a “southwestern university,” which “has announced that they plan to develop a solarized parking lot on campus, and they have tasked you with proposing designs.” The researchers created a CAD model version of the campus parking lot for participants to design in (Fig. 2). Participants were allowed to use any of the three paradigms they had learned at their discretion when completing the OEDP. The activity was open-ended in that there were many acceptable solutions (i.e., there was no single “correct” answer [6, 46]), of which participants were told to submit as many designs as they wanted while optimizing two objectives: annual energy output and annual profit (each calculated by Aladdin’s simulation features). Though participants were not required to formulate their own problem statement, the activity was also open-ended in that it did not specify how they should explore the design space to achieve the two objectives.

5.2 Measures: Engineering Design Self-Efficacy

The Engineering Design Self-Efficacy Scale [16] was used to assess participant self-concepts of their overall self-efficacy for engineering design. On a 0 to 100 Likert scale (in intervals of 10), participants were asked to self-rate four concepts: their *confidence*,

motivation, *perceived success*, and *anxiety*. For each of the four concepts, the participant rated the same set of descriptions for nine general engineering design tasks: *conduct engineering design*; *identify a design need*; *research a design need*; *develop design solutions*; *select the best possible design*; *construct a prototype*; *evaluate and test a design*; *communicate a design*; and *redesign*.

5.3 Study 1 Pre-/Post-Test Survey Results

A total of 5 participants completed both the pre- and post-test Engineering Design Self-Efficacy Scale [16] to rate their *confidence*, *motivation*, *perceived success*, and *anxiety* for nine engineering design tasks. Changes in self-efficacy were calculated by subtracting their pre-test response from their post-test response to each Likert scale question. Our hypotheses were tentatively confirmed as participants on average showed increases in their *confidence* (24.66), *motivation* (10.44), and *perceived success* (10.44) across all nine tasks, and also showed an average decrease in *anxiety* (–16.22) for all tasks. See Fig. 3 for the average pre- to post-test changes for the four categories, and Fig. 4 for the average pre- to post-test changes for each task; averages for each can be found in Table 2. Changes for each participant for each task in each sub-construct and the average changes for each participant for each task and each sub-construct are in Table 3. *Confidence* in design tasks showed the largest change of the four concepts, with participants reporting the highest average changes in *evaluate and test a design*, *communicate a design*, *develop design solutions*, and *redesign* tasks. *Anxiety*

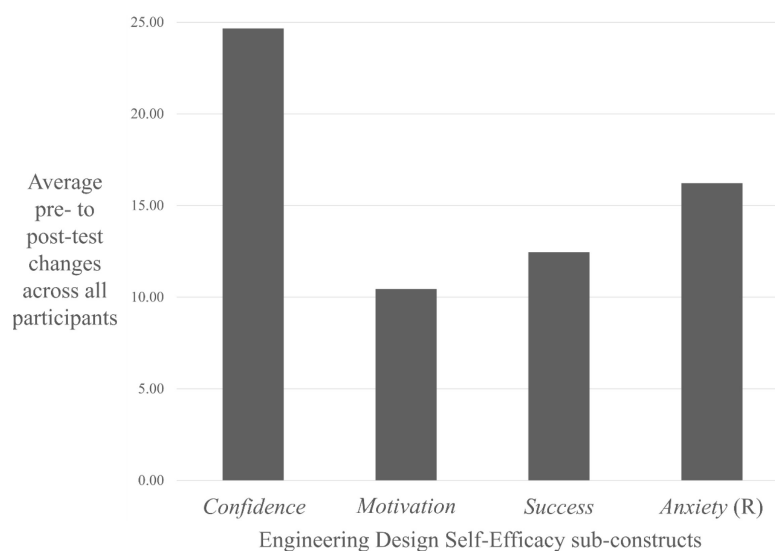


Fig. 3. Average changes in responses to the pre- and post-test Engineering Design Self-Efficacy Scale [16] across four sub-constructs: *Confidence*, *Motivation*, *Perceived Success*, and *Anxiety*. Note: pre- to post-test changes in *Anxiety* are reported as absolute values; R = reverse scored.

