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Human-Centered Generative Design Framework: An Early Design Framework to Support Concept Creation and Evaluation

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ABSTRACT

Generative design uses artificial intelligence-driven algorithms to create and optimize concept variants that meet or exceed performance requirements beyond what is currently possible using the traditional design process. However, current generative design tools lack the integration of human factors, which diminishes the efforts to understand and inject a broad set of human capabilities, limitations, and potential emotional responses for future human-centered product and service innovation. This paper demonstrates collaborative research in formulating a human-centered generative design framework that injects human factors early in the design for quick-and-dirty concept creation and evaluation. Three case studies overviewing our ongoing multidisciplinary research efforts in synthesizing human and mechanical attributes are presented. The results show that the framework has the potential to enhance human factors representation within generative design workflow. Strategies from a computational design perspective, such as data-driven generative design, digital human modeling, and mixed-reality validation, are discussed as alternative approaches that could be implemented to augment designers.

1. Introduction

Design philosophies such as *design thinking* and *emphatic design* have long provided general guidelines and best practices that helped designers develop products that meet users' needs (Brown, 2008). However, they fall short in providing essential design methodologies, tools, and techniques that can be part of the computational and data-driven human-centered design process (Laursen & Haase, 2019). Moreover, the advancements in production technologies (e.g., additive manufacturing), growing ecological constraints (e.g., sustainability), globally diversified customers (e.g., elderly), and rapid changes in design practices (e.g., responsible design) mandate more robust early design methods that enable designers to explore design space systematically.

With the emergence of data-driven research and analysis, computational design methods supporting design decision making and trade-offs have gained significant interest in engineering design, especially in generating and evaluating early design concepts. The computational design represents a broad category of algorithmic problem-solving strategies that assist designers in solving design problems using advanced computer processing. For example, generative design (GD), an artificial intelligence (AI) driven iterative computational design method, brings groundbreaking capabilities to design teams in exploring the design space (Lant, 2017).

Generative design platforms (software tools and a family of computational design toolkits) use AI-driven algorithms to create and optimize concept variants that meet or exceed performance requirements beyond what is currently possible using the traditional design process (Li, Demirel, et al., 2021). In traditional design, a group of designers meticulously work on trade-offs between performance parameters and user needs (McKnight, 2017). An increase in the number of design parameters constrains designers in generating and evaluating the best options. Designing with the GD approach brings the advancement of AI techniques in exploring thousands of design variants quickly and effectively, which is unattainable using the traditional design approach (Singh & Gu, 2012).

In contrast to other computational design methods (e.g., direct modeling), in the context of early design, GD provides the benefit of automating the concept creation, optimization, and evaluation, which augment human designers (Mountstephens & Teo, 2020). GD also enables designers to explore the expansive design space by concurrently evaluating performance requirements and identifying the best-performing concept variants much quicker than would otherwise be possible (Mountstephens & Teo, 2020; Singh & Gu, 2012). The added benefit of having an automatic and iterative design control also makes GD facilitate the reduction in time-to-market and the overall product development

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cost (Li & Lachmayer, 2019). Furthermore, with the advancements in digital design and fabrication technologies, the future GD platforms can help designers and customers (users and service recipients) to co-create product or service experience that suits their context. However, current GD tools lack the integration of human factors (Urquhart et al., 2022), which challenges the development of human-centered early design frameworks that enable learning, adapting, and making decisions directly or supporting decision-making. This shortcoming diminishes the efforts to understand and inject a broad set of human capabilities, limitations, and potential emotional responses for future human-centered product and service innovation. There is a need to develop GD frameworks that enable human input (both from human designers and customers) to work together with algorithms for a more effective design space exploration (Valdez et al., 2021).

The paper aims to summarize our ongoing research efforts in injecting human factors into GD workflow and encouraging designers to incorporate a broad set of human needs, capabilities, and limitations early in design. The human-centered GD framework presented in this paper is concerned with product design and development, mainly focusing on designing physical systems (e.g., transportation design, consumer goods) from mechanical engineering and human factors engineering domain knowledge perspectives. Generative design can also be used in software systems development; however, software systems design is outside the scope of this research. Our efforts in injecting human factors into GD workflow are represented via three case studies, framed around the *generative design thinking* (GDT) paradigm—a new form of design thinking enhanced by computational thinking (Li, Demirel, et al., 2021). Section 3 provides the conceptual framework, and Section 4 demonstrates our ongoing multi-disciplinary research contribution, split into three case studies: (1) Data Driven Generative Design Methods to Capture Customer Input (see Section 4.1) (2) Generative Design for Proactive Human Factors (see Section 4.2), and (3) Developing Generative Design Thinking Curriculum Modules (see Section 4.3). These case studies depict our ongoing efforts to integrate computational human factors engineering (HFE) and AI-based methods that support early design decision-making for human-centered product design.

2. Background

2.1. Generative design

Generative design (GD) is a transformative genre of design technology inspired by biological evolution (McCormack et al., 2004). Once the design criteria and constraints of a product are specified, a GD software program starts an evolutionary computation process that efficiently explores the entire parameter space supported by the software to find optimal solutions. During the iterative search for feasible solutions, the software automatically constructs a vast number of forms at each step, tests their functions using numerical simulations, evaluates their quality based on the given criteria and constraints, and then selects those that are closer to the goal for the next step (McKnight, 2017). By repeating these computational routines many times, a variety of designs that meet the goal eventually emerge. Engineers then review these outputs, often with the aid of interactive visual analytics for intuitive appraisal and comparison across the board (van Kastel, 2018), and choose one or more designs for prototyping. As leading computer-aided engineering (CAE) software companies such as Autodesk and PTC launched GD software (Keane, 2018; PTC, 2018) and industries embraced the technologies (Heaven, 2018), the year 2018 has heralded a new era of engineering.

Generative design emerged as one of the most prominent computational design methodologies that use an iterative approach within a software program to generate outputs that meet certain constraints. A designer can fine-tune the feasible region with the help of the GD software by selecting or changing input values (or ranges) and their distribution. The GD software uses mechanical, materials, manufacturing, spatial, and cost-related constraints to generate more optimized designs.

