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# Creative collaboration with interactive evolutionary algorithms: a reflective exploratory design study

Severi Uusitalo<sup>1</sup> · Anna Kantosalo<sup>2,3</sup> · Antti Salovaara<sup>1</sup> · Tapio Takala<sup>3</sup> · Christian Guckelsberger<sup>3,4,5</sup>

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## Abstract

Progress in AI has brought new approaches for designing products via co-creative human–computer interaction. In architecture, interior design, and industrial design, computational methods such as evolutionary algorithms support the designer’s creative process by revealing populations of computer-generated design solutions in a parametric design space. Because the benefits and shortcomings of such algorithms’ use in design processes are not yet fully understood, the authors studied the intricate interactions of an industrial designer employing an interactive evolutionary algorithm for a non-trivial creative product design task. In an in-depth report on the *in-situ* longitudinal experiences arising between the algorithm, human designer, and environment, from ideation to fabrication, they reflect on the algorithm’s role in inspiring design, its relationship to fixation, and the stages of the creative process in which it yielded perceived value. The paper concludes with proposals for future research into co-creative AI in design exploration and creative practice.

**Keywords** Human–computer co-creativity · Interactive evolutionary algorithm · Introspection · Autoethnography · Longitudinal study · Design

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✉ Severi Uusitalo  
severi.uusitalo@aalto.fi

<sup>1</sup> Department of Design, Aalto University, Espoo, Finland

<sup>2</sup> Department of Computer Science, University of Helsinki, Helsinki, Finland

<sup>3</sup> Department of Computer Science, Aalto University, Espoo, Finland

<sup>4</sup> School of Electronic Engineering and Computer Science, Queen Mary University of London, London, UK

<sup>5</sup> Finnish Center for Artificial Intelligence, Helsinki, Finland

## 1 Introduction

Although evolutionary algorithms' potential has long been recognized in the design domain [39], only within the last decade have they become available to design professionals, through incorporation into commercial computer-aided design (CAD) software. These algorithms provide an opportunity to move CAD applications beyond creativity support [8, 16], transforming them into *co-creative* systems [25] capable of not only augmenting but also complementing the creativity of human designers [3]. Furthermore, they hold potential to enrich design of personalized products by building on recent advances in manufacturing technologies [53].

Deployment of new tools and technologies for human–computer co-creativity transforms designers' work methods, inducing profound shifts in the design processes, creativity, and experience of agency. In this history [49], *interactive* evolutionary algorithms constitute a vital development by bringing guidance—rather than automation—to the exploration process's search for optimal designs. They permit the designer to intervene in the optimization process and selecting the best-performing candidates; thus, the human implicitly injects performance criteria that may be tedious, hard, or impossible to formalize explicitly. In other words, interactive evolutionary algorithms leave room in the optimization process for design intuition, tacit knowledge, and subjective criteria. Such qualities may be crucial for cultivating profoundly successful designs that win users' hearts.

Negotiating the balance of these algorithms' role in creative design remains tricky, e.g. due to the designer's reduction in control of the algorithm and results, and human cognitive bounds, e.g. on handling large volumes of information.

While some interactive evolutionary algorithms have found their way into established design software through third-party extensions such as Biomorpher [22], they are a fairly recent addition to the commercial design realm, so they are neither a standard feature of design software nor typically covered in contemporary design-school curricula. Accordingly, we have little understanding of how the ones available thus far can be incorporated appropriately into design practice, and, conversely, how design practice could inform algorithm development.

This article addresses these gaps through the lens of an introspective study focused on an industrial designer-researcher's use of an interactive evolutionary algorithm in a real-world creative design task. Its seeds lay in a conference paper [52] documenting the first author's experiences of using design software equipped with evolutionary design support over a span of 11 weeks, which encompassed the design of a solution space capable of visualizing pendant-lamp concepts. As is typical of creative design processes, the work involved focus and incubation phases, entailing large amounts of iteration and exploration. This portion of the account is condensed slightly from what was reported in the conference paper. This article affords deeper insight by documenting the evolution of the refactored co-creative design into physical prototypes presented at Espoo Museum of Modern Art (EMMA), near Helsinki, Finland, in September 2022. The prototypes, part of a complementary event to the exhibition "In Search of the

Present”, which explored the complex interactions between art, technology, and nature, exemplify genuine collaboration between a designer and an algorithm.

Our contributions are threefold. Firstly, we inform the adoption of interactive evolutionary algorithms in design practice by describing their use, benefits, and shortcomings in a real-world design task from the ideation phase through to three finished physical design prototypes (presented at the exhibition), as a representation of a single parameterized solution space. The parameterization and algorithm together facilitate creating and fabricating unique artifacts for individual users. The paper attends in particular to how the algorithm can complement the designer’s creativity, its connection with design fixation, and how it can aid in turning a digitally co-created artifact into a physical object. Secondly, we reflect on computer science development how algorithms of this nature could solidly support future design practice. The paper especially highlights opportunities related to the meta-evolution of parametric design definitions and for introducing visualization and manipulation of design instances as the process progresses toward the final physical prototype. Our final contribution is to reveal fruitful ways to study emerging work practices *in situ*. We find such a foundation necessary for longitudinal studies of practice-based experiences of emerging CAD tools. Covering the entire complex process from ideation, through design exploration and detail design, to manufacture of a physical product supports holistic understanding and comprehensive solutions.

After providing some grounding in design theory and evolutionary algorithms’ application to creative product design, the article offers an autoethnographic account of an algorithm’s part in the process, with regard to two phases: the steps from initial design to renderings (dealt with to some extent in the conference paper) and, after this, detailed physical design that ultimately led to the finished artifacts as presented at the museum. The article’s concluding discussion frames the resultant reflections in terms of design theory and computational co-creativity, then points to potential directions for future research.

## 2 Background

Our review of prior work presents the most significant research into the nature of creative design, then ties the recent development of evolutionary algorithms in with it.

We draw parallels between design practice and evolutionary algorithms, concentrating in particular on the dynamic construction and sculpting of solution spaces as analogous to the co-evolutionary construction of problems and solutions within design processes.

### 2.1 The process of creative design

Creative design is fundamentally a reflective process wherein the designer’s goals, interaction with the materials, and the opportunities and constraints entailed by the design problem shape each other. This view builds on Schön’s conceptualization of

design practice [44], which identifies a prominent role for both “reflection in action” (i.e., during the activity) and “reflection on action” (prior to and after the activity). In his characterization, reflecting contributes to “re-framing of the design problem” [44, pp. 94–95], where *framing* is the process of a designer making sense of the problem at hand, imposing a corresponding interpretation, and using that to generate ideas for small design experiments to probe the value of possible paths to more substantial solutions. Elsewhere, Schön describes this method as “reflective conversation with the materials in a design situation” [45].

Through framing, the designer constructs a mental image of the design and solution spaces within which the desired design can be explored and identified [14]. The problem space is not static: the designer’s creative re-framings may well change it. Likewise, the solution space might get re-framed through insight amassed amid efforts to solve a specific problem. Since the problem space and solution space consequently co-evolve [11, 15], a typical design process encompasses more than seeking optimal solutions to some given, fixed problem. The traditional use of evolutionary algorithms for optimization captures only one part of the process.