Table 2. Average pre- to post-changes across all participants for each sub-construct and for each task. M* = mean calculated with the absolute value for changes in *Anxiety*. Tasks from [16] are labeled as follows: 1 = Conduct engineering design; 2 = Identify a design need; 3 = Research a design need; 4 = Develop design solutions; 5 = Select the best possible design; 6 = Construct a prototype; 7 = Evaluate and test a design; 8 = Communicate a design; 9 = Redesign

EDSE Sub-construct	1	2	3	4	5	6	7	8	9	All (M)
Confidence	26	18	18	28	20	24	30	30	28	24.67
Motivation	14	2	8	14	2	20	14	16	4	10.44
Success	18	8	6	2	12	20	16	18	12	12.44
Anxiety	-18	-10	-2	-26	-12	-28	-16	-24	-10	-16.22
All (M*)	19	9.5	8.5	17.5	11.5	23	19	22	13.5	—

Table 3. Pre- to post-test changes for each participant in each of the nine engineering design tasks in all four sub-constructs from the Engineering Design Self-Efficacy Scale [16]. M* = mean calculated with the absolute value for changes in *Anxiety*. Tasks from [16] are labeled as follows: 1 = Conduct engineering design; 2 = Identify a design need; 3 = Research a design need; 4 = Develop design solutions; 5 = Select the best possible design; 6 = Construct a prototype; 7 = Evaluate and test a design; 8 = Communicate a design; 9 = Redesign

Participant #: EDSE Sub-construct	1	2	3	4	5	6	7	8	9	All (M)
1: <i>Confidence</i>	20	-10	50	40	30	10	20	60	30	27.78
1: <i>Motivation</i>	40	30	40	50	10	50	-10	60	0	30.00
1: <i>Success</i>	0	-10	20	20	30	20	10	60	20	18.89
1: <i>Anxiety</i>	-10	0	-30	-50	0	-30	-10	-50	10	-18.89
1: All (M*)	17.5	2.5	35	40	17.5	27.5	7.5	57.5	10	—
2: <i>Confidence</i>	10	20	0	10	20	20	10	10	10	12.22
2: <i>Motivation</i>	0	-10	-10	-10	0	-10	10	0	-10	-4.44
2: <i>Success</i>	30	20	10	10	20	30	10	10	0	15.56
2: <i>Anxiety</i>	-20	-20	10	-20	-60	-40	10	-20	0	-17.78
2: All (M*)	15	12.5	-2.5	7.5	25	20	5	10	0	—
3: <i>Confidence</i>	60	50	30	60	40	40	40	60	60	48.89
3: <i>Motivation</i>	0	0	-10	-10	-20	0	0	10	0	-3.33
3: <i>Success</i>	0	-10	-10	0	-20	-10	-10	0	0	-6.67
3: <i>Anxiety</i>	10	0	20	10	10	0	0	0	10	6.67
3: All (M*)	12.5	10	-2.5	10	-2.5	7.5	7.5	17.5	12.5	—
4: <i>Confidence</i>	20	20	10	10	0	20	40	0	20	15.56
4: <i>Motivation</i>	30	0	20	40	0	20	20	0	30	17.78
4: <i>Success</i>	30	20	0	0	20	30	40	10	30	20.00
4: <i>Anxiety</i>	-20	0	-10	-40	0	-50	-40	-20	-20	-22.22
4: All (M*)	25	10	10	22.5	5	30	35	7.5	25	—
5: <i>Confidence</i>	20	10	0	20	10	30	40	20	20	18.89
5: <i>Motivation</i>	0	-10	0	0	20	40	50	10	0	12.22
5: <i>Success</i>	30	20	10	-20	10	30	30	10	10	14.44
5: <i>Anxiety</i>	-50	-30	0	-30	-10	-20	-40	-30	-50	-28.89
5: All (M*)	25	12.5	2.5	7.5	12.5	30	40	17.5	20	—

for completing the design tasks showed the second largest average change of the four concepts. Four of the five participants reported an average decrease in anxiety with the fifth reporting only minor increases.

5.4 Study 1 Discussion and Limitations

We found encouraging trends in the changes of participant's engineering design self-efficacy after completing the curriculum materials. As our hypotheses predicted, average changes for each design task in all three positive concepts (*confidence*, *motivation*, and *perceived success*) increased,

while average changes for each design task in the negative concept (*anxiety*) decreased. Results suggest that reading the curriculum, completing the activities, and watching the lectures developed by the authors had a desirable effect on engineering design self-efficacy (as measured by [16]). Bandura's sources of self-efficacy [15, 18] suggest that providing mastery experiences via the curriculum may have driven the positive trends in pre- to post-test changes.