Although current GD applications have paved the way for products with improved mechanical performance (e.g., reducing product weight and improving fuel cost in transportation design), they lack the ability to consider human attributes as input parameters. Thus, the current GD-based design exploration efforts provide only a unilateral solution, which isolates the human-centered inputs and constraints being part of design space exploration. There is only a very limited number of studies focused on human factors within generative design context (Urquhart et al., 2022). This discrepancy forces designers to evaluate human aspects of the product design towards the later stages of product development; thus, increasing the likelihood of product retrofit, which escalates the cost and time to market. With the recent paradigm shift towards a universal GD design approach, future human-centered design practices require synthesizing human and mechanical attributes. Therefore, there is a pressing need to inject human attributes into a GD platform early in design before physical prototypes are constructed.

2.2. Injecting human factors into product design

Human factors engineering (HFE) domain utilizes knowledge and expertise gained from sciences, engineering, management, and technology to solve problems relating to the interactions between humans and the other elements of a system (Vincent et al., 2014; Wilson, 2000). Human factors research involves building a knowledge base about human needs, abilities, and limitations, then providing design guidelines to create products, processes, and systems (Dul et al., 2012; Wilson, 2000) safe to operate and comfortable to use (McSweeney et al., 2009). HFE practices focus on design activities and are primarily associated with engineering and industrial design (Chapanis, 1995; Dekker & Nyce, 2004; Karwowski et al., 2011; Schaffrina, 1991), making HFE a scientific discipline and an applied profession. Within the design context, improving human well-being and quality of

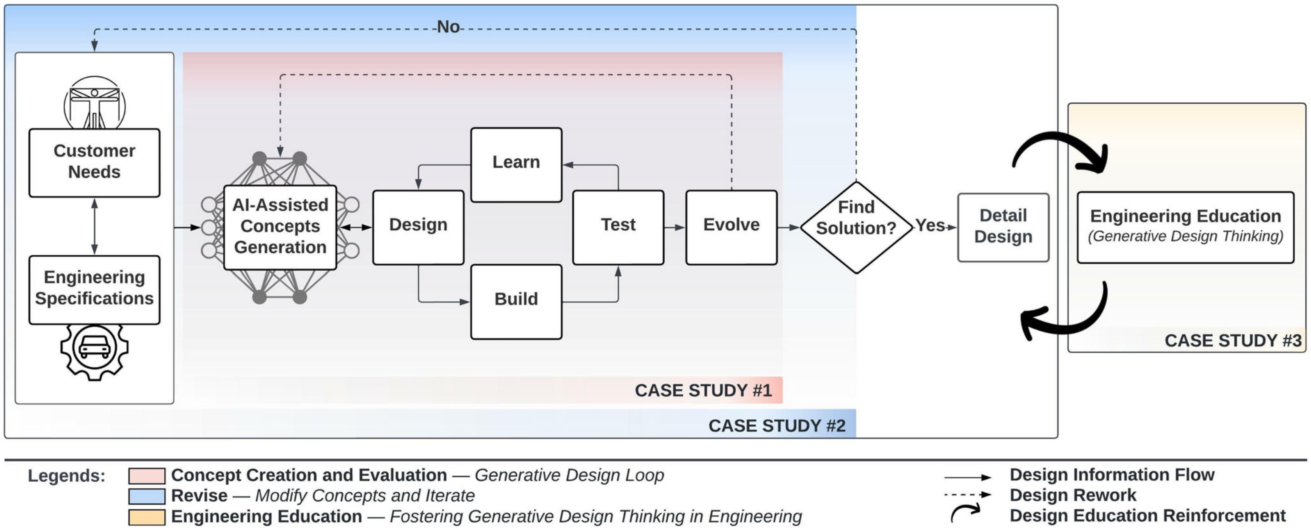


Figure 1. Illustration of the conceptual GD-based human-centered design framework. Case studies (Section 4) elaborate more on ongoing research efforts.

life is usually achieved by reducing hazards, discomfort, and fatigue while maximizing systems' utility, usability, and safety. Even with the utmost design emphasis, traditional HFE approaches focus on iterative refinement of physical prototypes towards the end of the design phase with actual human-subject experiments. HFE design guidelines are often applied as checklists, and human-product evaluations are executed manually.

While some computational HFE analysis methods provide valuable insights on some ergonomics issues (e.g., lifting index), they fail to pinpoint design deficiencies caused by human-product interactions because the design process is too far removed from the user. Typically, these assessments are a collection of reactive or corrective solutions which involve costly modifications to existing products. Recent advances in computational HFE, such as digital human modeling (DHM), provide tremendous opportunities to bring HFE design principles to be part of computational design and enable HFE experts to contribute earlier and directly to making modifications to products (Demirel et al., 2022). Integrating digital manikins with existing CAE platforms opens new frontiers for GD-based human-centered design research where human-product interactions can be modeled and evaluated systematically (Ahmed et al., 2021). However, only a very few HFE practitioners have the up-to-date skill set and expertise in GD-based engineering and system design methodologies. Therefore, there is a need for GD-based design methodologies within the HFE domain to support human-centered product innovation.

3. Methodology

Latent variables such as product appeal, comfort, and ease of use are some of the most critical attributes related to human factors of product design. Design thinking and emphatic design-driven practices have focused on gathering customer needs and addressing these attributes with iterative design. However, there is a lack of computational tools that assist designers in incorporating these attributes to concept creation and evaluation within GD context. The framework proposed (Figure 1) in this research injects human-related design attributes into product design synthesis via AI-assisted design approaches (e.g., generative design). This strategy promotes a proactive human-centered design that starts at the initial design phases with needs analysis and carries throughout the design process with keeping user needs and limitations in the loop.

The lack of seamless HFE-AI integration in early design causes a poor understanding of user needs and limitations, which leads to the partial representation of HFE in concept variants. Consequently, it also paves the way for ergonomics problems to be carried into concept variants. Therefore, engineers attempt to solve HFE-related issues reactively after the physical prototypes are built. In contrast to the conventional approaches described in Section 2, the framework discussed in this paper incorporates mechanical engineering and HFE design methods to generate early design ergonomics assessments proactively before high-fidelity physical prototypes are constructed. Overall, the intellectual merit lies in assessing human-product interactions in a computational setting with the help of AI by shifting the focus from safety and performance assessments conducted on full-scale physical prototypes to mixed prototypes with a human-in-the-loop approach.