The work of a designer is best regarded as “satisficing” rather than optimizing [48]. After all, design spaces are vast, with numerous possible designs in all directions [54]. Furthermore, design often concerns itself with *wicked problems*: the system’s intricate relations and even internal contradictions may render any solution suboptimal or downright harmful in some situations or as environments change [41]. For instance, industrial design requires tradeoffs among product-manufacturing efficiency, materials’ properties, costs, human factors, sustainability concerns, style trends, and other factors. These manifold requirements are typically far from straightforward to formalize in the objective function of a standard evolutionary algorithm for the optimization of a design problem.

The complexity of compromise-demanding objectives and the co-evolving nature of problem and solution spaces elucidate why designers could benefit greatly from *interactive* evolutionary algorithms as co-creation *partners*, as opposed to algorithms consigned to the role of solvers seeking an optimal solution in a stable design space.

## 2.2 Evolutionary algorithms

Among the various algorithmic solutions that can enhance the design process are improved differential evolution [56], and improved particle swarm optimization [57], both families that focus on optimization for given criteria. At present, evolutionary algorithms cannot replace humans in design practice; what algorithms *can* do is help designers *explore* the characteristics of problem and solution spaces and *articulate* them (spell them out and arrange elements in a structured manner [47]). For an evolutionary algorithm, the notion of re-framing a solution space as discussed above in the design context corresponds to altering the objective function that measures the success of the solutions generated. By generating alternative designs, algorithms may be able to counteract designers’ tendency to fixate on a certain subset of possible solutions [35].

While evolutionary algorithms have grown popular in architecture, there are fewer examples of them in product design. Their application in industrial product design has consisted predominantly of deploying non-interactive *genetic algorithms*, or GAs (in one case, to explore the design space of lamp-holders [30]). It has proven especially challenging to express subjective factors such as aesthetic preferences in the GA's objective function – notwithstanding various theory-inspired attempts to formalize aesthetics (e.g., of product shapes [31]), a satisfying solution for communicating subjective, intuitive qualities for GA purposes remains elusive. An alternative technique for dealing with such features is to employ a “human-in-the-loop” approach, which complements algorithmic selection (via an explicitly stated objective function) with a human selecting from among the alternatives generated. Our research was focused on exploring the design process from the angle of the latter approach, referred to as *interactive genetic algorithms* (IGAs).

Scholars have analyzed IGAs' value for the design of cameras [29], cars [10], fragrance bottles [26], wine-glass profiles [50], and fashion [18, 51], with their attention largely confined to the algorithms' benefits for exploring the design space [1, 2, 28] and to engineering aspects of the systems' architecture and implementation. Those few studies that have examined how IGAs are used and experienced by designers have restricted their gaze to one stage of design or just a few components of the larger process. When surveying the landscape in light of Howard et al.'s general six-stage model for engineering design processes [23], one finds that prior work covers no more than narrow windows from the process and usually focuses on conceptual design [10], the third stage in the process (identifying a need, analyzing the task, performing conceptual design, conducting embodiment design, executing detailed design, and implementing).

One exception is Bezirtzis et al.'s work [5] considering the fourth stage, in which the structural or product-architecture design identifies a myriad of opportunities and requirements for the process, in “embodiment.” From studying IGA use during the embodiment phase of a design process for designing an airport scooter, they present some basic techniques to frame and shape the solution space. The team introduces the concept of *meta-designers* to articulate the conclusion that designers who work with an IGA are the authors of a sufficient parametric design space which enables the creation of the final design by them or others. One fundamental challenge they pinpoint as linked with meta-designers' role is that of balancing diversity against fitness. In particular, adding details to the design can produce an exponential increase in the parameterization's complexity.

Our analysis of related work revealed a dearth of first-hand *longitudinal* accounts of *real-world designer experiences* of applying IGAs, yet only research with authentic industrial design problems outside laboratory conditions and covering the full breadth of multi-stage creative design can inform both the design of suitably refined algorithms and their appropriate, well-afforded adoption by practitioners. Any such work must examine the design system comprising the human designer and the software jointly. It must address this socio-technical system's creation of a complete design specification for not a single output but a solution space capturing the dynamics of a real-world design case. Thereby, scholarship and practice alike can

understand all the relevant objectives, requirements, and limitations, in awareness of the resources available and factors such as the intended use environment [38].

### 3 The design study

We found an autoethnographic method highly suitable for rich data promoting profound insight that fills the research gap. With this technique, our study not only builds on the established tradition of qualitative research in design research [7] but also tackles a concrete design task “in the wild.”

#### 3.1 The design task

Our study cohered around the real-world task of designing a pendant lamp fixture suitable for mass personalization. This framing, by constraining the primary manufacturing and assembly methods under consideration, already restricted the design space substantially. In its function, a pendant lamp fixture is a rather mature basic concept in interior design: typically, at least one bulb or other light source hangs from the ceiling via electrical wire or supports, with the fixture having a configuration of shades and reflectors attached to it. Pendant structure, however, manifests extensive variety, and the markets show constant interest in new designs. With these characteristics, the design of a pendant lamp offered an ecologically valid design problem for our purposes.

As for the temporal framing, the project’s Phase 1, lasting 11 weeks, was based on the designer-researcher’s personal interest rather than commissioned work. Phase 2 of six weeks, in contrast, entailed more significant time pressure and extrinsic motivation, in that the results were to be exhibited publicly as assembled unique artifacts.

#### 3.2 Methods

The research project situated this task within the *research through design* (RtD) framework. Evolving from a design-oriented stream of human–computer interaction research, RtD focuses on building knowledge through design practice [59]. It shares characteristics with constructive design research [27], a way of addressing design problems by design-specific means to produce design outcomes. With strong accountability directed principally toward design practice rather than other fields, the rigorous theoretical use of RtD in design research has recently attracted the design community’s interest [20, 36].

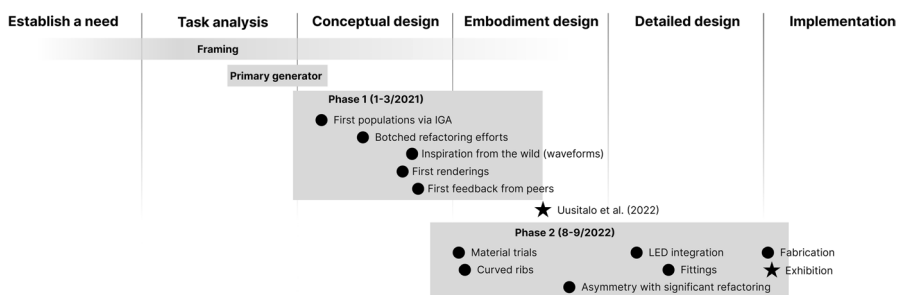
Some studies examining the design process have employed a think-aloud protocol. This method has propelled two contributions that informed our work: dividing a designer’s activities in a parametric-design process into two levels—application of design knowledge and a rule algorithm [58]—and developing a problem–solution co-evolution model for design [15]. However, protocol-based studies encompass only brief portions of the full design process. In their typically lab-based settings,

one cannot comprehensively chart the interactions among key components of the process, such as actors' capabilities, their actions, the artifact's creation, audiences, and the affordances of the material world [17].

Studies that adhere to protocols also presume a gulf between the researcher and the designer subject. While such splitting allows for reflection in action, this setting remains limited to researcher-imposed problems and discrete phases or steps, since the researcher seldom can accompany the designer for a longer time. This limitation renders the think-aloud method impractical for longitudinal, reflection-in-action studies of real-world design problems.

