

**Ceci n'est pas une Chaise:  
Emerging Practices in Designer-AI Collaboration**

van der Burg, V.; Akdag Salah, A.A.; Chandrasegaran, R.S.K.; Lloyd, P.A.

**DOI**

[10.21606/drs.2022.653](https://doi.org/10.21606/drs.2022.653)

**Publication date**

2022

**Document Version**

Final published version

**Published in**

Proceedings of Design Research Society International Conference (DRS2022), Bilbao

**Citation (APA)**

van der Burg, V., Akdag Salah, A. A., Chandrasegaran, R. S. K., & Lloyd, P. A. (Ed.) (2022). Ceci n'est pas une Chaise: Emerging Practices in Designer-AI Collaboration. In *Proceedings of Design Research Society International Conference (DRS2022), Bilbao* (DRS International Biennial Conference Series). Design Research Society. <https://doi.org/10.21606/drs.2022.653>

**Important note**

To cite this publication, please use the final published version (if applicable).  
Please check the document version above.

**Copyright**

Other than for strictly personal use, it is not permitted to download, forward or distribute the text or part of it, without the consent of the author(s) and/or copyright holder(s), unless the work is under an open content license such as Creative Commons.

**Takedown policy**

Please contact us and provide details if you believe this document breaches copyrights.  
We will remove access to the work immediately and investigate your claim.

Jun 25th, 9:00 AM

## Ceci n'est pas une chaise: Emerging practices in designer-AI collaboration

Vera van der Burg  
*TU Delft, The Netherlands*

Almila Akdag Salah  
*Utrecht University, The Netherlands*

Senthil Chandrasegaran  
*TU Delft, The Netherlands*

Peter Lloyd  
*TU Delft, The Netherlands*

Follow this and additional works at: <https://dl.designresearchsociety.org/drs-conference-papers>



Part of the [Art and Design Commons](#)

---

### Citation

van der Burg, V., Akdag Salah, A., Chandrasegaran, S., and Lloyd, P. (2022) Ceci n'est pas une chaise: Emerging practices in designer-AI collaboration, in Lockton, D., Lenzi, S., Hekkert, P., Oak, A., Sádaba, J., Lloyd, P. (eds.), *DRS2022: Bilbao*, 25 June - 3 July, Bilbao, Spain. <https://doi.org/10.21606/drs.2022.653>

This Research Paper is brought to you for free and open access by the DRS Conference Proceedings at DRS Digital Library. It has been accepted for inclusion in DRS Biennial Conference Series by an authorized administrator of DRS Digital Library. For more information, please contact [dl@designresearchsociety.org](mailto:dl@designresearchsociety.org).

# Ceci n'est pas une chaise: Emerging practices in designer-AI collaboration

Vera van der Burg<sup>a</sup>, Almila Akdag Salah<sup>b</sup>, Senthil Chandrasegaran<sup>a</sup>, Peter Lloyd<sup>a</sup>

<sup>a</sup>TU Delft, The Netherlands

<sup>b</sup>Utrecht University, The Netherlands

\*corresponding e-mail: v.vanderBurg@tudelft.nl

doi.org/10.21606/drs.2022.653

**Abstract:** Emerging practices of using 'off the shelf' AI as a creative partner in design processes are receiving increasing attention in design research. This paper takes the well-known concept of 'framing' in design, along with the Schönian concept of 'surprise' to explore how a human-AI dialogue could work. The approach taken is practice-based, with the human designer documenting her process of inquiry and decision making. We show how artificial creativity is expressed through misfiring object detection algorithms, and further how these 'mistakes' can be perceived and interpreted by the human designer. The contribution of the research is in laying the foundations for a novel human-AI dialogic practice.

**Keywords:** framing; surprise, artificial intelligence; computer vision; design

## 1. Introduction

Recent years have seen the application of Artificial Intelligence (AI)-based technologies to core aspects of everyday life. We encounter automatic design suggestions while using a presentation program or playing a game where the plot or the characters are prepared with the help of AI tools. The question of how designers are influenced by this change is also the topic of recent studies (Stembert & Harbers, 2019). For instance, AI has been used in analysing creative work (Maher & Fisher, 2012), in exploring the design space of possible forms for a given product (Burnap et al., 2016), and in generative design (Kazi et al., 2017; Matejka et al., 2018). AI-based systems have been successful in generating non-obvious solutions that match and sometimes surpass human ingenuity (Serra & Miralles, 2021). It is thus logical to expect AI to have the capability to support human designers in exploring non-obvious problem and solution spaces.

Designing is an act of abductive reasoning: a new design solution is offered as suiting the problem at hand, and both the design as well as the constraints of the problem are re-examined, often with the result that the understanding of the problem as well as the understanding of the solution changes (Kolko, 2010a). Simply put, this change in the



perception of the problem and the solution constitutes framing in design. Dorst (2015) writes: *“In questioning the established patterns of relationships in a problem situation, design abduction creates both a new way of looking at the problem situation and a new way of acting within it”* (p. 53). Framing is thus an essential part of designing, and novice designers are taught various methods as a way to challenge their assumptions and explore the non-obvious in problem and solution spaces.

Yet, methods are ‘passive’ tools for designing, in that a method by itself cannot engage or challenge a designer. In fact, it is the reverse: the effectiveness of a method is often dependent on the engagement of the designer, along with their experience and skill (Daalhuizen & Cash, 2021). In a world of increasingly interconnected and complex problems, along with information that is widely shared and accessible, it is becoming increasingly difficult to explore the non-obvious in processes of design.

In this paper, we report the practice-based explorations of one of the authors—henceforth referred to as ‘the designer’—in her interactions with AI in processes of design. We present three explorations where the designer engages with computer vision and object recognition algorithms. The first two explorations are purely interpretive where the designer looks at creative content and attempts to view the AI’s “interpretation” of the content as an alternative perspective with which to consider the content. The final exploration takes the form of a dialogue between the design and the AI in a cycle of creation/modification and interpretation, while appreciating the value of the unexpected and surprising interpretations offered by the AI as an underlying thread.

