Proceedings of the Design Society, Volume 5: ICED25
https://doi.org/10.1017/pds.2025.10207

Generating preinventive structures: AI-driven creativity in product repurposing

Elisa Kwon [1] and **Kosa Goucher-Lambert** [2]

[1] *University of Toronto, Canada,* [2] *University of California, Berkeley, USA*

elisa.kwon@berkeley.edu

ABSTRACT: This study presents an AI-driven method for generating preinventive structures - initial precursors to creative design concepts - using the Geneplore model as a theoretical framework. Multimodal AI is leveraged to derive preinventive structures from combinations of components of an existing product. This method is evaluated by comparing AI-generated structures of a product to those reverse identified from real repurposing solutions for the same product (IKEA hacks). The appearance of AI-generated preinventive structures in the repurposed designs suggests that this method can inspire and lead to viable design concepts. Implications extend to sustainable design, creative ideation, and the theory-driven development of design methods that support design in constrained solution spaces. Future work can refine these approaches and investigate broader applications in diverse design contexts.

KEYWORDS: design methods, creativity, artificial intelligence

1. Introduction

Research in creativity and cognitive psychology can provide the theoretical basis for developing powerful methods and tools that enhance designers' capabilities. For example, design-by-analogy, a well-studied method in which designers solve problems in a target domain by gaining inspiration from an analogous source domain, builds upon foundational knowledge in analogical reasoning (Gentner, 1983; Moreno et al., 2014). This work adopts a theory-based approach to develop a design method based on the Geneplore model, a dual process heuristic model of creativity (Finke, 1992), responding to calls for increased theory-driven research in the design community (Cash, 2018; Eisenbart et al., 2023). In the Geneplore model, initial candidate ideas are defined as "preinventive structures", which are first generated, then explored and refined before developing into full design solutions. In this work, the design method proposed generates preinventive structures using AI, which can be subsequently explored and interpreted by designers, leading to the conceptualization of creative design concepts. This method is demonstrated through a case study on product repurposing, where preinventive structures are generated based on components of an existing product. The efficacy of these AI-generated structures in leading to refined design concepts is evaluated using outcomes from repurposed product designs.

The objective of this paper is to use a theory-driven approach to develop a new design method leveraging the Geneplore model. Using this theoretical framing, this paper 1) develops an AI-enabled method to generate preinventive structures to support design concept generation and 2) evaluates this method through a case study on product repurposing. To motivate the development of this design method, a brief overview of recent approaches to generative AI-enabled design is presented, followed by theory-driven design methods based in dual-process theory. Context is then provided for the specific dual-process-theory model explored in this paper, the Geneplore model, and for the case study investigated in product repurposing.

1.1. Motivating generative AI-enabled design methods

In this work, a design method based in dual-process theory using generative AI is introduced that aims to improve designers' ideation processes. In a framework developed by Cash et al. to assess design method effectiveness, two required components of a design method include the motivating need for the method and the specification of the development process used (2023). To motivate the need for this design method, related research calling for the exploration of and demonstrating the use of generative-AI design tools are reviewed. A dual-process-theory-based approach is then taken to provide the basis for the development of the proposed method.

1.1.1. Generative AI-enabled design methods

The application of generative-AI models in this work is motivated by the immense opportunities afforded by modern off-the-shelf AI systems. In a recent research agenda for generative AI-enabled design, Thoring et al. motivate a need for exploring these technologies, highlighting capabilities of generative-AI models to augment designers across broad areas, including creating variation in existing design concepts through mutation and recombination (2023). Jin et al. additionally motivate the development of new design methods based in AI-generated content (AIGC) technologies, which they report can afford opportunities to drive innovation in product design (2025). Continued development of generative-AI-enabled design methods is further encouraged by their evidenced potential across numerous recent studies. Multimodal generative models are powerful candidates for enhancing human design capabilities, by leveraging the ability to reason about visual or textual design representations. Recent work has explored the application of large language models (LLMs) or text-to-image models to directly generate design concepts. Design concepts generated by LLMs, for instance, were found to match to or exceed human-generated concepts in terms of outcomes such as feasibility, but not in others including novelty (Ma et al., 2024). Text-to-image AI systems were, by contrast, found to generate concept images that lacked clarity and realism when evaluated by design students (Brisco et al., 2023). LLMs have additionally been used to automate reasoning processes across a variety of design methods and activities, such as to apply TRIZ to support problem solving (Jiang & Luo, 2024), automate and enhance design requirements elicitation (Ataei et al., 2024), or infer functions, behaviors, and structures from design concepts, supporting concept generation and evaluation (Chen et al., 2024). These represent only a few recent examples showcasing the prevalence of leveraging these technologies in recent engineering design research. Multimodal models present further opportunities for advancing new design generation across representation modalities, including text, images, and CAD (Chong et al., 2024; Edwards et al., 2024). Furthering the methods presented in this section, and addressing the need for continued investigation, this paper focuses on using generative AI to assist design ideation processes by generating preinventive structures for new ideas based on existing designs.