Results should be interpreted in relation to the low number of participants, which was a major limitation of Study 1. A total of 63 participants

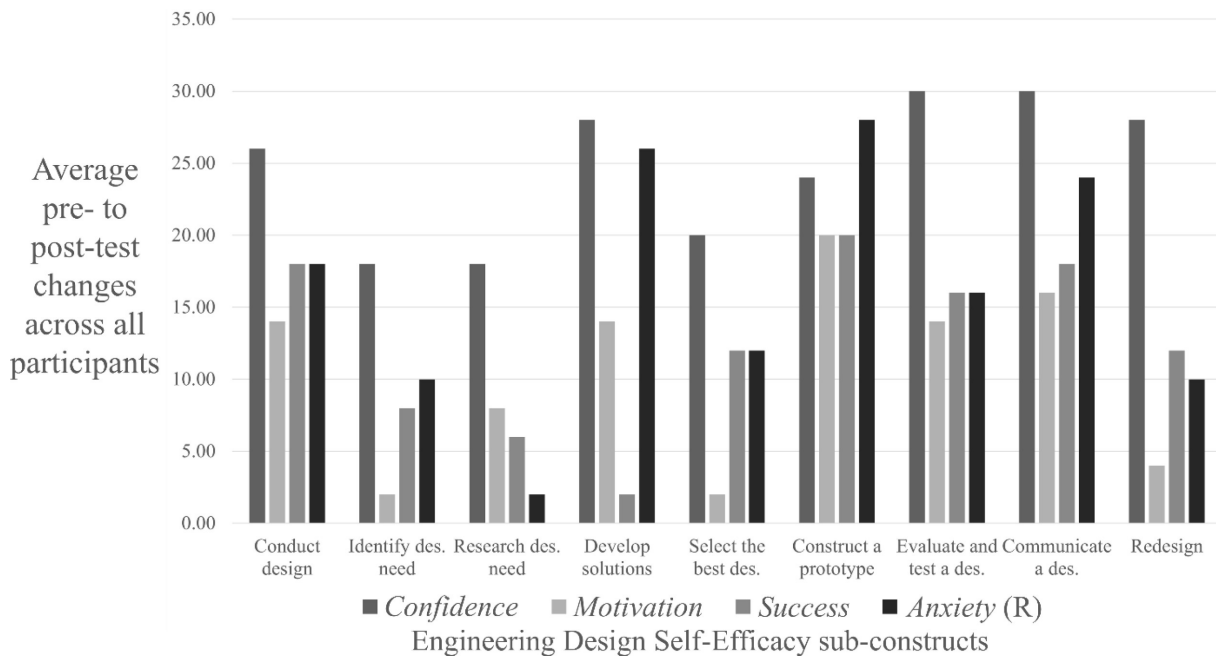


Fig. 4. Average changes in responses to the pre- and post-test Engineering Design Self-Efficacy Scale [16] for nine engineering design tasks across four sub-constructs: *Confidence*, *Motivation*, *Perceived Success*, and *Anxiety*. Note: pre- to post-test changes in *Anxiety* are reported as absolute values; R = reverse scored.

either began the study or signed up to participate, but only 5 completed the full study. We believe the high attrition rate was due to the length of the study (around five hours) and because participants completed the curriculum materials without researcher guidance. We chose not to conduct repeated measures ANOVA due to the low number of participants. We plan to pursue class implementation of our curriculum to address low participation and allow for more in-depth statistical analysis.

6. Study/Curricula 2: Teaching Freshman Generative Design Thinking

This section contains a description of a lecture on Generative Design Thinking and accompanying topology optimization-based design activity, an in-class bridge design activity, and an overview of the human-subjects data collected with these materials. Section 6.1 describes study procedure (6.1.1), participant demographics (6.1.2), the in-class lecture and activity given to participants (6.1.3), and the bridge design task that was used to gauge student comprehension of these materials (6.1.4). Sections 6.2 and 6.3 report and discuss the results of the study and address limitations.