The conceptual framework depicted in Figure 1 is based on the design-build-test-learn (DBTL) loop, which promotes (1) analog and digital processes of planning and modeling (Design), (2) physical, virtual and mixed prototyping (Build), (3) experimentation and simulation-based optimization (Test), and (4) applying automation and machine-learning (Learn) to predict better design solutions. In this four-step approach, designers use ubiquitous cyber-physical systems (hardware and software) to capture data (e.g., internet-of-things), generate concepts (e.g., sketch- and natural language-based ideation tools), model variants (e.g., functional decomposition), and evaluate assumptions (e.g., multi-physics simulation). Finally, the design infrastructure will bring engineering (e.g., form, fit, and function) and human behavior (physiological and psychological) parameters to be part of early design decision-making, enabling designers to learn from concept variants.

The conceptual GD-based human-centered design framework illustrated in Figure 1 aims to support the design of human-centered products by aiding designers in understanding a broad set of human needs, capabilities, and limitations. The theoretical contributions in our conceptual framework are split into three case studies, which provide a glance into fundamental design method development within the GDT context. Accordingly, the following section overviews our ongoing efforts in synthesizing human and mechanical design attributes within the GD context at a high level. Section 4.1 summarizes our current work in enabling designers to integrate measured (observable) or indirectly observable (latent) human data to support decision-making models that can aid product innovation and engineering. Section 4.2 demonstrates how the DBTL approach discussed in Section 3 assists designers in conceptualizing products that improve human performance. Along with that, our ongoing efforts also focus on educating future engineers in GDT-related curriculum development. Section 4.3 presents some of our recent efforts in engineering education research that improves GD competency.

4. Case studies

4.1. Data driven generative design methods to capture customer input

Besides the measurable engineering functionalities of a product, indirectly observable (latent) attributes such as customers' subjective preferences and perceptions heavily influence purchasing decisions (Poirson et al., 2007). For example, the shape of an automobile explains 70% of the variance in customers' purchase intent (Cheutet, 2007). Accordingly, to develop engineered products that could appeal to customers, objective requirements (such as functionality, cost, and structural integrity) and subjective requirements (such as product shape) must be considered early in design (Ulrich, 2003). Furthermore, during the conceptual design stage, product shape is usually a key consideration and is closely related to the aesthetics and engineering performance of the product (Mountstephens & Teo, 2020; Ulrich, 2003). In the past, deep generative models (e.g., variational autoencoders (VAEs) (Kingma & Welling, 2013) and generative adversarial networks (GANs) (Goodfellow et al., 2014) have been used in developing data-driven GD methods, which promote design creativity and increase the efficiency of concept generation of product shapes (Regenwetter et al., 2022). Although the emulative learning behavior of data-driven GD methods ensures that the designs generated are realistic and similar to existing design data, these methods could hinder designers in generating creative concept variants due to the lack of HFE consideration (Elgammal et al., 2017). To encourage design creativity and inject human attributes into concept creation via the data-driven GD process, we aim to explicitly take human factors into account during the design process. Our research in this area focuses on strategies to integrate HFE design principles and intelligence in a data-driven GD process.

For example, one of our current studies focuses on concept sketching. The sketches developed early in design could trigger creative ideas for exploring emerging design concepts (Pratt et al., 2005), which could be a promising way to allow human input in the design process. In automobile design, for example, silhouette contour lines are often used as sketches to support the conceptual design of vehicle body frames (Cluzel et al., 2012; Gunpinar et al., 2019; Reid et al., 2010). Different users (e.g., novice or expert sketchers) have diverse sketching skill levels, and the resulting sketches' quality could vary significantly. Our current research explores GD-based tools for standardizing the 2D sketch input to ease the burden of developing professional sketching skills. This approach also assists novice designers in examining design concepts with the aid of computer tools. Gunpinar et al. (2019) propose to use nine characteristic lines (e.g., front bumper, grille, rear windshield, and trunk) to represent the silhouette of a car. Bézier curves (Bézier, 1968) can be used to mathematically represent these lines with predefined control points (e.g., three control points for quadratic curves and four points for cubic curves). With such a system, users can create a diverse set of silhouettes by adjusting the control points of each characteristic line. In this work, we integrate the technique from Gunpinar et al. (2019) into our GD framework. This approach enables designers to create 3D mesh shapes using a novel target-embedding variational autoencoder (Li, Xie, et al., 2022). Our framework can take human input as 2D silhouette sketches and output authentic[1] 3D mesh shapes. The GD-based concept creation approach introduces how one can collect 2D automobile silhouette sketches from designers and auto-populate 3D vehicle designs that are authentic.

In developing the user interface that enables the above GD-based vehicle design, it was essential to identify the boundary within which users can adjust the control points of their desired curves and silhouette sketches. To obtain a reasonable boundary limit for each characteristic line, authentic automobile models were used as references. We randomly sampled 20 models from a set of automobile models (Umetani, 2017) and obtained the contour points using the method introduced in our previous work (Li, Xie, et al., 2022). The top portion of Figure 2 shows the contour points of the 20 car models sampled. Starting and ending point of each line were manually identified. The smallest right triangle that can enclose one characteristic line was created by identifying its two legs (e.g., H_1 and H_2 in the lower image of Figure 2). After getting the data for all 20 car models, we averaged the length of each leg to get the boundary limits. To promote more diverse sketches, we set a rectangle boundary for some lines based on the features of different lines (i.e., lines with more variations of shapes), as shown in the first row of Figure 3. Users can move around the control points within the corresponding boundary to input the silhouette sketch that best matches their preferences.