These considerations were among the factors guiding us toward *researcher introspection*. In this family of methods, researchers' investigation of their own ongoing experiences serves as the primary source for generating knowledge. Xue and Desmet in particular stress its value for human–computer interaction researchers wishing to access insider experiences in a specific domain [55]. The researcher-introspection technique we chose is *autoethnography*, a means of bringing together autobiographical reflection and ethnographic principles for inquiring into cultural phenomena through self-observation and reflexive investigation [33]. From a survey of the literature, Lucero has compiled criteria for successful ethnography (well-set study boundaries, authenticity, plausibility, criticality, self-revealing writing, interlacing of ethnographic material and confessional writing, and generalizability) [32]. Offering further guidance, Chien and Hassenzahl examined how autoethnography can be combined with the RtD approach [9]. They put emphasis on the richness of the data obtained from the designer's accounts, alongside the analysis's systematic nature and anchoring the interpretation of the data in theory-based knowledge.

Adhering to the principles specified by Chien and Hassenzahl, the paper's first author conducted autoethnographic research utilizing screenshots from the software (encapsulating interim genotype versions and phenotypes developed by an evolutionary algorithm) and textual notes taken during and right after design sessions (in line with practical considerations detailed by design researchers [37, 55] in relation to material such as diary entries). Hence, our study benefited from both concurrent and retrospective introspection, with emphasis weighted toward the latter.



**Fig. 1** The design study's activities depicted in line with Howard et al.'s [23] six stages of engineering design processes, where the dots marking the key events in the reflection reported upon point to how IGA was used throughout the design process



Presenting the study's design and key steps, Fig. 1 highlights the longitudinal nature of the project and its exploration-oriented goal. We sought to identify areas worthy of future study rather than find generalizable answers to a specific question. Our discussion section details the steps necessary for the designer to reach that crucial goal.

### 3.3 Designer perspective

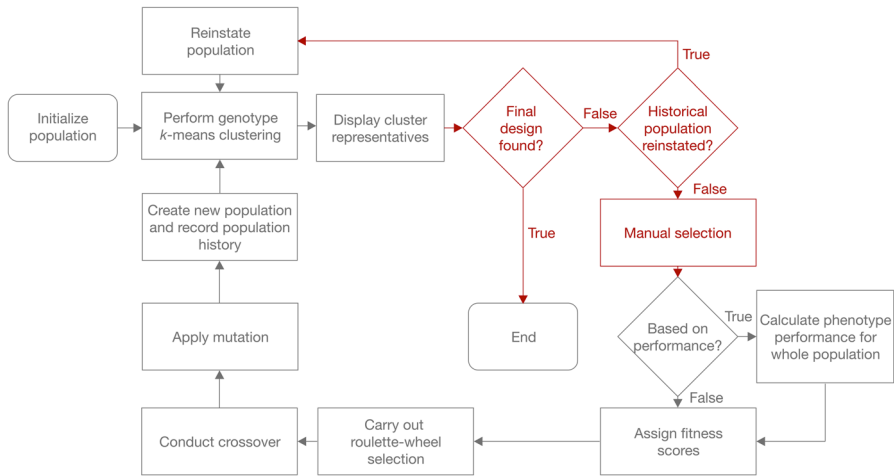
Especially with regard to the findings and their interpretation, this researcher-introspection study was shaped by all authors. However, at the heart of it is the autoethnography by the first author, an experienced researcher and designer. Alongside eight years of human-centered design research, this author's background includes a decade of industry experience as a consulting and in-house industrial designer in Europe and the US. Work as a surface modeler in the automotive industry and as an industrial designer for e.g. occupational protective equipment has supplied expert-level skills in surface and parametric solid CAD. Also, the designer-researcher has been teaching the use of CAD tools at design universities part- and full-time. As for the software employed in our study, the first author can be considered an advanced user but not an expert.

### 3.4 The software tools and algorithm

Dovetailing with the objectives of constructive design research, one of our major goals is to advance the adoption of IGAs in industrial product design. This necessitates empowering other designers to apply our insights. For ready application in their practice, we turned to a set of off-the-shelf software tools that are already popular in real-world design.

The designer's co-creation partner in our case study was a multiple-component system. In it, the visual programming extension *Grasshopper* [19] provides a parametric design environment (PDE) for the second component, the 3D modeling application *Rhinoceros 3D* [40]. For the environment's construction, parameterized nodes get connected to form a directed acyclic graph, where the nodes represent shape-grammar rules. Finally, freely available add-on *Biomorpher* provides an IGA serving to optimize the parameters (see Fig. 2). To this end, *Biomorpher* encodes all parameters in a normalized real-number genotype vector. It provides a user interface for manipulating the algorithm's initial parameters, such as mutation rate, population size, and single-point crossover. The interface also facilitates later evaluation and selection of design candidates that the human partner deems worthy of retention and further evolution.

Generative design algorithms in general can effortlessly produce innumerable design candidates; however, reviewing these outputs and choosing the best of them for further development can quickly grow overwhelming [18, 46]. To reduce user fatigue, *Biomorpher* exploits a *cluster-orientated genetic algorithm* (COGA) [6] that applies *k*-means clustering to the whole population of candidates and presents only 12 instances of the clusters' centroids to the designer for review, as shown in Fig. 3.



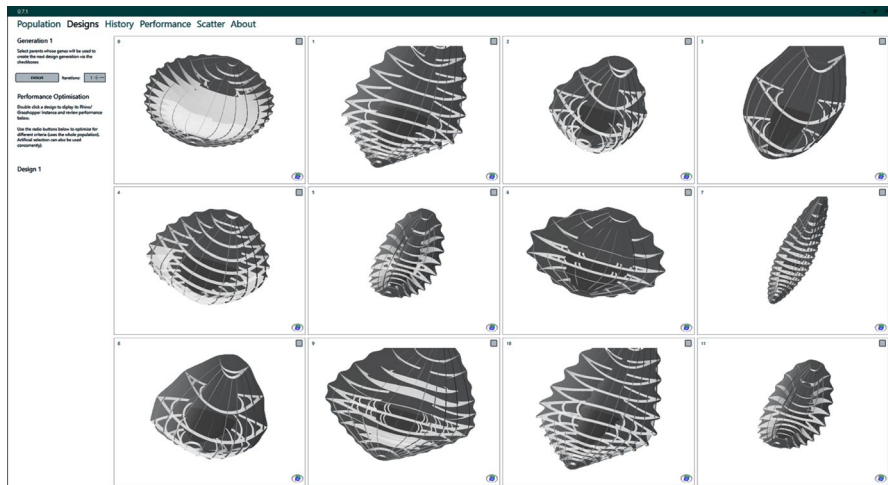
**Fig. 2** The Biomorpher process, with human-interaction stages in red—flowchart adapted and extended from Harding and Brandt-Olsen’s work [22] (Color figure online)

In a similarity to Krish’s “represented regions” of the solution space [28], the clusters can be thought of as representing the various designs’ spread of locations in a multi-dimensional space of quality characteristics. All instances are accompanied by details such as the number of non-shown instances in the cluster. The system assigns all user-selected candidates a maximum fitness of 1.0. A designer may complement the chosen set of design candidates by specifying objective performance criteria for further evolution; these criteria correspond to standard evolutionary algorithms’ objective function. Any optional criteria supplied get transformed into a single fitness value (in which they are granted equal weight) applied to all candidates not yet picked by the user. When creating a new population from the fittest individuals, Biomorpher maintains a record of the previous population so that the user can return to previous generations if evolution leads in an undesired direction in the parameterized solution space. After having terminated the process, the designer can commence further design/fabrication from a given instance’s 3D geometry. Biomorpher’s operation and interaction with the designer, outlined in Fig. 2, are detailed more fully from a technical standpoint elsewhere [22].