The goal of these explorations is to lay out an interaction process or dialogue between an AI and a designer, to drive the designer to a sense of inspiration and to trigger ‘new ways of thinking’ about an image of an artifact.

## 2. Background

### 2.1 Exploration as a search for inspiration

When working on a given design brief, designers typically explore the space of possible interpretations of the brief to identify the ‘right’ problem to solve, while also exploring the space of possible solutions to solve the problem in the ‘right’ way. The interpretation of the word ‘right’ in the prior sentence depends on the goal of the designer: it could be a novel approach that is necessary to solve a hitherto unsolved problem or a novel solution to a previously solved problem that adds value in some way. Within this interpretation also lies the role of creativity in the design process: most notions of creativity in design research have focused on novelty and usefulness (Mayer, 1999).

The idea of novelty in design—or its antithesis, fixation—has been the subject of considerable research (Crilly & Cardoso, 2017), and several methods for mitigating fixation and promoting novelty have been proposed. Some of these methods involve a perturbation of the current outcome or process to introduce novelty, either by inserting another

individual's ideas into one's own—such as C-Sketch (Shah et al., 2001) and Brainwriting (VanGundy, 1984)—or by systematically changing parts of the solution to change existing ideas—such as SCAMPER (Eberle, 1971) or morphological matrices (Zwicky, 1967). Other methods—such as the creation of mood boards (McDonagh & Storer, 2004) or seeking biological inspiration for design (Deldin & Schuknecht, 2013)—incorporate the model of design as an information-seeking activity.

Yet, information seeking in design is often seen as need- or goal-driven, with designers working on a given design brief or with an objective in mind.

In today's world of data- and information-rich online experiences, the value of exploration has been gaining importance in information spaces (Dörk et al., 2011), with the focus on observing and following cues that interest the explorer, while also critically examining new values and conflicts they encounter through such an exploration. Such a notion can also be imagined for design space exploration, where a designer browses new forms and interpretations, taking pleasure in the inspiration offered while also critically examining the inspiration offered. In such a scenario, AI can be seen as a companion that might offer new views and perspectives, which can sometimes be helpful, but not always. The work presented in this paper is an interpretation of AI in such an exploration, involving an act of designing motivated more by curiosity and engagement than by specific needs or goals.

## *2.2 Framing in design processes*

'Framing' in design is seen as one of the key steps in a design process. The effort of framing a design situation is a mental act that offers possibilities for opening the problem space to find new approaches for solving it (Thurgood & Lulham, 2016). Consequently, creating this 'problem frame' can facilitate an alternative perspective on a problem and thus influence ideas generated in the ideation phase of a designer (Silk, 2021).

In general, a frame can be described as a knowledge structure schema - characterized by "*expectations based on prior experience about objects, events, and settings*" (Tannen, 1986). In the context of designing, this expectation forms a 'view' on a problematic situation and is characterized and followed by a series of 'design moves' a designer can take, which allows the situation to 'talk back', causing novel perspective on the situation and allowing for the construction of new meanings and intentions (Schön, 1984). Adopting a new frame and performing design moves related to that frame can be described as 'reframing', which occurs as a result of reflection, throughout a design process (Paton & Dorst, 2011).

The design research literature describes framing as an individual mental act that occurs within a designer. This mental act of framing, however, is examined as a collaborative effort in the context of an interaction with an external agent, for example a fellow design student (Schön, 1984), a colleague, a client (Paton & Dorst, 2011) or even a design brief (Silk, 2021) that is 'framed' in a certain way.

It is thus entirely possible for a designer to have framing interactions with an Artificial Intelligence. AI systems themselves can be perceived as knowledge structures, or knowledge frames on their own, due to the way they are constructed and trained. Training data contains preset ideas about the world, in the form of images and/or text, as well as the context in which they are situated. Adding to the sense of a frame, many 'off the shelf' AI Computer Vision algorithms (*explained in Section 3.2*) visually present results as an actual frame (i.e., a bounding box) to communicate the detection of a specific object.

To draw on this insight we examine an AI's potential to have agency in a creative process through operationalising the concept of framing. By doing so, we aim to get a better understanding of how AI could potentially be used more widely as a tool for framing for design purposes.

### *2.3 AI tools as Ideation Partners in Design Contexts*

A prominent role that is often bestowed on AI lies in the assessment of it as a new design material (e.g., Holmquist, 2017; Roozendaal et. al., 2019). In this approach, designers should gather knowledge about AI and its 'material' qualities, opportunities, and limitations. In doing so, designers can then join the debate about how to use this technology in, for example, smart objects, or in specific contexts in which AI's benefit is not yet fully established. Designers can be invited to use their design skills in the UI and UX for AI, in which the goal can be to make the technology's workings less opaque to its users (Dove, 2017; Roozendaal et. al., 2019).

Another approach evaluates AI as an ideation partner or tool during a design process (Dove et. al., 2017). This relatively underexplored area attaches a process-oriented view to AI and aims to identify opportunities for AI tools to support a design process by having it interact with designers during a design-related task. In these setups, specific roles for the AI are identified beforehand. For example, Fu & Zhou (2020) explore the tutor capabilities of an AI which comments on a design task by giving a variety of suggestions (the AI in question is based on a Wizard of Oz scenario, i.e., the comments are actually given by a human disguised as AI). Zhang et. al. (2021) examine the potential of AI 'performing' as a collaborative tool in design teams and assess if this role improves team performance in solving a design problem. They argue that AI boosts the initial performance of low-performing teams as compared to high-performing teams. Such studies recommend interaction scripts that an AI should have to be beneficial to a designers' process, based on fixed design tasks that are given to the participants. While the results of such studies are interesting, they are also limited. There is no sense of the 'explorative' and fluid process of design thinking often exhibited in actual practice.