6.1 Methods

6.1.1 Experimental Design and Procedure

Study 2 used a repeated measures (within-subjects) design to examine changes in performance of artifacts submitted to an in-class design activity after

(vs. before) participants heard a lecture on Generative Design Thinking and completed a topology optimization-based design activity. Our hypothesis was that the performance of artifacts designed by students would increase after hearing the lecture and completing the activity. Participants began the study by applying Forward Design principles in TD which were taught earlier in the semester to manually design and 3D print bridges for a class assignment (Section 5.1.4). This initial design served as a control to identify improvements attributable to the intervention. Participants then listened to a lecture on Generative Design Thinking and completed an in-class design activity (Section 5.1.3). The lecture and activity both occurred on the same day less than a week after the completion of the initial bridge design. Participants were then given one week to redesign their solutions to an identical problem statement while applying concepts they learned in the lecture/activity, and 3D print the new solutions. 3D printing the new designs was optional for the participants due to course time constraints. Original and redesigned bridges were evaluated via applying an increasing load until failure to compare solutions designed before vs. after the lecture/activity.

6.1.2 Participants

A total of 82 participants from a primarily undergraduate institution completed both the initial and final surveys and consented to the use of their survey data. The sample comprised 76 male and 6

female participants. Participants self-identified their engineering majors as follows: mechanical engineering ($n = 48$), electrical engineering ($n = 17$), computer engineering ($n = 3$), mechatronics ($n = 6$), and other or undecided ($n = 8$). All students above age 18 in the first-year, first-semester design course taught by the researcher were eligible to participate and receive extra credit for completing the study.

6.1.3 Generative Design Thinking Lecture and Shelf Bracket Design Activity

The goal of the lecture on Generative Design Thinking was to teach participants the iterative process of design-objective space co-evolution driven by the human focusing on the objective space but while using topology optimization (TO; a computational method to determine the optimal geometric layout of a structure via finite element analysis techniques [47–48]) instead of generative AI tools. This approach is similar to Backward Design as taught in the EDGE curriculum (Section 5) but differs in that Backward Design using GD in Aladdin fully automates design space exploration, while objective-driven design using TO in Onshape still requires the human to manually remove material from the CAD model after running the stress analysis function. Teaching the mechanics of using GD tools was out of the scope of the course's learning objectives as the participants were first-semester freshmen studying the basics of CAD and the engineering design process. Thus, an emphasis on GD thinking over GD tools was chosen to prepare students to apply formal Backward Design methods later in their academic or professional careers by improving their understanding of the design space and offering experience with computational-based objective-driven design processes over traditional, manual methods.

After the lecture, participants undertook an in-class CAD activity intended to lay the foundation

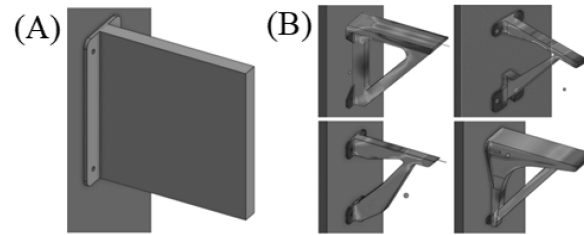


Fig. 5. Shelf bracket before (A) and after (B) participants used topology optimization to examine stresses and remove unnecessary material.

for them to eventually use a Backward Design process. The goal of the activity was to modify a shelf bracket (Fig. 5) by iteratively evaluating bracket stresses and removing unneeded material using the material simulation tool in Onshape. Participants were told to repeat the process until they felt they had minimized the bracket's material without exceeding the yield strength of the material and without removing a functionally required component (e.g., flat top, wall mounts). They were not required to upload their final designs or number of iterations, but the instructors observed that participants usually iterated between 1 to 3 times.

6.1.4 Bridge Design and Redesign Activity

Participants completed an in-class activity as part of their course to design a bridge. Each participant was prompted to individually design their own bridge in Onshape which satisfied all functional and manufacturing requirements in the problem statement (Table 4). They were then paired with another participant and asked to combine the elements of the individually designed bridges into one final design for their group which was 3D printed and evaluated.