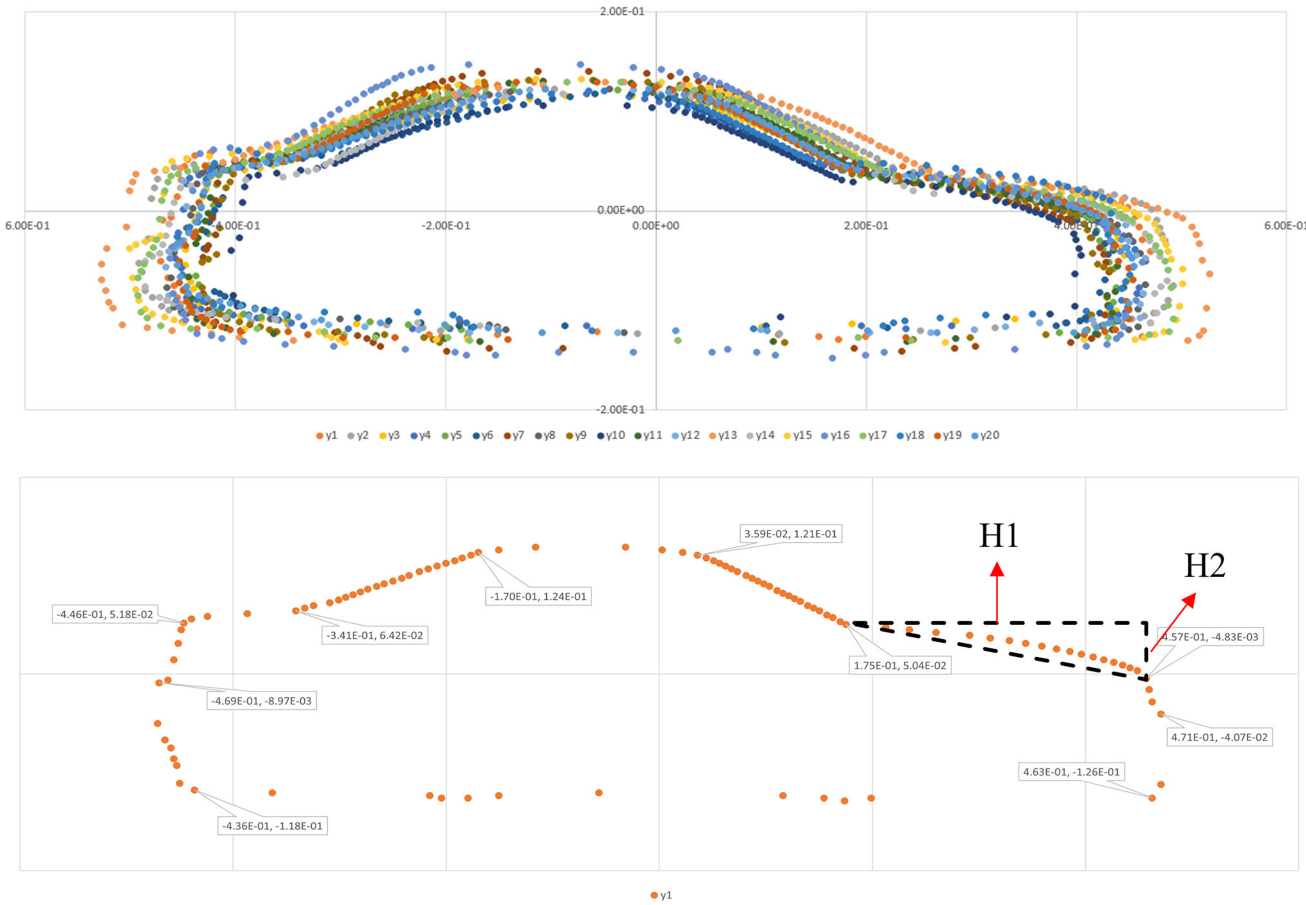


Figure 2. Contour points of the 20 sampled car models with an example to show how we obtain the boundary for control points of a characteristic curve.

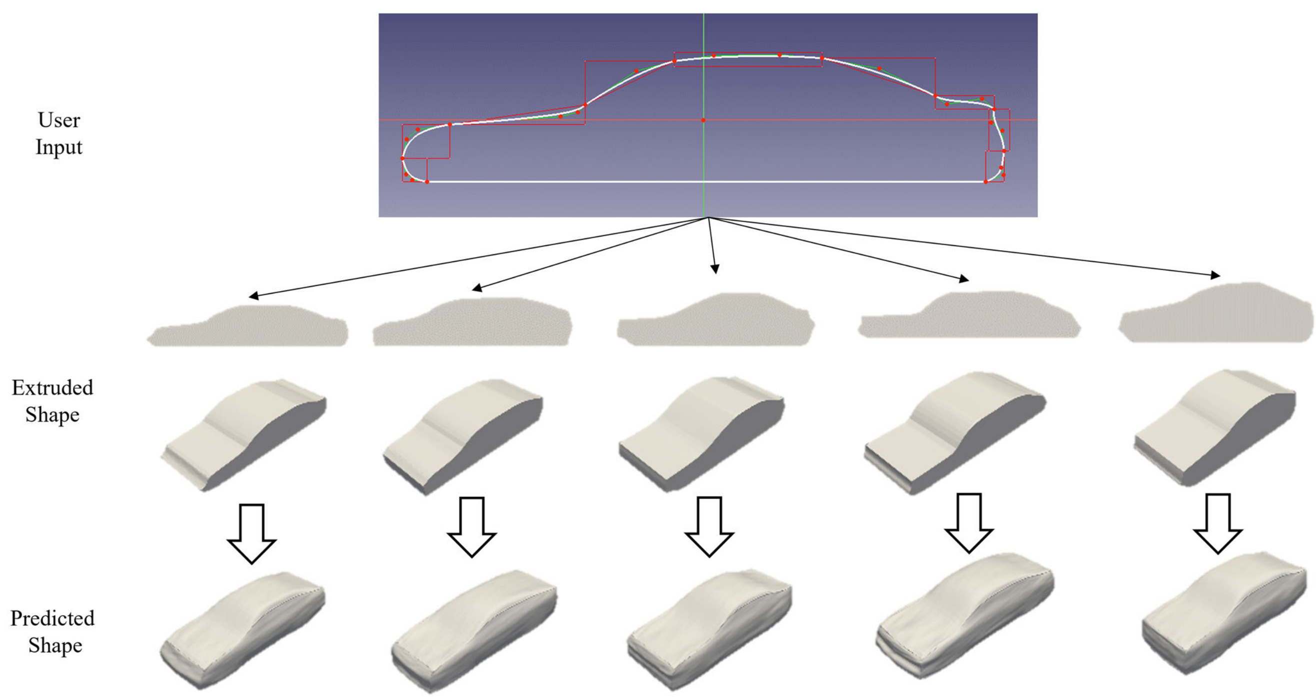


Figure 3. Prediction of 3D shapes from 2D sketches input from users.