One of the opportunities of AI that has not yet been widely explored in literature is how AI-powered design processes can be set up (Malsattar et. al, 2019; Chen et. al., 2019). This is partly due to the lack of AI techniques that are specifically created for designers, with an easy-to-use interface. Malsattar et. al. (2019) respond to this shortcoming by introducing an

AI research tool for designers to explore the potential of AI and how it might fit their design processes and concepts. This puts the stress on instances of when a designer's understanding changes due to 'seeing' the world from the perspective of AI. Therefore AI, in its ways of seeing, could be seen as a knowledge frame with pre-set ideas of what a world looks like. By exposing the designers to this 'way of seeing', new ideas can be generated.

### **3. A conversation with an AI: Object framing**

#### *3.1 Starting points*

The designer and the AI start an interaction in an open-ended, non-briefed design situation. The results obtained from the AI are used as an additional information source for the designer to make decisions on which steps to take next. This explorative, non-guided approach is chosen to get to the core of the interaction: How would the designer and the AI respond to each other when there are little or no predefined expectations or rules?

To investigate the information-seeking activity of a designer with an AI algorithm, we conducted explorations in which a designer and an AI interact in order to develop a design process collaboratively. The explorations were characterized by practice-led research, with the goal to advance knowledge *about* the practice itself (Candy, 2006). A second goal was set to identify when instances of framing or reframing occurred due to the interactions between the designer and the AI. The explorations we undertook are closely documented and described below, with the thoughts of the designer integrated into the text.

#### *3.2 Object detection systems*

One of the most popular applications of AI is in computer vision. Given the visual nature of our explorations, the AI models that we decided to use fall within the umbrella of computer vision. This research line investigates how to derive meaningful information from visual input to take pre-defined actions or to make recommendations based on that information. For example, biometric software relies on computer vision to detect and recognize faces, i.e. to classify a photograph of a person according to gender, age, and sometimes even to match the face to a person in a pre-existing dataset.

One of the established applications of computer vision is *object detection* which deals with detecting instances of semantic objects that an image might contain, such as humans, buildings, or everyday objects, etc. (see Papageorgiou & Poggio, 2000). Object detection generally applies two core methods: those pertaining to neural networks or those that are based on non-neural approaches (Zou et al., 2019). Today, convolutional neural networks (CNNs) offer the preferred framework for computer vision tasks.

For the purposes of the exploration, we used one open-source software library, with well-documented guidelines. Tensorflow 2.0<sup>1</sup> is a software library (Abadi et al., 2016), which

---

<sup>1</sup>Tensorflow is an end-to-end open-source platform for Machine Learning, containing a comprehensive ecosystem of tools to build and deploy machine learning models for researchers (<https://www.tensorflow.org/>)

includes a CNN pre-trained for image classification, accompanied by a step-by-step tutorial called *Tensorflow for Poets*<sup>2</sup>. The pre-training was performed on the ImageNet dataset (Krizhevsky et al. 2012), which contains 14,197,122 images, allowing the model to differentiate 1,000 classes of images.

The performance of a neural network depends on the training phase and the parameter space. For training a computer vision algorithm, a well annotated dataset that covers different image classes, i.e., images depicting a variety of objects, is needed. A good representation of each class is equally important. Pre-trained algorithms sometimes allow for re-training with a smaller dataset to allow more specific transfer learning. Transfer learning is a Machine Learning methodology where knowledge gained while solving one problem is applied to a different but related problem. In this context, an object detection algorithm such as YOLOv4's pre-training in COCO datasets make it easier to channel it to detect objects that are not within its image classes, for example when used in detecting objects in artworks.

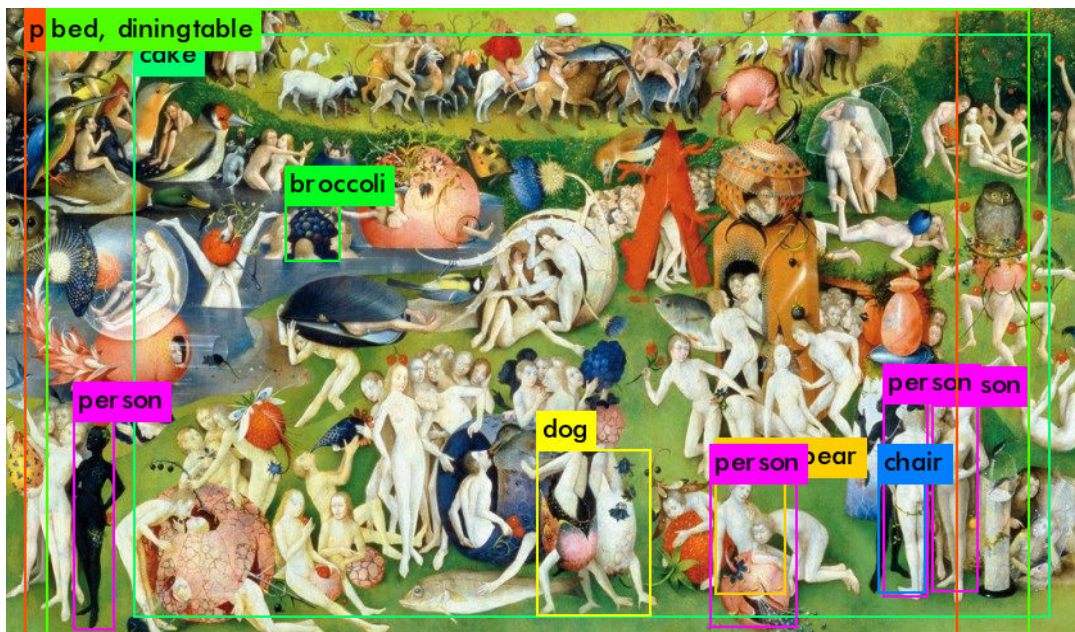


Figure 1. Objects detected via YOLOv4 in Hieronymus Bosch, "Garden of Earthly Delights". The grapes are framed as broccoli.