### 3.5 Findings: introspective design reflections

This section presents an experientially oriented account of using the IGA software described above. It is written in the first-person singular to emphasize the autoethnographic reflections and for readily distinguishing from the analysis based upon it.

The presentation begins with the Phase 1, the 11 weeks in which the designer used the IGA software to delimit a solution space capable of visualizing pendant-lamp concepts. From section “Operationalizing disorder” onward, the account deals with the six weeks within which Phase 2 refactored the design and fabricated a set



**Fig. 3** Biomorpher's selection view from the second phase of the project: drawn from the full generation of 48 instances, 12 example design instances intended to present maximally different designs, as determined by *k*-means clustering in Biomorpher (the whale-skeleton-like rib structure is a primary-generator feature retained throughout the process)—screenshot taken and used with permission from Biomorpher's authors [22], with white balance adjusted for clarity

of physical prototypes for the EMMA exhibition. The report focuses on reflections that illuminate how developments in the designer's *knowledge-level* problem space affect *rule-level* considerations, an issue elaborated upon below in the context of design fixation.

### 3.5.1 Aesthetic objectives

The pendant would need to be rather large: the actual interior I had in mind was a  $9 \times 5$  meter space in a lakeside cabin with a contemporary ethos, where the ceiling is five meters high on average. The harsh, often windy north-European locale of this shoreline site bears resemblances to the northern Atlantic coast. My initial concepts for the design borrowed from the aesthetics of aviation, specifically the wing foil and truss structures of airplanes. Another design cue came from cetaceans, even a whale carcass with the rib cage visible as bare bones. Vaguely linked to this in my mind was an Inuit kayak: flashes from some old films of Inuit life hit my mind occasionally during the intentionally low-key incubation process. Hence, the cues were conceptual in nature.

At this early stage in the design, I performed no searches (e.g., of the Internet) for images, since that might have constrained the mental imagery of the structures during a very sensitive stage in the design process. My objective was to channel an experience of people enjoying the interior with subtle visual cues, leading to interpretations stemming from their personal experience. I framed the artifact as one intended to raise questions, not model any existing entity. Success in honoring the design intent for the pendant must be judged by these multi-interpretive semantics.

The initial design space was not informed by visual cues and form semantics alone, however; materials and manufacturing technology often restrict the design space significantly. In a product architecture, no clear line exists between the structure's visual elements and various functions. The balance for this particular product lay more toward aesthetics' significant role in interior design, and few stakeholders with conflicting requirements were involved.

For the material, I contemplated plywood, because of its affordances for design. Even high quality plywood is available locally. This material is lightweight, relatively inexpensive, long-lasting, easily and safely disposable, and rather sustainable from a manufacturing point of view. Such techniques as laser cutting make it easy to cut accurately from a sheet, and assembly, in turn, can rely on simple separate fittings if any are needed at all. It can bend, though only in a single direction at a time. Another aesthetic element is thin sheets' ability to let some light through. Finally, plywood is visually suited to many environments.

### 3.5.2 A definition and genotype from conceptual cues

I used the IGA for a low-intensity process of initial fixture design from January to early March 2021, often with days between consecutive sessions. When the initial design cues, aesthetic considerations, and material selection had circumscribed the concept sufficiently for proceeding with embodiment design [23], I developed the initial parameters for the model. My objectives for the parameterization and its genes were to 1) create valid geometry; 2) enable easy growth of the solution space, for greater diversity of fabricable designs; and 3) sufficiently factor in the capabilities and limitations of the materials, manufacture, and assembly methods.

While the aforementioned cabin interior functioned as an environment cue, I did not confine my focus to delivering a single design. Instead, the objective was a robust parametric representation and genotype capable of ultimately covering a large enough solution space for efficient product personalization, aligned with the promise of industry 4.0 [53]. Accordingly, the co-creative system had to mesh seamlessly with the final stages (detail design and implementation [23]), since it would be inconvenient to leave any significant steps of manual post-processing for individual phenotypes.

I generated the initial populations during the first design session with the computer, after parameterizing the design and setting up the initial gene configuration. Thus began an iterative process with the IGA: After creating a few generations via one parametric definition, I compiled insight for re-framing the problem. Once the generated populations had served their purpose in facilitating this re-framing, I discarded them. The insight then guided my further development of the definition and changes to the gene value domain limits (i.e., shaping of the solution space).

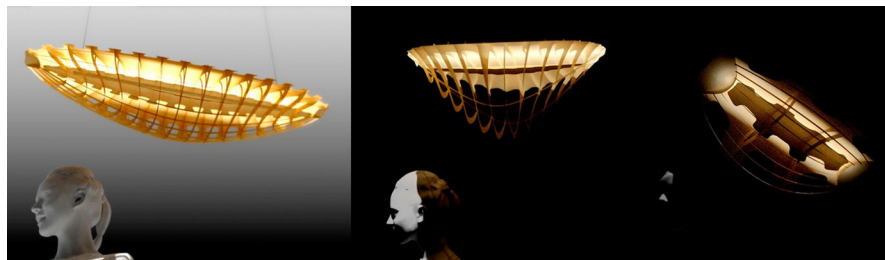
To support exploration of the solution space, I directed the IGA's generation of populations, sometimes without a clear objective in mind. With an aim of exploring the current solution space, I was attuned to unexpected versions and details. Awareness of the solution space's limitations motivated me to encourage variety in what the system produced. The visual representations and an ability to both manipulate and render them at different degrees of fidelity on the screen were imperative for

assessment and for decisions on future definition changes. In the majority of cases, I found the plain visualization furnished by Biomorpher's user interface (an example of which is shown in Fig. 3) sufficient. In both the first and the second phase of the project, I carried out rudimentary lighting studies via computer renderings after half of the parameterization effort (Fig. 4 presents a few of these renderings). For such renderings to be representative enough for full-fledged analysis, a certain level of model fidelity is necessary. Current PDE tools require the human partner to put some effort into the model.

For further development of the design, I engaged in individual sessions at intervals of several days. In some of these sessions too, I generated populations for exploring the solution space where inspiration led me, without making changes to the parameter settings, while focused parameterization work ensued on other occasions.

### 3.5.3 A patch of botched efforts

After five design sessions (of 2–4 h each) in phase 1, I created a new parametric definition, with a wider solution space, from scratch. Ultimately, I had to discard this after a few hours of work because a critical mistake became evident with regard to the objective constraints of the material: geometry that requires curvature in two dimensions, of which plywood is incapable. When defining the initial parameters,



**Fig. 4** Computer-generated renderings as used for the assessment of diversity within the parameterized solution space and for visual appeal of both the basic structural concept and the individual instances when lighting is simulated

I was aware of the constraints linked to the material choice, but I later forgot the reason for setting them as I had. Upon finding the resulting instances beyond the viable design space, I back-pedaled to an earlier version, which I refactored for added robustness and greater capacity to produce further variations. Later on, sharing the state of the “evolution in progress” with three peers (on separate occasions) left me demotivated: disappointed that they had not seen anything particularly creative in the output, I felt pressure to pursue more novel output.