1.1.2. Developing design methods leveraging dual-process theory

In this work, generative-AI-enabled support is developed towards improving designers' ideation processes, as informed by the Geneplore model - a dual-process model of creativity. This approach is taken to ensure that the development process of the method is specified, in this case by an underlying theory, adhering to Cash et al.'s design method framework (2023) as well as responding to broader calls in the design research community for increased theory-driven research (Cash, 2018; Eisenbart et al., 2023). The adoption of dual-process theory in this work is further motivated by the proposed use of these models in design research (Cash et al., 2019; Lawrie et al., 2024). By clearly distinguishing different cognitive pathways (i.e., Type 1 and 2 thinking), dual-process theory offers a foundation for developing design methods that account for changes in designers' thinking and activities during design (Cash et al., 2019).

Generally, dual-process models of creativity suggest two distinct phases of idea generation and idea evaluation (Kleinmintz et al., 2019). In design research specifically, Gonçalves and Cash developed a dual-process model that also considers how ideas evolve over time (Gonçalves & Cash, 2021). They propose that Type 1 (i.e., implicit and fast) and Type 2 (i.e., deliberate and slow) processing are used when linking between ideas via implicit similarities to and explicit reference to prior concepts. The Geneplore model defines two generative and exploratory processes (Finke, 1992). “Generation”, according to this framework, involves the initial construction of “preinventive structures”, defined as precursors to final creative results, that are subsequently interpreted and transformed following "exploration". In early research evaluating this model during creative imagery, Finke found that preinventive structures, constructed from the combination of different abstract shapes, could lead to creative inventions when the function of the intended design was revealed after the preinventive forms were generated (Finke, 1996). In this study, a Geneplore-based method for AI generation of form-based preinventive structures is examined and the potential for these structures to lead to new design concepts is evaluated.

1.2. Product repurposing: IKEA hacking as a case study

To demonstrate the method developed in this work to construct preinventive structures using generative AI, this paper presents a case study contextualized in product repurposing. Supporting and understanding design processes leading to product redesign or repurposing can improve sustainable design methods and creativity insights (Kwon et al., 2019). In this work, the phenomenon of IKEA hacking is considered, where common IKEA products and furniture are 'hacked' to accommodate new user needs based on product affordances or functional requirements (Chan & Lim, 2023). Prior work by Olteteanu & Shu explored an alternative uses test (AUT) using IKEA products, examining the effect of orientation on revealing new uses for products (Olteteanu & Shu, 2018). Taking different perspectives and considering multiple instances of an object were found to influence creativity measures. This study uses AI to derive preinventive structures from components of an IKEA product and assesses the prevalence of these AI-generated structures in repurposed designs of the same original product (i.e., IKEA hacking solutions). The successful generation of preinventive structures leading to real product redesign solutions has implications not only for improving ideation processes, generally, but product repurposing, specifically.

2. Methodology

This work demonstrates an approach to generating preinventive structures from component product parts. This approach is evaluated by comparison to the output from the reverse identification of preinventive structures from designs incorporating the same parts. The methods underlying the forward, component-first, and reverse, solution-first, pathways are summarized in Figure 1 and described in this section. Contextualized within a case study on product repurposing, forward AI generation of preinventive structures is performed using an initial product design as input (the IKEA LACK side table) and reverse identification extracts preinventive structures from redesign solutions of the same product (IKEA hacks). The selection of this product as the basis of investigation in this paper is first motivated, followed by the introduction of additional details about the products and hacking solutions discussed.