### 3.3 AI creates 'surprise'

As described in 3.2, Object Detection systems are deployed for situations in which a predefined goal is set. When it comes to creative processes, or design processes, a predefined clear outcome or goal is lacking due to the fluid and exploratory nature these processes can have, but the Schönian idea of 'surprise' often drives what are termed 'moving experiments' (Schön 1983). If we want Object Detection systems to be able to contribute to

<sup>2</sup> <https://kiosk-dot-codelabs-site.appspot.com/codelabs/tensorflow-for-poets/#0>



this fluidity and perhaps have a level of understanding of what is there to be seen in an image that, for example, has creative content, there is still a long way to go.

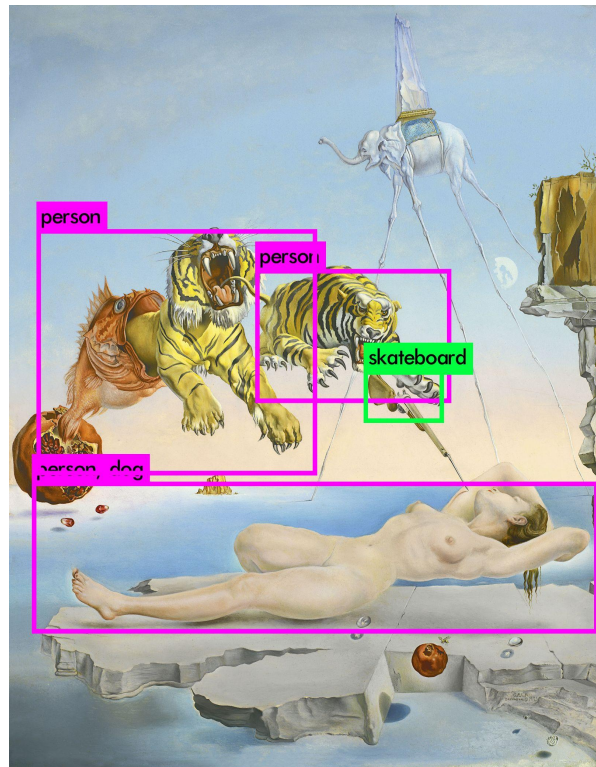


Figure 2. Objects detected via YOLOv4 in Salvador Dalí, “Dream Caused by the Flight of a Bee around a Pomegranate the Second before Waking” (1944). The paw of the tiger, perhaps along with the stock of the rifle, is framed as a skateboard.

An example of a well-trained Object Detection algorithm is YOLOv4<sup>3</sup> (Bochkovskiy et al., 2020). This network is trained on the MS COCO dataset (Lin et al., 2014), a large-scale object detection, segmentation and captioning dataset (91 categories with 2,5 million labelled instances). When these systems ‘look’ at creative content, like artworks, the result is often ‘faulty’ interpretations of what the designer can clearly see. In other words, the AI ‘mislabels’ what it sees, in human terms, though it nonetheless presents a frame for interaction. For example, in Figure 1, a painted bunch of grapes is mislabelled as ‘broccoli’, perhaps due to the dense depiction of the grapes which resemble broccoli stumps, or perhaps due to the position in the composition. In Figure 2 the mislabelling is even less related to the original object’s visual features: a tigers’ paw is mislabelled as ‘skateboard’. In both instances although a mislabelling has occurred in human-terms, the surprise of the mislabelling sets a concrete frame for human-AI engagement. A question arises: what features of the image is the AI seeing in order to make its classification?

Even though the cause of this mislabelling can be explained in terms of technological characteristics (i.e., what is detected minimally corresponds with a feature found in the

<sup>3</sup> <https://pjreddie.com/darknet/yolo/>

'skateboard' category of the dataset), it does open up a possible exploration space for design research. The mislabelling can be appreciated as providing an alternative view, or a new frame about the original content, that in some cases is even experienced as a 'surprising' perspective due to its unexpectedness.