4.2. Generative design for proactive human factors

Another area that our ongoing GD-based human-centered research projects concentrate on is human performance assessment during preliminary design. This research investigates methods to quantify obstruction zones caused by automotive A-pillars. Pillars are vertical structural elements found in modern cars, connecting the windshield and windows with the roof. Overall, pillars provide structural integrity (e.g., increasing roof-crush and frontal impact performance) and protection to occupants. The forward-most vertical support elements, A-pillars, have an essential design impact on the design language of the car, which impact aerodynamic performance. Although their presence is vital for performance and safety, the increased A-pillar thickness causes a reduction in drivers' forward field of view (FoV), which leads to unforeseeable accidents or mishaps (Srinivasan & Demirel, 2022). Figure 4 illustrates the blind spot formed by the A-pillar obstruction angle denoted A_α. Any increase in A-pillar cross section enlarges the forward blind spot zone defined by A_α, which hinders drivers' ability to detect traffic objects. We argue that providing a better pillar design that embodies a human-centered design approach by enhancing forward FoV could avoid such incidents.

In this research, we propose an early design approach that integrates GD and DHM to demonstrate a proof-of-concept study that quantifies A-pillar obstruction in realistic traffic scenarios. This research also aims to illustrate how the framework functions through a traffic simulation study, which compares concept pillar designs with cutout sections (see-through holes) to conventional pillar models (without see-through holes) in reducing the obstruction zones. The framework assesses whether the concept pillar variants improve the overall drivers' visibility of traffic objects that would otherwise be obscured behind current pillars.

One should note that we used parametric and non-parametric design approaches when creating cutout geometries for the concept pillars with see-through holes. The concept pillar models included circular, hexagonal, and triangular cutouts. These cutout geometries generated the see-through gaps by removing material from the pillar frame. The concept variants represented under the non-generative category were created using traditional CAD modeling without parametrization. For concept variants created via the GD approach, we parametrized each model, then ran many iterations with varying sizes and distributions using condensers and attractors to mimic a simplified GD modeling approach without the aid of AI. This process created a large pool of concept pillar variants. Then, we selected candidate pillar models that promoted better visibility and carried them into DHM analysis to quantify percent visibility obscuration. The parametric design process differs from the generative design. However, both are subsets of computational design, and the evolution of the theories and applications that fuel the GD development incorporates many elements from the PD approach. The significant difference is that PD does not necessarily involve AI-based algorithms to generate design alternatives automatically. Thus, the design space exploration still depends on human expertise and heuristics. One way to think is that PD is the manual and crude version of GD without AI-based algorithms. In this study, running PD is regarded as the first step towards a more sophisticated GD algorithm and incorporating optimization in the future.

Both pillar models (conventional and see-through) were implemented in a 3D vehicle representing a typical sport utility vehicle (SUV) (Figure 5). Next, we created a DHM simulation that replicated a typical in-city traffic scenario where a pedestrian crossing a two-lane road was hidden within the A-pillar obstruction zone (Figure 6). The simulation model used a 50^{th} percentile U.S. male manikin, representing the driver and pedestrian, based on the Anthropometric Survey of U.S. Army Personnel (ANSUR) database.

4.3. Developing generative design thinking curriculum modules

Design is essential for engineering education and practice (Crismond & Adams, 2012; Daly et al., 2012), but it is hard to learn and arguably harder to teach (Dym et al., 2005). Computer-aided design (CAD) is a standard design tool used in engineering practice and by students. While CAD is often taught in the undergraduate engineering curriculum, generative design is not. Generative design is an emerging technology that allows designers to iteratively explore design solutions with the aid of AI-driven software in a CAD

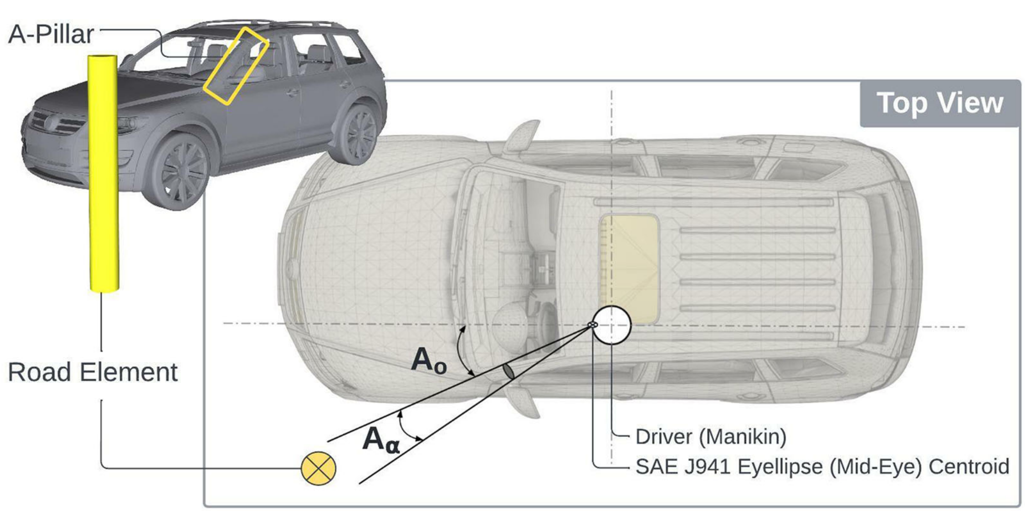


Figure 4. A road element (a generic post yellow in color) represents an object within the A-pillar blind spot defined by the obstruction angle (A_α).