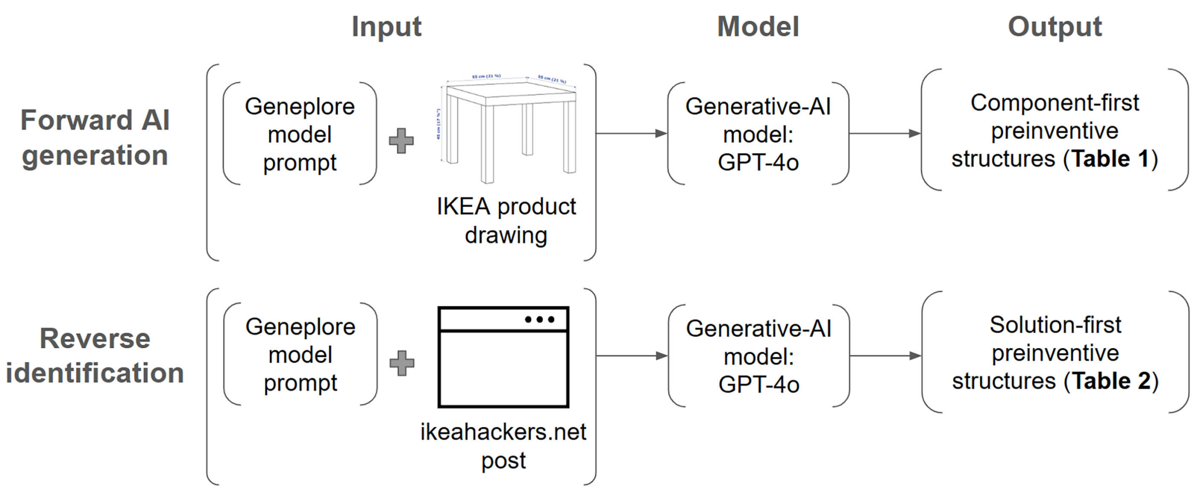

Figure 1. Overview of forward AI-generation and reverse identification of preinventive structures outlined in Sec. 2.2

2.1. Case study problem: IKEA "LACK" product series

A popular IKEA hack involves the "LACK" product series, leading to posts on the IKEA Hackers website[1] such as "IKEA LACK side table: 26 surprising ways to hack it". LACK products are chosen to study in this case study based on their high frequency of appearance on IKEA Hackers, demonstrated by the following procedure. All 6649 posts on the website (from 2006 to present) were scraped, with 3174 posts mentioning the use of a product from a current list of all 231 IKEA product series. The most hacked product series among these was the "LACK" series (881 posts), with each product referenced in the specified number of posts: side table (152), coffee table (106), wall shelf (29), TV bench (27), console table (6), wall shelf unit (1). Included in these counts are exact term matches to existing products only, and additionally exclude hacks explicitly referencing more than one IKEA series or product. While limiting the hacks explored, this constraint ensures consistency with the methods fully described in Sec. 2.2. where AI generation of preinventive structures is based on one product only. In this case study, only the most frequently 'hacked' product is considered: the IKEA LACK side table, pictured in Figure 2.

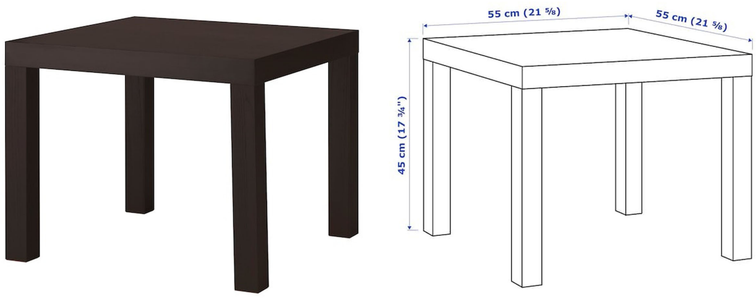

Figure 2. IKEA LACK side table[2] a) image (left) and b) drawing (right)

2.2. AI generation and reverse identification of preinventive structures

This study demonstrates a forward component-first approach to generating the preinventive structures afforded by an example product (IKEA LACK side table) by inputting a visual rendering of the product into a multimodal model. To evaluate the effectiveness of this approach in defining preinventive structures that can lead to new design concepts, preinventive structures are identified through a reverse solution-first approach from descriptions of product redesigns. These repurposing solutions were derived using components of the same product, and thus preinventive structures underlying or leading to their conception are easily identifiable. By comparing the structures resulting from these forward component-first and reverse solution-first pathways, the ability for AI-generated structures to enable feasible and innovative designs, such as those contributed by IKEA hackers, can be evaluated. First, a list of preinventive structures from a product drawing of the side table are generated by a multimodal model (Sec. 2.2.1). For all redesign solutions of the side table, the preinventive structure extracted from each design was assigned to one of the AI-generated categories, or else assigned a new category (Sec. 2.2.2). Detailed methods for these procedures are described in the following subsections.