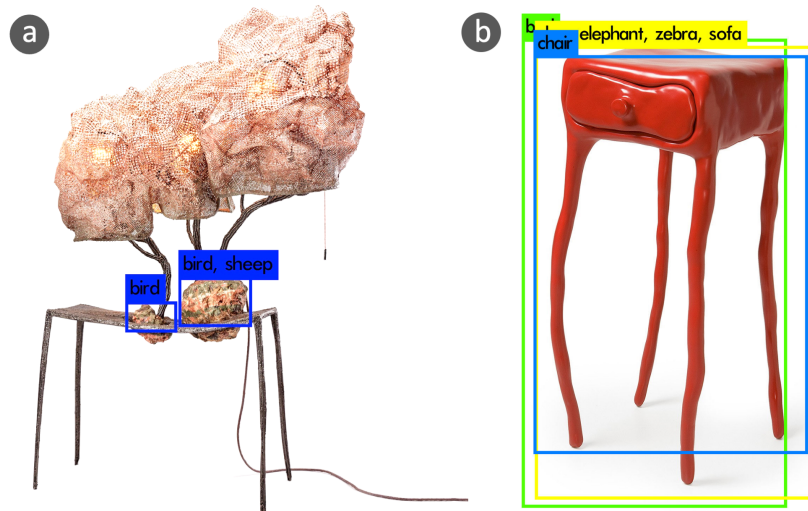


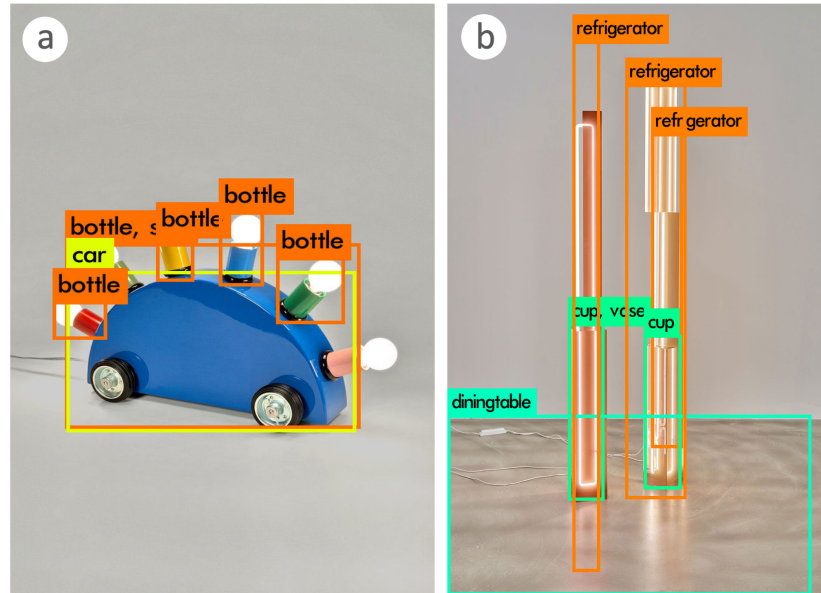
Figure 3. AI interpretation of designed objects: (a) *Light Mesh Series* by Nacho Carbonell, (b) *Clay Furniture* by Maarten Baas.

### 3.4 AI interprets design objects

Continuing from the previous exploration, the next interaction with AI explores the reframing potential of (mis)labeling designed objects. What will the AI make of the functional and aesthetic intentions of a designer? When looking at images of designed objects that are being analysed by YOLOv3, similar insights from mislabeling emerge. Two types of AI behaviour are noted: In Figure 3(a) the AI sees several features of one object as separate objects whilst in Figure 3(b), multiple selections span almost the entire object. The selections display considerable overlaps between them, with each selection associated with different and diverse predictions.

Again, in Figure 4 (a) the AI ‘divides’ the original object by detecting multiple features, and something similar happens at figure 4(b). These labels are either slightly correct or false, but provide an alternative and perhaps surprising way to “look” at a design through the




Figure 4. (a) *Super Lamp* by Martine Bedin, (b) *Totem Lights* by Sabine Marcelis.



perspective of an AI. This surprising perspective, then, could activate reflective thought about the original design.

The label frames for the designed objects given by the AI again trigger surprise. An opportunity is presented to reevaluate the original designs and ideate further on specific elements. A tentative understanding of the AI begins to emerge, but the interaction so far is limited. How can richer conversation be generated?

Table 1. Predictions for successive iterations of the designed object from Sec. 3.5.

					
<b>Image 1</b>		<b>Image 2</b>		<b>Image 3</b>	
<b>Prediction</b>	<b>Probability</b>	<b>Prediction</b>	<b>Probability</b>	<b>Prediction</b>	<b>Probability</b>
Knife	0.766	Chair	0.609	Chandelier	0.973

Chair	0.087	Chandelier	0.119	Chair	0.001
Kitchen	0.080	Sunflower	0.072	Kitchen	0.001
Tulips	0.055	Accordion	0.030	Tulips	0.001
Roses	0.017	Menorah	0.023	Roses	0.0003

### 3.5 An iterative conversation with AI

The labels given by AI should be taken as frames - ways of seeing the images presented. To start an actual interaction action there should be a connection to the labels given. Questions arise: *How to talk back to the AI? How to reframe the perspective? How to show the AI a different understanding?*

For this conversation, Tensorflow 2.0 is re-trained with the CalTech101 dataset which contains 101 object categories for transfer learning. Each category holds from 40 to 400 images of mundane user-objects and natural artefacts (i.e., flowers, trees, animals). The re-trained CNN is given an image for object detection. This results in the AI predicting what the objects it sees are, assigning probabilities to each object.

To start a cycle of interaction with the AI, an image of a designed artefact was selected to ideate on: an image of a chair. The chair was photographed against a neutral background to prevent any visual noise to disrupt the object recognition process. The image was input to the CNN, and the predictions and corresponding probabilities are noted.

The ranking order of several objects that was backed up with a statistical prediction could be seen as an alternative “way of seeing” by the AI, therefore functioning as an alternative ‘visual frame’. It was unclear, however, how the AI had ‘seen’ these artefacts in the original image. To get a better understanding of this ‘gaze/perspective’ of the AI for the designer, the predictions were appreciated as criteria for a design brief: Adjust the object (chair) by following (loosely) the given percentages.

The design brief started a cycle where the designer used their own interpretation of what the object categories could be. When the designer finished adjusting, the new artefact was photographed, and the image file was given to the algorithm for classification. A dialogic practice emerges; the AI dictates what the next iteration of the object should be. The three iterations that emerged from this dialogue are shown in Table 1.

The nature of this interaction has become circular, a feedback loop in which the designer and the AI iteratively interpret the image. The image of the "new object" is used as an input to the AI again, resulting in a new interpretation. This cycle continued for 3 iterations until it became difficult for the designer to alter the object any further. The creative dialogue ends.

This interaction loop creates a script for a framing/reframing dialogue of ‘seeing’ and ‘moving’:

AI interprets → Designer interprets and adjusts → AI interprets → Designer interprets and adjusts

Having an AI give surprising interpretations of the designed object resulted in actions that would never have been taken. There is a notion of control and being controlled, of listening and acting. Surprise keeps the designer from more routine behaviour, the AI opening up problem and solution space, but also a space of reflection. 'Seeing' knives in a chair opened up a range of possibilities for the designer, whose notes from the exploration include such questions as: *How to add these knives to the original chair? What materials to use for this? How can the chair still function if it has 'knives' added to it?* The AI moves the designer to a new space of possibilities by framing and reframing.

## 4. Discussion

This paper has shown how a practice-based dialogue between a human designer and an AI can be conceptualised through the idea of framing and associated concepts, in particular 'surprise'. Dorst & Cross (2001) emphasize that surprise keeps a designer from routine behaviour, independent of whether this occurs in problem or solution exploration. The practice developed by the designer in the present study aligns closely to Schön's (1992) description of designing as a reflection-in-action whose basic structure- *seeing-moving-seeing* - is an interaction of both designing and discovering: *"Working in some visual medium [...] the designer sees what is 'there' in some representation of site, draws in relation to it, and sees what has been drawn, thereby informing further designing"* (p. 135).