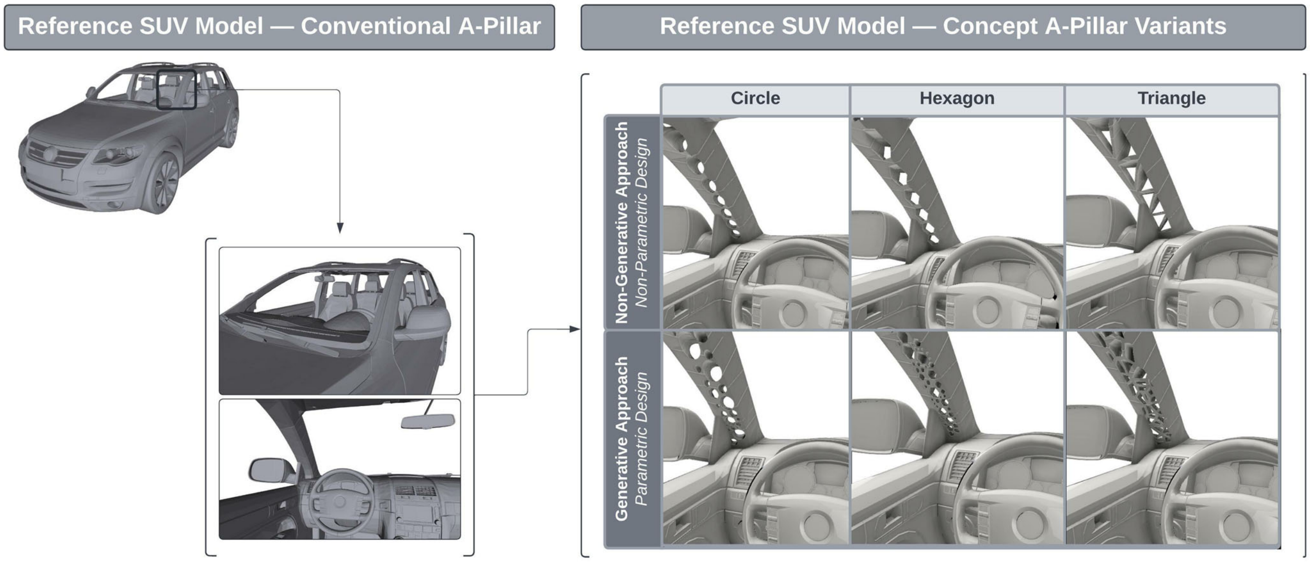
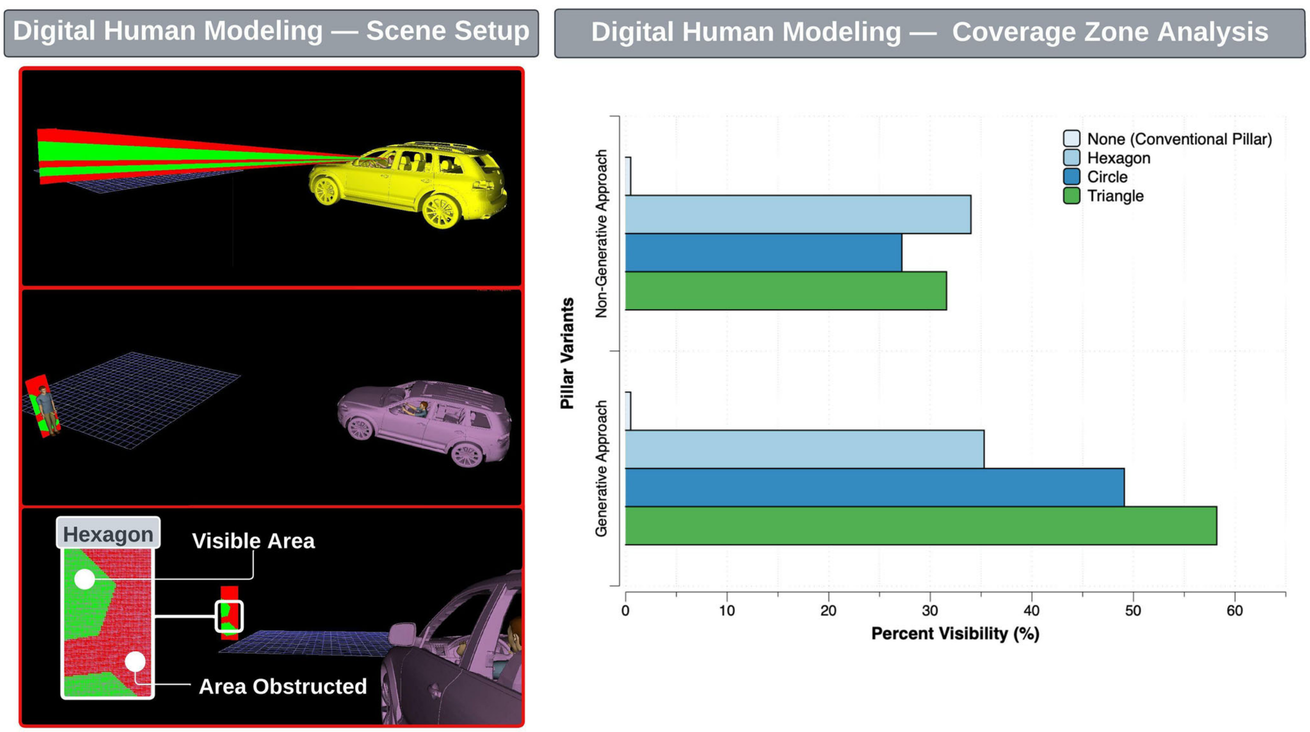


Figure 5. The figure illustrates the base SUV model and concept see-through A-pillar variants created by non-generative and generative design approaches.



(a) Ray casting analysis conducted to quantify percent obstruction

(b) Percent visibility differences between A-pillars concept variants with non-generative and generative design approach

Figure 6. The image illustrates simulation output based on the ray-casting method, which quantifies areas visible and obstructed due to A-pillar geometry.

platform (Chester, 2007). This paradigm shift in design methods entails a fundamental change of mindset for design thinking that must be addressed in the engineering education of the future workforce. By preparing students for this shift, our ongoing efforts in fostering GD-based design thinking will contribute to the core research on the Future of Work at the Human-Technology Frontier, one of NSF's 10 Big Ideas, from the field of engineering.

While current successes tout the promise of generative design in engineering design (e.g., Airbus, NASA) (Mountstephens & Teo, 2020), because it is such a recent technology, very little research has been conducted surrounding how students and designers learn to interact with it. Moreover, there is a lack of research on incorporating generative design techniques into traditional design thinking, particularly for undergraduate engineers. This case study describes a module-based approach that introduces undergraduate engineering students to generative design and describes our method to investing students' conceptions of generative design.