2.2.1. Forward AI generation of preinventive structures from product components

In the forward, component-first pathway, a multimodal AI model was instructed to generate preinventive structures using components of or combinations of IKEA LACK side tables. GPT-4o from Open AI[3] was used by interacting with the Open AI API in Python. This model was selected due to its ability to support generation of text responses based on multimodal inputs, e.g., combined images and text. The model was first provided with context about the Geneplore model and the definition of a preinventive structures as "precursors to final creative results". Through prompt engineering, the expected output the model was instructed to produce was described as a list of preinventive structures, where components of the product shown in the image could be combined or multiple instances of the object could be used.

[1] https://www.ikeahackers.net/

[2] https://www.ikea.com/ca/en/p/lack-side-table-black-brown-80104268/

[3] https://openai.com/index/hello-gpt-4o/

The model was specified not to provide design solutions resulting from the preinventive structures. The drawing of the product (Figure 2b) was then input into the model, chosen over the product image (Figure 2a) for the added context of the dimensions specified in the drawing and emphasis of shapes in the line drawing. The AI-generated preinventive structures resulting from this process are presented in Sec. 3.1.

2.2.2. Reverse identification of preinventive structures from product redesign solutions

The second method used to define preinventive structures of the IKEA LACK side table was to extract them from product redesign solutions (IKEA hacks), which use components of single or multiple side tables. While these structures were not generated by AI, the same AI model (GPT-4o) was used to semi-automate their identification from the design descriptions. For each post, the model was similarly provided with definitions of the Geneplore model and preinventive structures and then instructed to identify a preinventive structure leading to the textually described solution provided. The model was provided context that the described design was a redesign of the IKEA LACK side table, which consists of 1 table top and 4 legs, to ensure that the generated response focused on the relevant content of the post. When the preinventive structure extracted by the model from the description was not clear, the original post on IKEA Hackers was revisited for manual inspection. This lack of clarity may have been due to there being multiple hacks discussed in the same post, the post including only a short description of the hack and link to another website, or the side table not featuring prominently in the design. Designs involving a single component (tabletop or leg) of the side table combined with other objects or IKEA furniture were also excluded, since AI-generated structures were explicitly instructed to be combinations of components from one or multiple tables. A common example was to use a single tabletop as a wall or ceiling-mounted surface, e.g., as a decorative canvas or light fixture. If the tabletop was replaced with a different surface, these hacks were also excluded, as the main structural configuration of the four legs were the same as in the original product. The final exclusion criteria were hacks that maintained the whole table in its typical configuration (4 legs and tabletop), with additions or modifications with external objects or products. These modifications could be aesthetic (e.g., decorative elements) or functional, such as to shorten table legs or add castors, cushioning, or a shelf to the table. Following a mixed deductive and inductive coding approach (Mayring, 2004)**,** each of the remaining 49 preinventive structures reverse identified from IKEA hacking solutions was assigned to one of the AI-generated codes. If none of the codes matched, a new code was created. The new preinventive structures that emerged from this solution-first pathway are presented in Sec. 3.2.

3. Results

Following the methods outlined in Sec. 2, preinventive structures of components and combinations of an original product are generated using a forward component-first AI-enabled approach. Preinventive structures underlying redesign solutions of the same product are identified using a reverse solution-first approach. We find that most of the AI-generated structures appear in the product repurposing solutions, revealing that this method can produce design precursors that can effectively lead to new idea generation. This finding is furthered by the AI generation of structures that do not appear frequently in the redesign solutions, implying that this method can support and augment human capabilities. However, we also find new preinventive structures that appear only in product redesigns, suggesting that there is uniqueness in human-generated ideas absent from this component-first approach and potential for improving this method.

3.1. Component-first preinventive structures

The full list of component-first preinventive structures and accompanying descriptions generated by AI based on the original IKEA LACK side table are found in 0. Visual depictions of these preinventive structures are shown in Figure 3 to convey how each structure was interpreted to configure various components of the table or multiple tables. The number of IKEA hacks coded as containing the described preinventive structure are also specified in 0. This approach was found to generate preinventive structures identified in most IKEA hacks, suggesting that these AI-generated structures can lead to the development of human-like solutions.