When we translate this theory to the interaction script of the designer and the AI, we find that the AI 'saw' the object which then provided a frame for the designer to explore in a 'move-experiment'. An iterative practice thus emerged whereby the AI then "sees again" the reinterpreted design. It is intriguing that, even 30 years ago, Schön was considering how AI could work with designers, considering the forms of knowing-in-action that a 'knowledge-based system' would need to have in order to meaningfully support design activity (Schön 1992): *"I conclude that the practitioners of Artificial Intelligence in design would do better to aim at producing design assistants rather than knowledge systems phenomenologically equivalent to those of designers"* (p.131). Ironically, we have shown that the intuitive reflection-in-action process that Schön describes when humans design together provides a far better model for how present day 'off-the-shelf' AI can interact with human designers.

The exploration has two limitations that reveal the AI is not unbiased. The retraining dataset has more images of knives than it does of chairs (mostly with the appearance of barstools). Should the mislabelling be trusted? Is there any reality to the AI's classifications? Furthermore, due to the uneven distribution of the images in each of the categories (some categories have more image examples) the AI tends to detect well-represented categories with higher-level of accuracy than those categories with a poorer representation.

The second limitation is a paradox: if a computer vision model that is trained on a wide range of chairs is shown an image of a chair, it detects a 'chair' with high accuracy. In other words, a well-working AI system, which is set up for detecting what objects are present in an image, will render predictable results by successfully listing all the objects correctly. On the other

hand, a completely random prediction that shows no connection to the designer's interpretation is unlikely to inspire the designer. What, then, is the right level of unpredictability that will provide 'appropriate incongruity' (Ludden et al. 2012) to prompt or inspire the designer? A possible direction is to adopt the approach of a 'creativity slider' introduced by Benjamin et al. (2014) in their clipart composition interface, *Juxtapoze*. The interface suggested related search results in response to strokes sketched by the user, and the 'relatedness' of the search results is controlled by the creativity slider. Perhaps an interface in our case that allows the designer to control the breadth of the interpretation by the AI—allowing for broader interpretation at the earlier exploratory stages of designing and narrower interpretations in later stages—can be incorporated in future explorations.

Although the AI has agency in the design interaction, the roles of each party are not equal. Though the AI takes on a controlling role, it is largely passive and restricted to 'seeing'. By ceding power to the AI the designer takes on a more active role, conducting the 'moving', before reframing takes place. Nevertheless, the AI does generate surprise from its necessarily limited training data. As we noted, there is a balance to be struck between predictability and randomness in generating classifications, but in the present sequence of explorations surprise was triggered through the 'mislabelling' of image contents. Mislabelling, of course, depends on a human interpretation of the image, but as we showed, whether the label is correct on human terms does not alter the fact that it can be used as a productive creative frame. A future direction for our research is to more fluently incorporate AI triggered surprise to disrupt the process and provoke instances of reflection.

It is interesting to speculate on what kind of datasets could be relevant and representative for the kinds of creative practices described in the present paper. The training datasets that were used for this exploration was one containing images and labels of mundane objects. As this dataset is generally used for the goal of detecting objects in images, its usefulness for augmenting a designers' creative practice can be questioned. If the goal of the AI is to offer inspiration for the designers, the datasets could be constructed and labeled differently with categories that could be more design related. Thinking about what these design related categories could be or what categories are relevant for a design context is a direction for future research. As a first direction we could look into labeling the data differently with more design-related concepts. For example, instead of labeling a category 'chair', could a category be labeled according to a functionality, for example 'sitting'? Another approach could be to create datasets that contain different images, for example visual design styles or design related objects. Transfer learning offers considerable opportunities and comes closer to thinking of AI as a material that can be adapted and changed to enhance different kinds of creative practice. This, then, additionally asks for practice-based research in how a designer could interact with an adapted AI to augment their creative practice. Much additional work needs to be done in this area before 'seamless' creative partnerships between humans and AI can be achieved. This specific paper can be seen as a first step in setting up an interaction process or dialogue between an AI and a designer during the very early stages of a design

process, with the goal for the AI to surprise and therefore inspire the designer in the exploration phase.

## 5. Conclusion

This paper has shown how a practice-based dialogue between a human designer and an AI can be conceptualised through the idea of framing and associated concepts, in particular 'surprise'. Our explorations had the goal of providing the foundations of a theoretical framework combined with illustrative explorations. In future research we will further explore the complexities of how '*seeing-moving-seeing*' can inform human-AI dialogues in processes of design. From the perspective of the AI we will examine what datasets and collecting/labeling strategies could be relevant for a design related context. Another direction for our future research is to more fluently incorporate AI triggered surprise into an early design process to provoke framing/reframing actions and instances of reflection.