### 3.5.4 Inspiration from the wild

Then, in the third week of the first phase, viewing a television program with swimming whales inspired me to test a wave pattern for the strips under the pendant's belly. This knowledge-rooted inspiration sparked rule-articulation efforts: I set out to find patterns that fitted the materials and furnished a visually appealing feature. Although the re-designed parameterization and solution space in the second phase would not end up utilizing these patterns—development of other parts made it unnecessary—the renderings with the wave patterns did provide seeds for generating visual appeal via the gradient generated by the interplay of curved plywood and light.

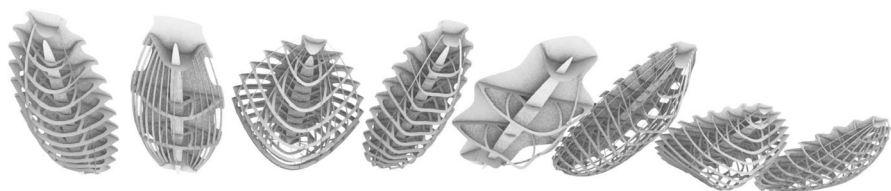
Another ultimately influential factor lay in the material I procured after the first main phase was complete: I ended up using thinner plywood than originally envisioned, for both bending and light-passing properties. This three-ply wood bends easily with the direction of the surface grain. Combined with aspirations for greater three-dimensionality in the outcome (for aesthetics and lighting appeal), this led toward a final configuration wherein the fixture's louvers (the ribs) follow a curve. The definition evolved iteratively as the design process uncovered further material- and geometry-related opportunities and constraints.

### 3.5.5 Operationalizing disorder

In the second phase of the work, I selected several form-describing attributes to equip the system with objectives for the design of the solution space. These entailed continua such as symmetric–asymmetric and organized–disorganized. My aim of expanding the solutions' variance required steering clear of the popular modeling practice of mirroring. Even though refactoring from disorganized definitions in insufficiently commented visual code demanded precious time and necessitated changes from the original principles for parameterization, both the underlying form principles and the design of the details improved in consequence. This is not uncommon in the course of remodeling something.

All told, 20 distinct genes control the geometry in the final version. The final parameterization for the artifact's asymmetrical undulation can be characterized thus: One gene is binary, for asymmetry being either on or off. In the former case, the amplitude of asymmetrical undulation of the features and, thereby, the global form can vary under the control of another gene. A gene that can take different values provides the seed for a random-number generator that dictates the locations of geometry change. Since evolution requires traits to pass to the next generation, the system can retain this.

Figure 5 presents an illustrative set of both symmetric and asymmetric instances—i.e., solutions with and without the randomly generated undulation in shape of the belly curves.



**Fig. 5** A collection of generated instances that showcases some of the diversity (the instances shown could be fabricated by unrolling the parts and cutting from sheet material; for explication, Fig. 6 presents the instance fourth from the left here as a fabricated prototype

### 3.5.6 Fabrication

For the move to creating a solution for prototype fabrication, I made a few post-evolution adjustments to the selected phenotype in each instance, by tuning the variables (individual “genes”) that guide feature-generation. The aim was to accentuate key characteristics, since one role for the fabricated prototypes was to demonstrate the extent of the variability that the parameterization could create. Accordingly, I adjusted such elements as the length, amplitude, and frequency of the wave-formed perimeter of the reflection-shield profile (which, in turn, controls the quantity of ribs) and the amplitude of the ribs’ asymmetric undulation. Even in this “tweaking” step, the solution-space exploration still involved the

**Fig. 6** A photograph of fabricated instances from the solution space, as exhibited at the museum





IGA through an evolutionary process. Once evolution had led me to an appealing instance, the tuning process applied alterations for its fabricated version.

The first fabricated instance was cut from 1.4 mm plywood with a laser cutter. Assembly was surprisingly smooth, leaving me proud that so little “real” prototyping had yielded such a successful outcome. Figure 6 presents photographs of three of the fully assembled artifacts at the museum. The third prototype’s asymmetrical undulation showcases the degree of versatility possible across instances from the solution space established.

## 4 Discussion

Proceeding from the autoethnographic material, the team of authors reflected collectively on the nature of the design process that emerged, on the creation performed by the designer and IGA together, and on the study’s limitations.

In sum, the introspective RtD study revealed the IGA’s multifaceted part in the design process. It helped the designer articulate the design space and, thereby, also understand that space’s boundaries. It played a role also in visualizing and conceptualizing the landscape of possibilities within them. Moreover, the algorithm functioned as a pathfinder too: the designer could take a passive role and let the IGA offer its suggestions, for rejection or to be picked up for further exploration. Finally, the algorithm aided the designer in visualizing and fine-tuning the vision for the final design. These roles prompted consideration of designer–IGA co-creation on several fronts, discussed below.

### 4.1 Early compassing of the design space

In that the designer set the initial objectives in response to particular visual cues for the design’s direction (e.g., a whale skeleton), the design process seems to have been informed by a *primary generator* [13], or a promising conjecture, often cited as supplying a basis for the design as it begins to unfold. However, the process deviated from the typical method of collecting visual material to serve as or develop primary generators. The designer searched for visual images aligned with the design cues only after developing a parametric definition and population generations based on this. The notes reproduced above express a concern that perusing actual images early on might be constrictive. For this reason, it seemed beneficial to use the IGA for probing aesthetic directions. Indeed, the IGA provided further cues of potential within the design space from early on. This observation provides evidence of IGAs’ potential utility as partners in actualizing and refining a designer’s visions. Proceeding from the primary generators, the co-creators can follow directions worthy of exploring by sculpting the parameterized solution space.



## 4.2 Support in problem–solution co-evolution

The initial parameter sets took only a few hours to develop, after which the designer utilized the IGA for population generation and evolution. The process of developing some populations and iteratively looping back to develop the definition further (or to correct the genes' scaling to reflect the design space's constraints) resembles the problem–solution co-evolution process as delineated by such scholars as Bernal et al., who note that, while generative design approximates the co-evolution problem and solution characteristic to expert designers, it lacks mechanisms for reformulation [4]. Because co-creativity with an IGA naturally steers a design process toward such dialogue, IGAs may help equip some of designers' processes with more expert-oriented characteristics.

A technique applied in the study's second phase may point to a mode of meta-design and IGA application that has received little scholarly attention (with few exceptions [5]) in the context of product design. This involves placing focus on sculpting the solution space. When developing the parameter definition's final version that resulted in the actual prototypes, the designer resolved to apply the IGA in phase 2's third parameterization session. Building on the earlier phase's results, the work now focused on attempting to expand the solution space via further features and control of them. While there was less need to "play with" IGAs in the early steps after some initial parameterization setup, the IGA ended up getting used constantly to inform the shaping of the solution space. The ability to visualize the variability of phenotypes encapsulated in the solution space and, on this basis, proceed further in some intriguing directions through evolution benefited the creative process. This afforded a meaningful, concrete mode of reflection and analysis that deserves greater attention.

The findings support the contention that employing an IGA in the design process can be valuable for informing and filtering the design space [21] through a cycle of population generation, analysis, and editing of the genotypic representation. In our case, by filtering the design space, the IGA exposed areas for potential inquiry, thus motivating the designer to redefine the constraints of the space. The role evident here is quite different from merely serving as a meta-heuristic tool for finding unexpected but iteratively optimized solutions to quantifiable problems: the IGA assisted in redefining the problems themselves, in addition to offering solutions.