Table 1. Component-first preinventive structures generated by GPT-4o from product drawing

ID	Preinventive structure	Description of preinventive structure	Number of IKEA hacks
1	Shelving Unit	**Stack multiple tables vertically** to create shelves or storage units.	21
2	Partition Wall	**Align multiple tabletops vertically** to act as a partition or screen.	8
3	Flat Surface Module	Use **multiple tabletop surfaces** to create a larger platform or layered structures.	6
4	Trestle Bridge	**Position the tables in a series** to create a bridge or elevated walkway.	6
5	Leg Framework Structure	Combine sets of table legs into a **grid-like framework** or vertical support system.	2
6	Modular Cubes	Arrange four or more tables to form a **cube-like structure**.	1
7	Platform Staircase	Use the tabletops as ascending steps in a **layered staircase configuration**.	1

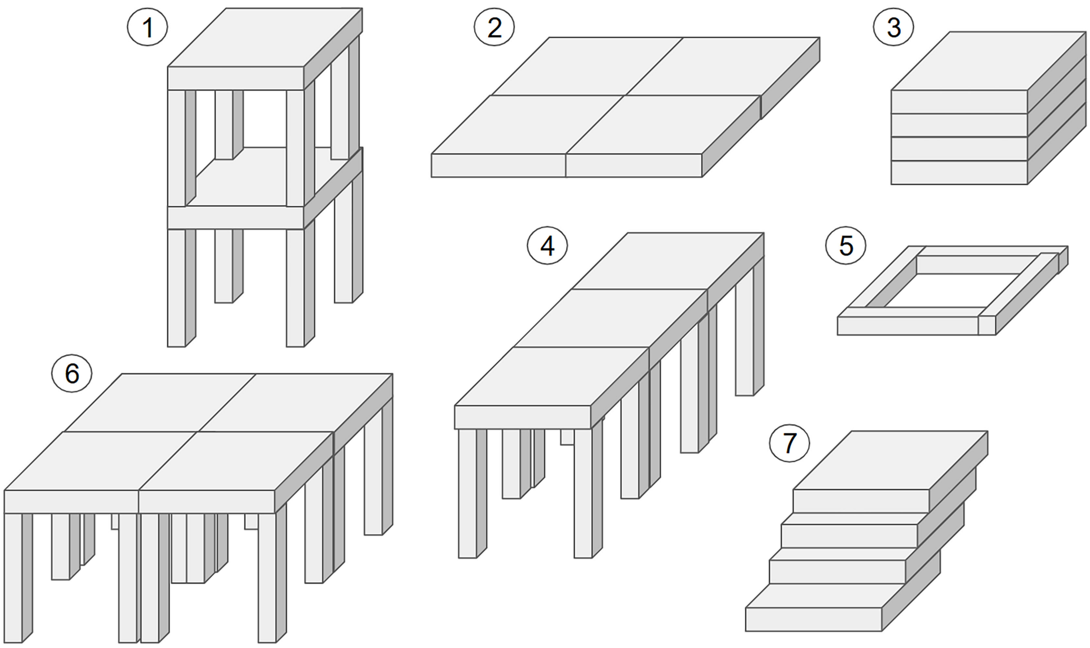

Figure 3. Visual representations of AI-generated component-first preinventive structures from the original product (labelled according to Table 1)

Included in the count of IKEA hacks containing each preinventive structure are those that reference multiple structures. For example, one coffee table project combined eight tabletops by attaching four by the sides (2 - partition wall) and across two layers (3 - flat surface module). This surface was then glued to a low base, which combined horizontally oriented table legs into square frames (5 - leg framework structure). The implications of using generative AI to construct component-first preinventive structures to aid concept generation and exploratory processes are discussed in Sec. 4.1.

3.2. Solution-first preinventive structures

As described in Sec. 2.2.2, the preinventive structure inferred to form the basis of each redesign solution was identified, adhering to a solution-first approach, and then compared against the AI-generated set of categories. The numbers of designs containing each AI-generated preinventive structure are indicated in 0. Design solutions that were not excluded and did not contain any of the AI-generated structures were assigned a newly identified preinventive structure. At the end of the process, the list presented in Table 2 emerged, where each new structure is visually interpreted in Figure 4.

Table 2. New solution-first preinventive structures identified from IKEA hack solutions

ID	Preinventive structure	Description of preinventive structure	Number of IKEA hacks
A	Perpendicular tabletops	L or T shaped configuration of tabletops	4
B	Single cube	Tabletop added to base of whole table.	3
C	Vertical tabletop	Legs attached to sides of tables	3
D	Perpendicular table legs	L-shaped configuration of legs	1
E	Stacked legs	Vertically stacked table legs	1