After hearing the lecture on Generative Design Thinking and completing the topology optimization-based design activity, participants received the identical problem statement and were asked to

Table 4. Requirements for bridge designs and redesigns

No.	Requirement Description
1	A marble had to easily roll from the top surface of one side of a test fixture, across the bridge, and onto the top surface of the other side of the test fixture. The test fixture has a 10.5-inch-wide gap.
2	The bridge surface where the marble would roll had to be flat and flush with the top of the test fixture all the way across the bridge.
3	The bridge had to include a method for preventing the marble from falling off.
4	All bridge pieces had to be identical.
5	A single bridge piece could not span more than 6 inches.
6	No more than 8 bridge pieces were allowed per bridge.
7	All parts had to be 3D printed from PLA filament.
8	Each bridge piece had to have a mass of less than 30 grams (after removing support added during the printing process).
9	At no time could the bridge touch the bottom surface of the test fixture between the two ends of the gap.

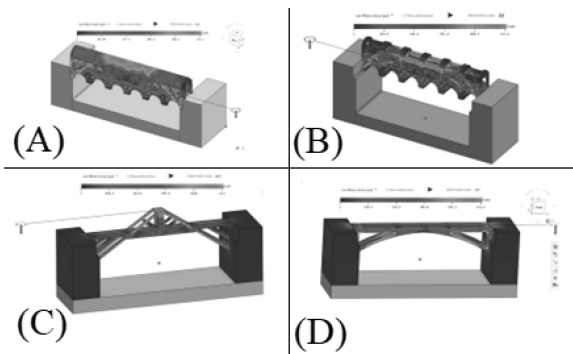


Fig. 6. Example bridge designs before (A, C) and after (B, D) participants learned and applied GD thinking concepts to redesign their bridges. Each row in the image shows a different group's bridge designs.

redesign the bridge they had designed previously (Fig. 6). Specifically, they were prompted to apply objective-driven design as learned in the lecture/activity. Bridge redesigns had to meet the same set of requirements in Table 4, though participants were not required to 3D print their redesigned bridges due to course time limitations. However, 22 groups chose to receive extra credit for 3D printing and evaluating their redesigned bridge.

6.2 Study 2 Results

The original and redesigned bridges were tested on consecutive class days. Participants who did not complete either the pre-test or the post-test were removed from the dataset. The original bridges were designed before participants heard the lecture on Generative Design Thinking and completed the corresponding topology optimization-based design activity, and the redesigned bridges were completed after the lecture/activity. Bridges were placed on the test fixture (Fig. 7, A) and a hydraulic press applied a load to the center of the bridge until the bridge failed. The maximum force before failure was recorded along with the mass of the bridge. The

maximum load was divided by the mass and the resulting value was used to compare each group's original bridge to their redesigned bridge.

Of the 22 groups that tested both their original and redesigned bridges, 15 (68%) of the redesigned bridges had a higher strength-to-mass ratio. Of the teams whose redesigned bridges performed better, the average improvement was 141%. The redesigned bridges ($M = 6.93$, $SD = 5.96$) showed a significantly better strength-to-mass ratio than the original bridge designs ($M = 5.61$, $SD = 5.31$), $t(21) = 2.07$, $p = 0.05$. 3 of the groups had an improved strength-to-mass ratio of over 500% and were considered outliers. These large increases were due to their very low performance ratio for the initial bridge design (each in the bottom 5 of the sample). Overall, our hypothesis that bridge performance would increase after the lecture/activity was confirmed.

6.3 Study 2 Discussion and Limitations

Study 2 found improvements in the average participant bridge design performance (strength-to-mass ratio) following the lecture/activity vs. before. These results suggest that the intervention had a positive effect on student learning, given that students solved an identical problem statement and had access to the same functions in Onshape before vs. after the lecture/activity. The lecture introduced students to two key operational principles of GD tools: (1) their iterative nature, and (2) their use of stress simulation to inform and guide exploration within the design space. Results suggest that emphasizing these principles is a valuable pedagogical strategy for fostering student comprehension and engagement with black-box GD tools.