## 4.3 The fixation trap and escaping it

As the foregoing discussion explicates, genetic algorithms open a door whereby their users (designers and others) can discover unexpected, serendipitous solutions to problems. Indeed, the designer's introspective report identifies several occasions on which this occurred in our single case study alone. However, hindsight enabled identifying something else alongside these: negative impacts on the design process from the interaction with IGAs. These correspond to three "fixation modes" conceptualized by Robertson and Radcliffe in the context of CAD more generally [42].

Firstly, a form of *bounded ideation* is evident in the session wherein the designer started creating an alternative genotype from scratch but later recognized the solution to be outside the limits of the fabrication possibilities accepted. Since expert designers intuitively grasp the many constraints involved and frame the problem accordingly [12], this can be regarded as a “newbie error.” While having attended to the constraints initially, the designer forgot a fundamental one after getting captivated by the engaging computational-design task of defining a parameterization with a large enough solution space and growing immersed in the suggestions presented by the partner. In the language of Yu et al.’s model of parametric design [58], cognitive load from work at rule-algorithm level led to mistakes in knowledge-level work.

Secondly, while one of the initial reasons for devising a new genotype was to open new angles of approach to the design space so as to avoid *premature fixation*. In the initial genotypic representation, the interaction with the software distracted from the creative tasks at the core of the project. Coupled with time constraints, this distraction resulted in returning to the older version of the genotypic representation rather than creating a new one. Likewise, the labor perceived as connected with untangling the convoluted codebase culminated in delays to the inevitable refactoring of the definition for the asymmetry features. These compromised the end result’s operationalization of asymmetry. As one might expect, the threshold to significant changes rose with complexity. Such coding practices as proper commenting and good general organization could have ameliorated this manifestation of premature fixation by decreasing the cognitive burden of refactoring and considering further changes.

Finally, *circumscribed thinking* became prominent in the process observed. From among all possible ways of using Grasshopper, with its numerous features and plugins, the designer chose to approach the design task primarily by means of parametric modeling schemas encountered previously. By circumscribing the designer’s thinking, prior experience may have resulted in missed opportunities to develop a genotype for broader design-space exploration— e.g., applying an evolutionary approach that affords greater variability [24]. The diary from the second phase of the project captures a second example, through contemplation of whether directly modeling one or a few instances might support accumulation of design knowledge better than does immersion at algorithm level with all its attendant difficulties of widening the solution space for generation of instances. The notes imply a feeling of being “swamped” by rule-development work, with accompanying worries about general progress and the resulting design quality. In another telling incident, building a physical prototype sparked awareness that the rule definition had caused an unappealing inflection in the instances’ longitudinal strips whenever the asymmetry gene was active. Stepping outside the digital design environment uncovered new design knowledge, prompting changes at rule-algorithm level. This interplay too highlights circumscribed thinking as an outgrowth of challenges in propagating design knowledge to operations (algorithm) level.

While much of the fixation identified in connection with these modes may plague work with PDEs more broadly, applying an IGA certainly influenced their magnitude. We can conclude that genetic algorithms, while offering general benefits

through their capacity to generate unexpected, seemingly creative design solutions, may also limit the designer's field of vision, foster complacency and overlooking of biases, and lead to suboptimal work practices.

#### 4.4 The IGA as a creation partner

Creativity is most commonly defined in terms of two components, novelty and value [43]. In conditions of a fitting parameterization, IGAs provide an opportunity to search for unexpected, novel solutions from a meaningful (i.e., valuable) solution space. Moreover, they permit inclusion of objective selection criteria if needed. By virtue of their ability to assess both novelty and value, we consider them *partners* in co-creative interaction.

The IGA's capacity to draw out instances previously unknown to the designer spurred the human partner to generate new populations and generations accordingly, even in the absence of a corresponding explicit objective. Accordingly, the risk of user fatigue, articulated by, among others, Shackelford [46], likely depends on the role, expectations, and motivations of the person performing the selection: a designer striving to improve the meta-design differs in exploration-drivers from one merely aiming for a sufficient solution from some solution space. In any case, the practical flow of the designer's work sits well within frameworks of a creative process comprising mutually distinct phases of active doing plus thinking (i.e., parameterization) and spans of lower-intensity incubation (in which one might apply IGAs "for fun") [34].

For the IGA to act as a creative partner, the algorithm must encode some of the human designer's knowledge of the design space. How close it comes to the necessary level of expertise depends on the designer's ability to encode the design space in a creativity-conducive manner. Notwithstanding the success of the case project, we cannot conclude that it is universally achievable. Being a rather new addition to designers' toolboxes, IGAs probably will undergo substantial experimentation in various design communities before best practice for representing design spaces becomes clear and established.

By following the intricate lines of relations between the co-creative partners, along with the flows of the process's materials and environment, our study shed light on several avenues for improving the partnership further, particularly in relation to the fixation modes discussed above, support for design co-evolution, and means of inspiring designers (e.g., through visualization). These paths offer a starting point for developers embarking on further adaptation of IGAs in co-creative design.

The method followed in the project develops diverse configurations with the same basic structure, rather than disparate instances [24], as Fig. 5 illustrates. This stems from the primary generator driving the initial work, in conjunction with the focus on producing tangible outcomes in awareness of the constraints imposed by the materials and manufacturing methods. Another factor directly affecting variability is the designer's skill in transferring design knowledge to rule-algorithm level. One could argue that the computer is only as good a designer as its human partner is.

Co-creation with the resulting parametric definition can produce variety-rich sets of valid geometries that are suitable for fabrication. From the selections to fabrication in the case project, little extra labor was needed to generate the vectors for cutting the parts from sheet material (e.g., with laser or water-jet tools) for the prototypes in Fig. 6. Upon the conclusion of the design process, the IGA's role had evolved from playing a part in developing the design (i.e., in the meta-design effort) to that of a partner entity with which the personalized instances underwent evolution and ultimate selection.

The outcomes are conditioned also by the partners' concept of the design project: how both humans and algorithmic tools express it. The final "tweaking" of the designs before fabrication is a case in point. In a contemporaneous note, the designer mentions perceiving them as sub-types of instances and undertaking fine-tuning to create a prototypical example of a certain sub-type. The designer saw the solution space not as uniform but as regions represented by certain prototypical instances.

#### 4.5 Limitations of the study

Though our report fruitfully expands the picture from our earlier work by covering, in addition, the design-project phases of late concept design, embodiment design, detail design, and to some extent the implementation stage, it could be extended further, beyond the stages of Howard et al. [23]. Co-creative commercialization of the solution space would benefit from refining the design for lean manufacturing and assembly.

The reader should bear in mind also that our study is anchored in experiences from a single designer and design case. Often, first-person methods such as the one employed here face justified criticism for their limited potential to offer generalizable conclusions. While we judged a reflection-based longitudinal case study to hold particular value for tool-creators' endeavors to explore how a given tool gets used and experienced in practice, we were keenly aware that such work primarily pin-points areas meriting further study. To produce general conclusions, the research must encompass a broad spectrum of participants and cases, and it would benefit also from quantitative measurement instruments. The paper's final section elaborates on our plans for precisely such efforts.