This study took place in an introductory design and graphics course at a large, land-grant university in the

Midwest United States that aims to introduce students to the design process, using the CAD platform, Fusion 360 (Goldstein et al., 2021). (The study was approved by The University of Illinois at Urbana-Champaign Office for the Protection of Research Subjects, Institutional Review Board (IRB) protocol # 21252.) As part of the course, students completed nine individual modules in order to learn Fusion 360. The final module, MA9, walked students running a generative design study within the Fusion 360 and asked them to approach an open-ended design scenario to understand students' design process. This required assignment included the submission of three short-answer prompts: In what scenarios would you use a generative design or shape optimization? Does manufacturability play a role in your decision? In addition, students had the option to complete an extra credit lab module in which they reviewed a set of generative design solutions and made their recommendation regarding which solution within the set was "best." In Part 1 of this extra credit assignment (MA10), students acted as design engineers working to create a lightweight bracket with which a consumer would mount a bicycle to a wall (Figure 7).

For both modules, a research assistant collected all student responses from the course learning platform, compiling them into one spreadsheet, with all responses numbered and anonymized. We took a qualitative approach to thematically analyze all student response to the open-ended prompts in the modules. MA9 responses were coded in three phases, first, to separate the responses by levels of understanding (low, moderate, and sophisticated), and then broken down further by design elements the students mentioned (Fusion 360 recommended, volume/mass, safety factor, appearance, cost, material, manufacturing process, Von-Mises stress, reproducibility/functionality, etc.). MA10 responses were coded using Sadler & Zeidler's informal reasoning framework (Sadler & Zeidler, 2005). This descriptive coding technique allowed us to categorize each student response as rationalistic, intuitive, emotive, or a combination of these categories.

5. Results

5.1. Data driven generative design methods to capture customer input

The research question in this study focused on whether a GD approach can predict authentic 3D shapes from 2D sketches input from users. To examine this question, we created a simple human-computer interface (introduced in Section 4.1) using FreeCAD 0.18 [2], which was used to collect human input of silhouette sketches. These sketches served as 2D profiles, which were used to create extruded car models of meshes. Figure 3 shows some of the extruded car models in side view and isometric view based on 2D silhouette sketches. After the 3D extrusions were created, our deep neural network-based predictive model (Li, Xie, et al., 2022) stepped in and generated authentic 3D shapes. The final row in Figure 3 shows a few examples of the predicted car models. It is observed that the predicted 3D shapes resemble the 2D sketches in terms of the side view, but provide finer geometric details in the third dimension, thus making the car shapes authentic. Since those 2D sketches are entered by users based on their preferences, the predicted 3D shapes will facilitate their ideation process. We expect that these 3D shapes will provide an additional outlet for users to help better understand their designs. In addition to the predictive function, the generative function of our deep neural network model (Li, Xie, et al., 2022) can further generate novel 3D shapes to inspire users with a variety of new design ideas. Since the entire process is automated, the efficiency of exploring 3D shape concepts can be greatly improved.

5.2. Generative design for proactive human factors

This study examined whether DHM integrated within the GD framework enables designers to assess the vision obstruction of pillars with different form factors. Since forward FoV visibility is identified as one of the most significant factors affecting driving safety, any reduction in

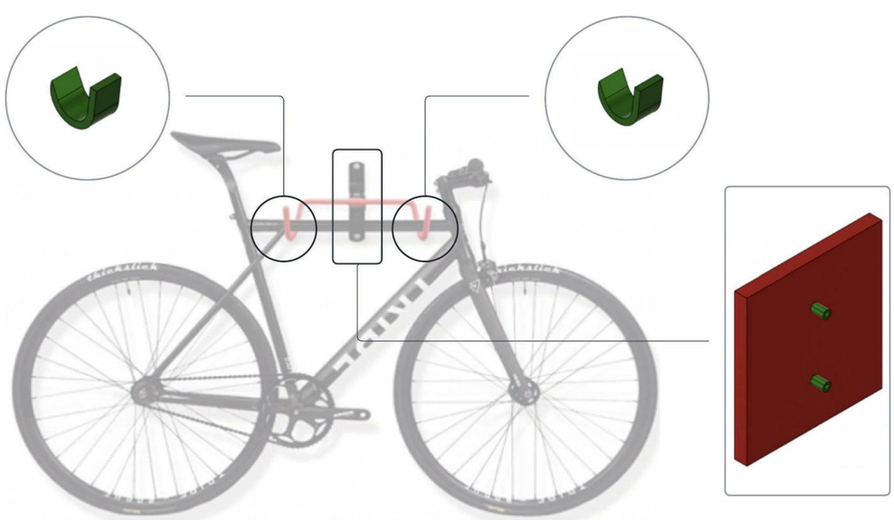


Figure 7. Generative design extra credit module. Context of challenge and starting bike bracket geometry with constraints.

obstruction zones is expected to support design efforts to mitigate accidents and mishaps. The results from the study described in Section 4.2 show that the conventional solid A-pillars blocked the pedestrian, which was hidden within the pillar's obstruction zone. The solid A-pillar geometry yielded 0% forward visibility (100% obstruction). In contrast, concept pillar variants with different see-through designs improved the visibility by around 35% in non-GD models and up to around 55% in GD models for circular, hexagonal, and triangular cutout geometries (Figure 6).

Overall, this study has shown how integrating generative design techniques within the DHM can enable designers to quantify obstruction zones early in concept modeling. Furthermore, the ability to quantify the vision obstruction can enable designers to:

- Explore the effects of anthropometry in different vehicle design settings,
- Test and re-test concept vehicles for improved forward FoV, and
- Evaluate the impact of A-pillar design in different traffic scenarios.