## 6. References

- Abadi M., Barham, P., Chen, J., Chen, Z., Davis, A., Dean, J., Devin, M., Ghemawat, S., Irving, G., Isard, M., Kudlur, M. (2016). Tensorflow: A system for large-scale machine learning. In 12th {USENIX} symposium on operating systems design and implementation ({OSDI} 16) (pp. 265-283).
- Benjamin, W., Chandrasegaran, S., Ramanujan, D., Elmqvist, N., Vishwanathan, S. V. N., & Ramani, K. (2014). Juxtapoze: supporting serendipity and creative expression in clipart compositions. In Proceedings of the ACM CHI Conference on Human Factors in Computing Systems (pp. 341-350). <https://doi.org/10.1145/2556288.2557327>.
- Bochkovskiy, A., Wang, C. Y., & Liao, H. Y. M. (2020). YOLOv4: Optimal speed and accuracy of object detection. arXiv preprint arXiv:2004.10934.
- Burnap, A., Liu, Y., Pan, Y., Lee, H., Gonzalez, R., & Papalambros, P. Y. (2016). Estimating and exploring the product form design space using deep generative models. In Proceedings of the ASME International Design Engineering Technical Conferences and Computers and Information in Engineering Conference (Vol. 50107, p. V02AT03A013). <https://doi.org/10.1115/DETC2016-60091>
- Candy, L. (2006). Practice based research: A guide. CCS report, 1(2).
- Chen, L., Wang, P., Dong, H., Shi, F., Han, J., Guo, Y., ... & Wu, C. (2019). An artificial intelligence based data-driven approach for design ideation. *Journal of Visual Communication and Image Representation*, 61, 10-22.
- Crilly, N., & Cardoso, C. (2017). Where next for research on fixation, inspiration and creativity in design?. *Design Studies*, 50, 1-38. <https://dx.doi.org/10.1016/j.destud.2017.02.001>
- Daalhuizen, J. & Cash, P. (2021) Method content theory: Towards a new understanding of methods in design, *Design Studies*, 75, 101018, pp 1-34, <https://doi.org/10.1016/j.destud.2021.101018>.
- Deldin, J. M., & Schuknecht, M. (2014). The AskNature database: enabling solutions in biomimetic design. In *Biologically inspired design* (pp. 17-27). Springer, London. [https://doi.org/10.1007/978-1-4471-5248-4\\_2](https://doi.org/10.1007/978-1-4471-5248-4_2)
- Dörk, M., Carpendale, S., & Williamson, C. (2011, May). The information flaneur: A fresh look at information seeking. In Proceedings of the ACM CHI conference on Human Factors in Computing Systems (pp. 1215-1224). <https://doi.org/10.1145/1978942.1979124>.

- Dorst, K. (2015). *Frame innovation: Create new thinking by design*. MIT press.
- Dorst, K., & Cross, N. (2001). Creativity in the design process: Co-evolution of problem-solution. *Design Studies*, 22(5), 425–437. [https://doi.org/10.1016/S0142-694X\(01\)00009-6](https://doi.org/10.1016/S0142-694X(01)00009-6)
- Dove, G., Halskov, K., Forlizzi, J., & Zimmerman, J. (2017, May). UX design innovation: Challenges for working with machine learning as a design material. In *Proceedings of the 2017 chi conference on human factors in computing systems* (pp. 278-288). <https://doi.org/10.1145/3025453.3025739>
- Eberle, R. (1971). *SCAMPER: Games for Imagination Development*. D.O.K. Publishers, Buffalo, NY.
- Fu, Z., & Zhou, Y. (2020). Research on human–AI co-creation based on reflective design practice. *CCF Transactions on Pervasive Computing and Interaction*, 2(1), 33-41. <https://doi.org/10.1007/s42486-020-00028-0>
- Holmquist, L. E. (2017). Intelligence on tap: artificial intelligence as a new design material. *interactions*, 24(4), 28-33. [10.1145/3085571](https://doi.org/10.1145/3085571)
- Kazi, R. H., Grossman, T., Cheong, H., Hashemi, A., & Fitzmaurice, G. W. (2017). DreamSketch: Early Stage 3D Design Explorations with Sketching and Generative Design. In *the ACM Symposium for User Interface Science and Technology* (Vol. 14, pp. 401-414). <https://doi.org/10.1145/3126594.3126662>
- Khodabandeh, M., Vahdat, A., Ranjbar, M., & Macready, W. G. (2019). A robust learning approach to domain adaptive object detection. In *Proceedings of the IEEE/CVF International Conference on Computer Vision* (pp. 480-490).
- Kolko, J. (2010a). Abductive thinking and sensemaking: The drivers of design synthesis. *Design issues*, 26(1), 15-28. <https://doi.org/10.1162/desi.2010.26.1.15>
- Kolko, J. (2010b) Sensemaking and Framing: A Theoretical Reflection on Perspective in Design Synthesis, in Durling, D., Bousbaci, R., Chen, L, Gauthier, P., Poldma, T., Roworth-Stokes, S. and Stolterman, E (eds.), *Design and Complexity - DRS International Conference 2010*, 7-9 July, Montreal, Canada.
- Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). Imagenet classification with deep convolutional neural networks. *Advances in neural information processing systems*, 25, 1097-1105.
- Lai, J. Y., Roan, E. T., Greenberg, H. C., & Yang, M. C. (2008). Prompt versus problem: Helping students learn to frame problems and think creatively. In *Proceedings of the 2nd Design Creativity Workshop, Third International Conference on Design Computing and Cognition* (pp. 1-6).
- Lepri, G., McPherson, A., & Bowers, J. (2020). Useless, not Worthless: Absurd Making as Critical Practice. In *Proceedings of the 2020 ACM Designing Interactive Systems Conference* (pp. 1887-1899). <http://dx.doi.org/10.1145/10.1145/3357236.3395547>.
- Lin, T. Y., Maire, M., Belongie, S., Hays, J., Perona, P., Ramanan, D., Dollár, P., & Zitnick, C. L. (2014). Microsoft COCO: Common objects in context. In *European conference on computer vision* (pp. 740-755). Springer, Cham. [https://doi.org/10.1007/978-3-319-10602-1\\_48](https://doi.org/10.1007/978-3-319-10602-1_48)
- Ludden, G. D., Kudrowitz, B. M., Schifferstein, H. N., & Hekkert, P. (2012). Surprise and humor in product design. *Humor*, 25(3), 285-309. <https://doi.org/10.1515/humor-2012-0015>.
- Maher, M. L., & Fisher, D. H. (2012). Using AI to evaluate creative designs. In *Proceedings of the 2nd International Conference on Design Creativity Volume 1*.
- Malsattar, N., Kihara, T., & Giaccardi, E. (2019, June). Designing and Prototyping from the Perspective of AI in the Wild. In *Proceedings of the 2019 on Designing Interactive Systems Conference* (pp. 1083-1088). <https://doi.org/10.1145/3322276.3322351>
- Matejka, J., Glueck, M., Bradner, E., Hashemi, A., Grossman, T., & Fitzmaurice, G. (2018). Dream Lens: Exploration and visualization of large-scale generative design datasets. In *Proceedings of the ACM*