In this study, the researcher was part of the experiment. While separation between designer-participant and researcher may have mitigated risks of bias, it would also have removed the researcher from the experience. For studies building on our work, we recommend a mix between independent participants and designers acting also as researchers, for reducing any bias while still permitting some researcher introspection. Also, the introspection method, while valuable, shows sensitivity to time and context. When comparing the Phases 1 and 2 of the experiment in hindsight, the designer reported feeling differently about some of the earlier self-reflection, likely through experience gained with the algorithm and work with the physical prototype. This highlights that one's contemplation perspectives can vary and develop even within a single creative process. To circumvent such issues with introspection's validity and address note-taking granularity, we engaged in further reflection on

action when framing the designer's notes against the backdrop of design literature and when preparing this article.

When reviewing the project's documentation, we found little reflection in action: most notes were retrospective reflections on the activities, even if the insight was recorded not long after the design session. Future research could attend more closely to balance in this respect. A think-aloud method with simultaneous screen-capture from the software could have encouraged different thoughts, on a wider range of topics. However, anyone applying such techniques to a project several weeks long (and potentially involving incubation periods during which additional insight may develop) must wrestle with vast quantities of data. Furthermore, these data-collection methods bring their own validity threats – for instance, as things get interesting and a certain flow state is established, note-taking may interfere with pivotal moments [37]. That said, additional *in-situ* documentation methods, such as capturing video of the activities for subsequent analysis, would provide higher-fidelity results. We intend to implement these to enrich future work.

## 5 Conclusions and future work

Our RtD-grounded report provides a thorough experiential overview of co-creative IGA application throughout a real-world creative design process – all the way from late concept design to tailoring for fabrication of working prototypes for products suited to personalized manufacture. At the same time, it presents methodology and rich practical insight contributing to the emerging body of research into how AI influences the experience, and perceived agency, of product-design practitioners specifically and professional creatives more generally.

Reflecting on our findings against theory from design research and computational design, we found that the relative ease of applying interactive evolutionary algorithms to support design-space articulation and exploration improved the designer's capabilities and highlighted alternative paths in the design process. On the other hand, the case study revealed the “darker side” too: how engaging with such algorithms can impinge on design practice (e.g., by exacerbating bounded ideation). Awareness of these potential pitfalls could serve as a first step toward avoiding them through both appropriate use of the software and developers' adjustments to it. Translating design knowledge emerged as particularly important. Its operationalization was rendered much more complex and daunting on account of the objective of a solution space of fabricable instances, as opposed to a single design instance. Acting as a meta-designer tackling these objectives requires skills that may require more advanced skills and, ultimately, specialization on designers' part.

The autoethnographic study highlights shifting and complex relations that are by no means straightforward. Hence, we plan to direct our future work toward offering deeper, generalizable, and more actionable insight pinpointing how AI algorithms can augment and also complement human creativity in design practice. To this end, we aim to conduct longitudinal research that combines small-scale first-person studies with larger protocol-based studies. This should produce highly reliable findings

fueled by broad-based reflection in action by a wide pool of designers. In scholarly work following from such efforts, large-scale quantitative studies should flesh out the picture still further by using custom-developed questionnaires and well-validated established instruments to check the generalizability of selected findings.

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## Declarations

**Conflict of interest** The authors declare that they have no conflict of interest.

**Ethical approval** The research complies with the general principles for ethical review of research in Finland.

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## References

1. J. Alcaide-Marzal, J.A. Diego-Mas, G. Acosta-Zazueta, A 3D shape generative method for aesthetic product design. *Des. Stud.* **66**, 144–176 (2019)
2. M.C. Ang, H.H. Chau, A. McKay, A. De Pennington. Combining evolutionary algorithms and shape grammars to generate branded product design. In: *Design Computing and Cognition '06*. pp. 521–539. Springer Netherlands, (2006)
3. A. Banerjee, J.C. Quiroz, S.J. Louis. A model of creative design using collaborative interactive genetic algorithms. In: *Design Computing and Cognition '08*, pp. 397–416. Springer, Berlin (2008)
4. M. Bernal, J.R. Haymaker, C. Eastman, On the role of computational support for designers in action. *Des. Stud.* **41**, 163–182 (2015)
5. B.G. Bezirtzis, M. Lewis, C. Christeson. Interactive evolution for industrial design. In: *C & C '07: Proceedings of the 6th ACM SIGCHI Conference on Creativity & Cognition*. pp. 183–192. Association for Computing Machinery, New York (2007)
6. C.R. Bonham, I.C. Parmee. An investigation of exploration and exploitation within cluster oriented genetic algorithms (COGAs). In: *Proceedings of the 1st Annual Conference on Genetic and Evolutionary Computation*, vol. 2, pp. 1491–1497 (1999)
7. K.H. Chai, X. Xiao. Understanding design research: a bibliometric analysis of design studies (1996–2010). *Des. Stud.* **33**(1), 24–43 (2012)