5.3. Developing generative design thinking curriculum modules

This research investigated how students approach generative design and integrate human attributes to support their design rationale. In this study, we have collected data for four semesters, from Fall 2020 to Spring 2022, and have taken a mixed-methods approach. Results from the introductory GD module (MA9) ($n = 94$) suggest that most students exhibit a moderate understanding of generative design—as evidenced by their response to when they would use generative design. Students were apt to discuss reasons such as manufacturing ease, cost-efficiency, safety factors, volume reduction, and overall efficiency of the GD process. Results from the supplemental GD module (MA10) show that students rely on rational thinking rather than emotion or intuition in selecting the "best" computer-generated GD solution (See Figure 8 for sample GD computer-generated solutions to bike brackets). Moreover, in discussing their own designs compared to the computer-generated solutions, students still were rational but relied on other intuition and feelings (empathy). This finding should be further investigated to understand how student involvement in the design process influences their engagement with decision-making processes, including how and to what degree students incorporate human elements into the generative design process.

6. Discussions

One of the overarching goals of this study is to summarize our ongoing research in injecting human factors into GD workflow and to encourage designers to incorporate a broad set of human needs, capabilities, and limitations early in design. The framework illustrated in Figure 1 creates venues for collaborative product design and value co-creation by enabling better product conceptualization and evaluation via an AI-assisted design approach. Although the results discussed in Section 5 provide promising outcomes in injecting HFE into generative design, there are challenges related to modeling and evaluation with AI-assisted computational tools.

One of the critical topics in current research in AI-assisted design is human-supervised GD methodology. This promising direction can enable traditional data-driven GD methods with the ability of "creative thinking." By leveraging human intelligence, the training data set of neural networks can be modified and expanded, creating more innovative designs that integrate human thoughts. In this process, human-machine interaction and human-machine interface design are the critical factors influencing human creativity in generative design. In addition to the sketch-to-3D method introduced in this paper, other deep learning of cross-modal methods, e.g., text-to-3D and text-to-2D, are potential means to further support human-centered GD. For more details, a comprehensive review of these methods in engineering design is summarized in recent publications of the co-authors (Li et al., 2022a, 2022b).

Another important topic in human-centered GD is to support human designers' performance-aware decisions in front of many design variations produced by generative models (Li, Xie, et al., 2021). For example, to evaluate the aerodynamic performance of the generated car shapes shown in Figure 3, computational fluid dynamics (CFD) software will be adopted to evaluate their drag coefficients. However, the processes of such engineering assessment are computationally expensive (the CFD assessment of a 3D car model could take hours to complete). Therefore, it is impractical to evaluate the large number of design alternatives obtained from GD models to support fast human-AI interactions and design decision-making. Research efforts are needed to develop inexpensive computational methods that can quickly evaluate generated design candidates. There is a need for such a novel GD approach to facilitate future

Figure 8. Computer-generated GD solutions created using Fusion 360.

human-AI design collaborations, where humans are sensitive to the response time of AI assistants (Poirson et al., 2013) and often require a fast or even simultaneous human-AI interactive experience.

Computational representation of humans via DHM software has gained significant interest. However, modeling with digital manikins often relies on mundane CAD operations to create and orient products representations within DHM software. Likewise, simulation modules such as occupational analysis and occupant packaging toolkits require designers to set the simulations environment manually and repetitively change design parameters (Gawand & Demirel, 2020a). Automation in DHM modeling and evaluation is vastly needed. For example, percent visibility analysis conducted in Section 4.2 requires designers to create CAD models, set up DHM scenarios, and run coverage zone analysis sequentially. Each step demands manual adjustment of the models and scenes, which adds time to design development and increases user error and bias. Without automation, the effort required to simulate the number of "what-if" scenarios for conceptual design can easily bottleneck the integration of DHM with other CAE software (Gawand & Demirel, 2020b). Moreover, the DHM domain has not yet reached maturity in providing holistic product design toolkits that foster simulation-based ergonomics practice (Demirel et al., 2022). Also, the adoption of DHM beyond the HFE domain remains an ongoing issue. Future DHM modeling could take advantage of the generative design approach to provide more robust decision-making capabilities to experts and newcomers from a broad set of design interests.

As engineering design is rapidly changing with the introduction of AI-assisted computational tools, there are opportunities for undergraduate students to access these commercially available tools before graduation. It will be necessary for undergraduate students to embody design skills that enable them to incorporate AI-assisted design and analysis methods in designing products and services. In parallel, teaching modules can be a successful approach to introducing new and challenging topics to students. Modules have been used in many engineering educational contexts, from mechanics (Streif & Naples, 2003) to product design (Gorman et al., 1995). In this research, we developed design modules to introduce students to the generative design process within the Fusion 360 environment and to investigate students' developing generative design thinking. Results suggest that students tend to incorporate human attributes into their design decisions even while learning a new design technique. In discussing reasons for using generative design, students were very human-centric in their response (i.e., manufacturing ease and safety). Moreover, in evaluating generative design outcomes, students relied on rational thinking when making decisions, and their rationale often involved human-centered attributes such as safety. Incorporating human-centered attributes into a rational design decision approach could be a productive way to help make generative design less abstract. This could be a step forward in supporting students' generative design thinking development. Since our results suggest that students keep humans in mind in generative design tasks, future modules could more explicitly help nurture that inclination by asking students to consider the human user in multiple contexts.

7. Conclusions

The case studies presented in this paper provided only a glimpse of how the proposed GD framework could improve future human-centered design efforts by synthesizing human and mechanical attributes. Although the results illustrated promising outcomes for making GD workflow more human-centric, they require further investigations to validate design assumptions. One important future direction is assessing whether the framework helps design teams discover creative concepts incorporating utility and novelty.

We hypothesize that the GD framework proposed in this research can generate a more diverse design space than when human and mechanical attributes are treated in isolation. In contrast to unilateral GD studies that only focus on mechanical performance parameters, having a multilateral lens can increase designers' likelihood of germinating concept variants with enriched novelty and utility. The validation of the above assumptions requires future research that includes a human subject study. We plan to compare (1) a benchmark group (uses no specific design software or guidance), (2) an experimental group (uses a generative design software), and (3) a control group (uses the proposed human-centered GD framework) to evaluate whether the proposed framework increases the likelihood of designers generating and selecting ideas that satisfy human factors and mechanical design requirements, thereby increasing creativity through attaining concept variants that are novel with increased utility.

Notes

1. In this paper, authentic shapes are referred to as products that are reasonable and realistic to consumers unless otherwise specified.
2. Obtained from https://wiki.freecadweb.org/Main_Page

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