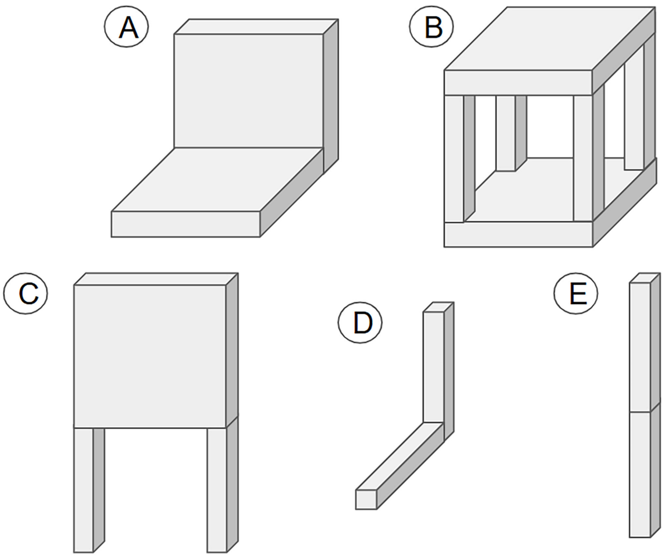

Figure 4. Visual representations of solution-first preinventive structures identified from product redesign solutions (labelled according to Table 2)

Of the 49 IKEA hacks that met the inclusion criteria defined in Sec. 2.2.2, 12 redesign descriptions contained a preinventive structure newly identified from the available solutions. Recurring structures included A - perpendicular tabletops (e.g., to create L-shaped wall-leaning surfaces, where one tabletop acts as a support), B - single cubes (e.g., to create a storage container with a base), or C - vertical tabletops (e.g., combined with a 1 - partition wall to form an upright bed headboard). While the identification of AI-generated preinventive structures in existing product repurposing solutions shows that this component-first approach can produce design precursors leading to real solutions, newly identified structures also reveal limitations to this approach and suggested areas for improvement. AI-generated preinventive structures were found to not fully cover the solution space of IKEA hacks explored by humans. Implications of these findings are further discussed in Sec.4.1.

Discussion

This paper presented an AI-enabled approach to support design creativity aligned with the Geneplore model. The method developed in this paper generated preinventive structures, defined in the Geneplore model as precursors to design ideas, from the main components of an initial product. In this case study, preinventive structures were generated by a multimodal model from the components of an IKEA LACK side table. An IKEA product was specifically used to enable evaluation of AI-generated structures using those reverse identified from IKEA hacks, i.e., IKEA product redesigns, of the same side table.

The findings from this case study revealed that a multimodal model could generate preinventive structures from components of a simple product. These component-first preinventive structures were found indeed to be present in real product redesign solutions, demonstrating that this method could lead to viable design solutions. Insights can be gained into how AI generation of preinventive structures can be improved by considering reverse identified solution-first preinventive structures from existing solutions that were not also AI-generated. Implications of these findings for design are next discussed, in addition to limitations of this work and areas for future investigation.

4.1. Implications of results for design

The first main result of this paper is the presentation of an approach to conducting component-first preinventive structure generation using AI. This approach can be valuable for developing methods to automate generation of such structures to provide real-time aid when designing within a constrained design space or with a limited set of design stimuli. As a designer conceptualizes an idea via sketch or 3D-modelling, for example, the reconfiguration and restructuring of components within these designs can be suggested. According to the Geneplore model, reinterpreting and transforming these initial preinventive structures as a starting point to design can support subsequent generation & exploratory processes (Finke, 1992). Recombination, more generally, is a known strategy central to creativity that can be facilitated by real-time AI-generated preinventive structures (Welch, 1946).

This paper also presents an evaluation of this approach by comparing AI-generated with reverse identified preinventive structures from existing solutions, in the form of IKEA hacks. IKEA hacking was chosen as the context area explored in this case study due to the unique use of a limited set of components in both an original base design and in repurposed solutions. Repurposed solutions containing preinventive structures not covered by the AI-generated set show that there is human ingenuity missing in the developed component-first approach. This is not surprising, as the generated preinventive structures composed a limited list, by definition, rather than an exhaustive consideration of all possibilities. However, to generate preinventive structures underlying more unique (i.e., less frequently occurring) design solutions, insights from the present study can uncover features of these structures not initially conceived of by AI. For example, IKEA hacks featured combinations of different structures - such as stacks and series of tabletops. In one example, tabletops could be connected by hinges, enabling vertical alignment (2 - partition wall) as well as perpendicular (A - perpendicular tabletops), and stacked arrangement (3 - flat module surface), resulting in a highly modular design. The presence of basic part configurations and their combinations in product redesigns can be applied to improve AI generation of preinventive structures (e.g. to generate basic structures and propose combinations).