8. Y.S. Chang, Y.H. Chien, H.C. Lin, M.Y. Chen, H.H. Hsieh, Effects of 3D CAD applications on the design creativity of students with different representational abilities. *Comput. Hum. Behav.* **65**, 107–113 (2016)
9. W.C. Chien, M. Hassenzahl, Technology-mediated relationship maintenance in romantic long-distance relationships: an autoethnographical research through design. *Human-Comput. Interact.* **35**(3), 240–287 (2020)
10. F. Cluzel, B. Yannou, M. Dihlmann, Using evolutionary design to interactively sketch car silhouettes and stimulate designer's creativity. *Eng. Appl. Artif. Intell.* **25**(7), 1413–1424 (2012)
11. N. Crilly, The evolution of “co-evolution” (Part I): problem solving, problem finding, and their interaction in design and other creative practices. *She Ji J. Design, Econ. Innov.* **7**(3), 309–332 (2021)
12. M.M. Dabbeeru, A. Mukerjee. Discovering implicit constraints in design. In: *Design Computing and Cognition '08*. pp. 201–220. Springer, Netherlands (2008)
13. J. Darke, The primary generator and the design process. *Des. Stud.* **1**(1), 36–44 (1979)
14. K. Dorst, The core of “design thinking” and its application. *Des. Stud.* **32**(6), 521–532 (2011)
15. K. Dorst, N. Cross, Creativity in the design process: co-evolution of problem-solution. *Des. Stud.* **22**(5), 425–437 (2001)
16. J. Frich, L. MacDonald Vermeulen, C. Remy, Biskjaer, M.M., Dalsgaard, P.: Mapping the landscape of creativity support tools in HCI. In: *CHI '19: Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems* (2019)
17. V.P. Glăveanu, Rewriting the language of creativity: the five A's framework. *Rev. Gen. Psychol.* **17**(1), 69–81 (2013)
18. D.W. Gong, G.S. Hao, Y. Zhou, X.Y. Sun, Interactive genetic algorithms with multi-population adaptive hierarchy and their application in fashion design. *Appl. Math. Comput.* **185**(2), 1098–1108 (2007)
19. Grasshopper: <https://www.grasshopper3d.com/>, accessed 22 March 2021
20. C. Grey Isley, T. Rider. Research-Through-Design: Exploring a design-based research paradigm through its ontology, epistemology, and methodology. In: *DRS Biennial Conference Series*. <https://dl.designresearchsociety.org/> (2018)
21. K. Halskov, C. Lundqvist, Filtering and informing the design space: towards design-space thinking. *ACM Trans. Comput. Hum. Interact.* **28**(1), 1–28 (2021)
22. J. Harding, C. Brandt-Olsen, Biomorpher: interactive evolution for parametric design. *Int. J. Archit. Comput.* **16**(2), 144–163 (2018)
23. T.J. Howard, S.J. Culley, E. Dekoninck, Describing the creative design process by the integration of engineering design and cognitive psychology literature. *Des. Stud.* **29**(2), 160–180 (2008)
24. P. Janssen, A generative evolutionary design method. *Digit. Creat.* **17**(1), 49–63 (2006)
25. A. Kantosalo, H. Toivonen, Modes for creative human–computer collaboration: Alternating and task-divided co-creativity. In: *Proceedings of the Seventh International Conference on Computational Creativity*. pp. 77–84. [computationalcreativity.net](http://computationalcreativity.net) (2016)
26. S.W. Kielarova, S. Sansri. Shape optimization in product design using interactive genetic algorithm integrated with multi-objective optimization. In: *International Workshop on Multi-disciplinary Trends in Artificial Intelligence*. pp. 76–86. Springer (2016)
27. I. Koskinen, P.G. Krogh, Design accountability: When design research entangles theory and practice. *Int. J. Design* **9**(1) (2015)
28. S. Krish, A practical generative design method. *Comput. Aided Design Appl.* **43**(1), 88–100 (2011)
29. H.C. Lee, M.X. Tang, Generating stylistically consistent product form designs using interactive evolutionary parametric shape grammars. In: *2006 7th International Conference on Computer-Aided Industrial Design and Conceptual Design*. IEEE (2006)
30. H. Liu, M. Tang, J.H. Frazer, Supporting creative design in a visual evolutionary computing environment. *Adv. Eng. Softw.* **35**(5), 261–271 (2004)
31. C.H. Lo, Y.C. Ko, S.W. Hsiao, A study that applies aesthetic theory and genetic algorithms to product form optimization. *Adv. Eng. Inform.* **29**(3), 662–679 (2015)
32. A. Lucero, Living without a mobile phone: an autoethnography. In: *DIS '18: Proceedings of the 2018 Designing Interactive Systems Conference*. pp. 765–776 (2018)
33. G. Maréchal, Autoethnography, in *Encyclopedia of Case Study Research*. ed. by A.J. Mills, G. Durepos, E. Wiebe (SAGE, Thousand Oaks, 2010), pp.34–45
34. C. Martindale, Creativity and connectionism, in *The Creative Cognition Approach*. ed. by S.M. Smith, T.B. Ward, R.A. Finke (MIT Press, Cambridge, 1995), pp.249–268



35. W.J. Mitchell, Constructing complexity. In: *Computer Aided Architectural Design Futures 2005*, pp. 41–50. Springer, Berlin (2005)
36. P. Murphy, Design research: aesthetic epistemology and explanatory knowledge. *She Ji J. Design, Econ. Innov.* **3**(2), 117–132 (2017)
37. O. Pedgley, Capturing and analysing own design activity. *Des. Stud.* **28**(5), 463–483 (2007)
38. P. Ralph, Y. Wand, A proposal for a formal definition of the design concept, in *Design Requirements Engineering: A Ten-Year Perspective*. ed. by K. Lyytinen, P. Loucopoulos, J. Mylopoulos, B. Robinson (Springer, Berlin, 2009), pp.103–136
39. G. Renner, A. Ekárt, Genetic algorithms in computer aided-design. *Comput. Aided Design Appl.* **35**(8), 709–726 (2003)
40. Rhinoceros3D: <https://www.rhino3d.com/>, accessed 22 March 2021
41. H.W. Rittel, M.M. Webber, Dilemmas in a general theory of planning. *Policy Sci.* **4**(2), 155–169 (1973)
42. B.F. Robertson, D.F. Radcliffe, Impact of CAD tools on creative problem solving in engineering design. *Comput. Aided Design Appl.* **41**(3), 136–146 (2009)
43. M.A. Runco, G.J. Jaeger, The standard definition of creativity. *Creat. Res. J.* **24**(1), 92–96 (2012)
44. D.A. Schön, *Reflective Practitioner* (Basic Books, New York, 1983)
45. D.A. Schön, Designing as a reflective conversation with the materials of a design situation. *Knowl. Based Syst.* **5**(1), 3–14 (1992)
46. M.R.N. Shackelford, Implementation issues for an interactive evolutionary computation system. In: *GECCO '07: Proceedings of the 9th Annual Conference Companion on Genetic and Evolutionary Computation*. pp. 2933–2936. Association for Computing Machinery, New York (2007)
47. W. Sharrock, B. Anderson, Organizational innovation and the articulation of the design space, in *Design Rationale*. ed. by T.P. Moran, J.M. Carroll (CRC Press, Boca Raton, 1996), pp.429–451
48. H.A. Simon, *The Sciences of the Artificial* (MIT Press, Cambridge, 1969)
49. D. Singh, N. Rajcic, S. Colton, J. McCormack, Camera obscurer: generative art for design inspiration, in *Computational Intelligence in Music, Sound, Art and Design*. ed. by A. Ekárt, A. Liapis, M.L. Castro Pena (Springer, Berlin, 2019), pp.51–68
50. J. Su, S. Zhang, Research on product shape innovation design method with human–computer interaction through genetic algorithm. In: *2010 IEEE 11th International Conference on Computer-Aided Industrial Design & Conceptual Design 1*. pp. 301–305. IEEE (2010)
51. N.A. Tabatabaei Anaraki, Fashion design aid system with application of interactive genetic algorithms. In: Correia, J., Ciesielski, V., Liapis, A. (eds.) *Computational Intelligence in Music, Sound, Art and Design*. pp. 289–303. Springer, Berlin (2017)
52. S. Uusitalo, A. Kantosalo, A. Salovaara, T.Takala, C. Guckelsberger, Co-creative product design with interactive evolutionary algorithms: a practice-based reflection. In: *Artificial Intelligence in Music, Sound, Art and Design*. pp. 292–307. Springer International, Berlin (2022)
53. Y. Wang, H.S. Ma, J.H. Yang, K.S. Wang, Industry 4.0: a way from mass customization to mass personalization production. *Adv. Manuf.* **5**(4), 311–320 (2017)
54. R.F. Woodbury, A.L. Burrow, Whither design space? *Artif. Intell. Eng. Des. Anal. Manuf.* **20**(2), 63–82 (2006)
55. H. Xue, P.M.A. Desmet, Researcher introspection for experience-driven design research. *Des. Stud.* **63**, 37–64 (2019)
56. Y. Yang , S. Peng, L. Zhu, D. Zhang, Z. Qiu, H. Yuan, L. Xian, A modified multiobjective self-adaptive differential evolution algorithm and its application on optimization design of the nuclear power system. *Sci. Technol. Nuclear Install.* **2019** (2019)
57. W. Yao, Y. Ding, Smart city landscape design based on improved particle swarm optimization algorithm. *Complexity* **2020**(7), 1–10 (2020)
58. R. Yu, N. Gu, M. Ostwald, J.S. Gero, Empirical support for problem-solution coevolution in a parametric design environment. *AI EDAM* **29**(1), 33–44 (2015)
59. J. Zimmerman , J. Forlizzi, S. Evenson, Research through design as a method for interaction design research in HCI. In: *CHI '07: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. pp. 493–502 (2007)