All participants in Study 2 were first-year, first-semester freshmen taking an entry-level engineering design course. Due to their lack of design experience, the lecture's emphasis on GD concepts may

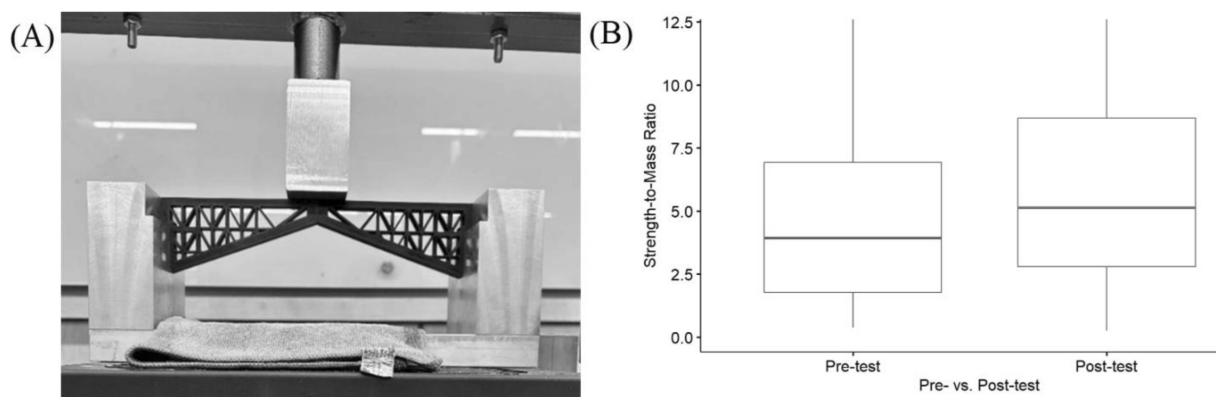


Fig. 7. (A) A 3D printed redesigned bridge on the test fixture prior to testing. (B) Average scores and confidence intervals for the pre- vs. post-test bridge design strength-to-mass ratio performance.

not have been the main contributor to performance on the bridge design task. Future studies should consider comparing student learning improvements after a GD lecture/activity to a “control” lecture which introduces human-driven engineering design without the use of AI. Similarly, student improvements may be attributed to gaining valuable experience in both engineering design and CAD, instead of specifically related to practicing design with topology optimization. Finally, participant improvements may be partially attributed to the *retest effect* (or, *practice effect*) phenomenon in which performance typically improves when a participant is asked to solve a problem a second time [49].

7. Conclusion

The goals of the present study were to share two sets of educational materials to teach Generative Design (GD), the new method for engineering design enabled by generative AI algorithms which automate design space exploration and shift the role of the human during the design process, and report the effectiveness of the curricula for enhancing student engineering design self-efficacy (EDSE; Study 1) and performance on an in-class team design prompt (Study 2). Study 1 found general trends of improvement in student EDSE after completing a curriculum with project-based learning CAD modules to teach both human-driven Traditional and Parametric Design, and AI-driven GD. Study 2 showed that the average performance (3D printed bridge strength-to-mass ratio) of artifacts designed by student teams significantly improved after (vs. before) hearing a lecture on GD and completing a topology optimization-based CAD PBL module.

Overall, these results suggest that teaching GD to undergraduate students may still enhance their EDSE (via building mastery experiences and inducing the associate physiological states) and perfor-

mance on future design activities despite the automation of previously human-driven tasks being outsourced to an AI agent. Given the trend of professional engineering design practices towards higher reliance on AI-driven, automated design exploration methodologies [4], the findings of our study imply that design faculty should embrace teaching GD to build student experience with applying generative AI in engineering design. Study 1 suggests that teaching GD may enhance, and likely does not decrease, EDSE, a crucial learning outcome in design education [7, 16, 17, 35–37], and Study 2 suggests that GD knowledge and experience aids student teams in developing higher performing design solutions. Educators may use the open-access curriculum materials displayed in the current study to inspire the development of additional GD educational content and to teach/build student mastery experiences in AI-driven GD. GD may be executed by different algorithms, and the present paper demonstrates curricula for teaching two different techniques: genetic algorithms in Study 1, and topology optimization (TO) in Study 2. Design faculty should consider which GD techniques they wish to teach students based on the design context, e.g., the design process stage. For example, genetic algorithms and other techniques like are more suitable for early-stage ideation and design concept generation, TO is best suited for optimization of design parameters, e.g., weight or stress. Future studies may build on our investigations by introducing additional experimental groups to delimit the contribution of learning/practicing human-driven vs. AI-driven on EDSE, and also consider using different design prompts to measure pre-to-post-test changes in design performance following an intervention.

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