Regarding the development of the design method presented in this work, while Cash et al. propose that the development process of a design method be specified and evidenced, the use of a theoretical model or framework is not directly suggested (2023). A contribution of this work to design method development is the adoption of a theory-based model to define design tool functionalities. This procedure can be especially relevant in developing AI-supported design methods and tools, where theories previously defining different roles or tasks of human designers can be used to implement AI-design tools in human workflows.

4.2. Limitations and future work

This paper presented an approach to using a multimodal model to generate preinventive structures from components and combinations of an initial design (an IKEA LACK side table). This approach was evaluated against preinventive structures reverse identified from human-generated descriptions of repurposed product designs for the same product. While intended as a case study to initially demonstrate the developed method, the first limitation of this work is that AI-generated preinventive structures are not directly compared or evaluated against human-generated preinventive structures. Human-subject studies are encouraged to directly task humans with defining preinventive structures towards generating new design concepts (e.g., IKEA hacks) to enable a more rigorous comparison with the proposed AI method. A second limitation of this work is the selection of IKEA products and hacking solutions considered. As a direct extension to the results presented here, a wider range of products in the IKEA catalogue can be studied for comparison against associated IKEA hacks. Web-scraping techniques can also be improved in future work to more accurately capture relevant solutions from the IKEA hacking website. More broadly, varied design contexts can also be investigated to demonstrate this design method, such as by comparing AI-generated preinventive structures from a constrained design space (e.g., parts in CAD assemblies) to crowdsourced solutions, for example. A standard product drawing of the side table was used in this study as the visual input for textual AI-driven preinventive structure generation. Future work can explore other modalities of input, such as 3D-model renderings of individual design components or textual descriptions, to understand the impact of representation modality on the effectiveness this method. Such insights can be meaningful for applying this method across multimodal design activities. Representation modality is also relevant in the reverse identification of preinventive structures from design solutions. In this study, this process was semi-automated from textual descriptions of hacks. However, as most design solutions are accompanied with photos, multimodal data can be used to improve this reverse identification process. Finally, the impact of AI-generated preinventive structures on creativity and design outcomes and processes can also be directly measured by providing designers with initial design components and AI-generated aid.

5. Conclusion

This paper presented a generative-AI-based approach for identifying preinventive structures from initial design concepts, which are defined in the Geneplore model of creativity as precursors to ideas that can enhance exploratory processes in design. The developed theory-based component-first method uses AI to derive these structures based on component building blocks of multimodally expressed designs, demonstrated by a case study using a simple example (IKEA LACK side table). Preinventive structures were also reverse identified following a solution-first pathway, by extracting the structure underlying redesigns of the side table from IKEA hacking solutions. Findings from this study 1) revealed how AI can generate preinventive structures from an existing constrained design space and 2) validated that AI-generated preinventive structures can lead to effective solution generation by uncovering their underlying presence in real product redesign solutions.

References

Ataei, M., Cheong, H., Grandi, D., Wang, Y., Morris, N., & Tessier, A. (2024). Elicitron: A framework for simulating design requirements elicitation using large language model agents. *IDETC-CIE2024*. https://doi.org/10.1115/DETC2024-143598

Brisco, R., Hay, L., & Dhami, S. (2023). Exploring the role of text-to-image AI in concept generation. *Proceedings of the Design Society*, 3, 1835–1844. https://doi.org/10.1017/pds.2023.184

Cash, P., Daalhuizen, J., & Hekkert, P. (2023). Evaluating the efficacy and effectiveness of design methods: A systematic review and assessment framework. *Design Studies*, 88, 101204. https://doi.org/10.1016/j.destud.2023.101204

Cash, P., Daalhuizen, J., Valgeirsdottir, D., & Oorschot, R. V. (2019). A theory-driven design research agenda: Exploring dual-process theory. *Proceedings of the Design Society: International Conference on Engineering Design*, 1(1), 1373–1382. https://doi.org/10.1017/dsi.2019.143

Cash, P. J. (2018). Developing theory-driven design research. *Design Studies*, 56, 84–119. https://doi.org/10.1016/j.destud.2018.03.002

Chan, T. H., & Lim, S.-Y. (2023). The emergence of novel product uses: An investigation of exaptations in IKEA hacks. *Management Science*, 69(5), 2870–2892. https://doi.org/10.1287/mnsc.2022.4486

Chen, L., Zuo, H., Cai, Z., Yin, Y., Zhang, Y., Sun, L., Childs, P., & Wang, B. (2024). Toward controllable generative design: A conceptual design generation approach leveraging the function–behavior–structure ontology and large language models. *Journal of Mechanical Design*, 146(121401). https://doi.org/10.1115/1.4065562