- CHI conference on human factors in computing systems (pp. 1-12).  
<https://doi.org/10.1145/3173574.3173943>
- Mayer, R. E. (1999). Fifty years of creativity research. In Handbook of Creativity, Sternberg R.J. (ed). 449-460.
- McDonagh, D., & Storer, I. (2004). Mood boards as a design catalyst and resource: Researching an under-researched area. *The Design Journal*, 7(3), 16-31.  
<https://doi.org/10.2752/146069204789338424>
- Papageorgiou, C., & Poggio, T. (2000). A trainable system for object detection. *International journal of computer vision*, 38(1), 15-33. <https://doi.org/10.1023/A:1008162616689>
- Paton, B., & Dorst, K. (2011). Briefing and reframing: A situated practice. *Design studies*, 32(6), 573-587. <https://doi.org/10.1016/j.destud.2011.07.002>
- Rozendaal, M. C., Ghajargar, M., Pasman, G., & Wiberg, M. (2018). Giving form to smart objects: Exploring intelligence as an interaction design material. In *New Directions in Third Wave Human-Computer Interaction: Volume 1-Technologies*, Springer, pp. 25-42. [https://doi.org/10.1007/978-3-319-73356-2\\_3](https://doi.org/10.1007/978-3-319-73356-2_3)
- Serra, G., & Miralles, D. (2021). Human-level design proposals by an artificial agent in multiple scenarios. *Design Studies*, 76, 101029. <https://doi.org/10.1016/j.destud.2021.101029>.
- Shah, J. J., Vargas-Hernandez, N. O. E., Summers, J. D., & Kulkarni, S. (2001). Collaborative Sketching (C-Sketch)—An idea generation technique for engineering design. *The Journal of Creative Behavior*, 35(3), 168-198. <https://doi.org/10.1002/j.2162-6057.2001.tb01045.x>
- Silk, E. M., Rechkemmer, A. E., Daly, S. R., Jablokow, K. W., & McKilligan, S. (2021). Problem framing and cognitive style: Impacts on design ideation perceptions. *Design Studies*, 74, 101015. <https://doi.org/10.1016/j.destud.2021.101015>
- Schön, D. A. (1983) *The Reflective Practitioner*, Basic Books, New York
- Schön, D. A. (1984). Problems, frames and perspectives on designing. *Design studies*, 5(3), 132-136. [https://doi.org/10.1016/0142-694X\(84\)90002-4](https://doi.org/10.1016/0142-694X(84)90002-4).
- Schön, D. A. (1992). Designing as a Reflective Conversation with the Materials of the Design Situation. *Research in Engineering Design*, 3, pp 131-147. [https://doi.org/10.1016/0950-7051\(92\)90020-G](https://doi.org/10.1016/0950-7051(92)90020-G)
- Schön, D. A., & Wiggins, G. (1992). Kinds of seeing and their functions in designing. *Design studies*, 13(2), 135-156. [https://doi.org/10.1016/0142-694X\(92\)90268-F](https://doi.org/10.1016/0142-694X(92)90268-F)
- Stembert, N., & Harbers, M. (2019). Accounting for the human when designing with AI: challenges identified. *CHI'19-Extended Abstracts*, Glasgow, Scotland Uk—May 04-09, 2019. <https://doi.org/10.1145/3290607>
- Tannen, D. (1986). Frames revisited. *Quaderni di Semantica*, 7(1), 106e109. Tonkinwise, C. (2011). A taste for practices: Unrepressing style in design thinking. *Design Studies*, 32(6), 533e545. <https://doi.org/10.1016/j.destud.2011.07.001>
- Thurgood, C., and Lulham, R. (2016) Exploring framing and meaning making over the design innovation process, in Lloyd, P. and Bohemia, E. (eds.), *Future Focused Thinking - DRS International Conference 2016*, 27 - 30 June, Brighton, United Kingdom. <https://doi.org/10.21606/drs.2016.218>.
- Ulrich, K. T. (2011). *Design: Creation of artifacts in society*. Karl T. Ulrich. University of Pennsylvania, Philadelphia, PA.
- VanGundy, A. B. (1984). Brain writing for new product ideas: an alternative to brainstorming. *Journal of Consumer Marketing*. <https://doi.org/10.1108/eb008097>

- Xu, M., Wang, H., Ni, B., Tian, Q., & Zhang, W. (2020). Cross-domain detection via graph-induced prototype alignment. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (pp. 12355-12364).
- Zou, Z., Shi, Z., Guo, Y., & Ye, J. (2019). Object detection in 20 years: A survey. arXiv preprint arXiv:1905.05055. <https://doi.org/10.48550/arXiv.1905.05055>
- Zwicky, F. (1967). The morphological approach to discovery, invention, research and construction. In New methods of thought and procedure (pp. 273-297). Springer, Berlin, Heidelberg. [https://dx.doi.org/10.1007/978-3-642-87617-2\\_14](https://dx.doi.org/10.1007/978-3-642-87617-2_14)

About the Authors:

**Vera van der Burg** is a PhD candidate at the Technical University in Delft, in the Industrial Design department. Her research interest is in the use of Artificial Intelligence in the creative design processes and the relationships between designers and non-human agents.

**Dr. Senthil Chandrasegaran** is Assistant Professor in the Faculty of Industrial Design Engineering at TU Delft. His research focuses on using computational and data visualization approaches to make sense of how designers work.

**Dr. Peter Lloyd** is Professor of Integrated Design Methodology in the Faculty of Industrial Design Engineering at TU Delft, Chair of the Design Research Society, and Editor-in-Chief for the journal *Design Studies*. His research focuses on how designers talk in practice, and in storytelling in the design process.

**Dr. Almila Akdag Salah** is Assistant Professor in the department of Information and Computational Sciences at Utrecht University. Her research interests combine qualitative and quantitative methods to study mainly humanities and social data. She is the Visual Media and Interactivity WG leader at DARIAH (the Digital Research Infrastructure for the Arts and Humanities).