Chong, L., Rayan, J., Dow, S., Lykourentzou, I., & Ahmed, F. (2024). CAD-prompted generative models: A pathway to feasible and novel engineering designs (arXiv:2407.08675). *arXiv*. https://doi.org/10.48550/arXiv.2407.08675

Edwards, K. M., Man, B., & Ahmed, F. (2024). Sketch2Prototype: Rapid conceptual design exploration and prototyping with generative AI. *Proceedings of the Design Society*, 4, 1989–1998. https://doi.org/10.1017/pds.2024.201

Eisenbart, B., Blessing, L. T. M., & Cantamessa, M. (2023). Two decades apart and looking forward – Exploring rigour in reporting on research in the engineering design research community. *Journal of Engineering Design*, 0(0), 1–26. https://doi.org/10.1080/09544828.2024.2327912

Finke, R. A. (1996). Imagery, creativity, and emergent structure. *Consciousness and Cognition*, 5(3), 381–393. https://doi.org/10.1006/ccog.1996.0024

Finke, R. A. (1992). Creative cognition: Theory, research, and applications. *MIT Press*. http://archive.org/details/creativecognitio0000fink

Gentner, D. (1983). Structure-mapping: A theoretical framework for analogy. *Cognitive Science*, 7(2), 155–170. https://doi.org/10.1016/S0364-0213(83)80009-3

Gonçalves, M., & Cash, P. (2021). The life cycle of creative ideas: Towards a dual-process theory of ideation. *Design Studies*, 72, 100988. https://doi.org/10.1016/j.destud.2020.100988

Jiang, S., & Luo, J. (2024). AutoTRIZ: Artificial ideation with TRIZ and large language models. *IDETC-CIE2024*. https://doi.org/10.1115/DETC2024-143166

Jin, J., Yang, M., Hu, H., Guo, X., Luo, J., & Liu, Y. (2025). Empowering design innovation using AI-generated content. *Journal of Engineering Design*, 36(1), 1–18. https://doi.org/10.1080/09544828.2024.2401751

Kleinmintz, O. M., Ivancovsky, T., & Shamay-Tsoory, S. G. (2019). The two-fold model of creativity: The neural underpinnings of the generation and evaluation of creative ideas. *Current Opinion in Behavioral Sciences*, 27, 131–138. https://doi.org/10.1016/j.cobeha.2018.11.004

Kwon, E., Pehlken, A., Thoben, K.-D., Bazylak, A., & Shu, L. H. (2019). Visual similarity to aid alternative-use concept generation for retired wind-turbine blades. *Journal of Mechanical Design*, 141(031106). https://doi.org/10.1115/1.4042336

Lawrie, E., Flus, M., Olechowski, A., Hay, L., & Wodehouse, A. (2024). From theory to practice: A roadmap for applying dual-process theory in design cognition research. *Journal of Engineering Design*, 0(0), 1–21. https://doi.org/10.1080/09544828.2024.2336837

Ma, K., Grandi, D., McComb, C., & Goucher-Lambert, K. (2024). Do large language models produce diverse design concepts? A comparative study with human crowdsourced solutions. *Journal of Computing and Information Science in Engineering*, 1–9. https://doi.org/10.1115/1.4067332

Mayring, P. (2004). Qualitative content analysis. In U. Flick, E. von Kardorff & I. Steinke (Eds.), *A companion to qualitative research* (pp. 266–269). SAGE Publications, Ltd.

Moreno, D. P., Hernández, A. A., Yang, M. C., Otto, K. N., Hölttä-Otto, K., Linsey, J. S., Wood, K. L., & Linden, A. (2014). Fundamental studies in design-by-analogy: A focus on domain-knowledge experts and applications to transactional design problems. *Design Studies*, 35(3), 232–272. https://doi.org/10.1016/j.destud.2013.11.002

Olteteanu, A.-M., & Shu, L. H. (2018). Object reorientation and creative performance. *Journal of Mechanical Design*, 140(031102). https://doi.org/10.1115/1.4038264

Thoring, K., Huettemann, S., & Mueller, R. M. (2023). The augmented designer: A research agenda for generative AI-enabled design. *Proceedings of the Design Society*, 3, 3345–3354. https://doi.org/10.1017/pds.2023.335

Welch, L. (1946). Recombination of ideas in creative thinking. *Journal of Applied Psychology*, 30(6), 638–643. https://doi.org/10.1037/h0054074