

Beyond Average Tools. On the use of ‘dumb’ computation and purposeful ambiguity to enhance the creative process

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Abstract: In the early phases of the design process, embracing chance intrusions, seeming irrelevance and ambiguity can lead to considering concepts in different ways and provoke new ideas. However, the computational tools we are increasingly using in these phases value efficiency over serendipity; technologies whose foundations are an average. This paper presents a ‘Beyond Average’ approach that was used to develop two tools that use ‘dumb’ computation and purposeful ambiguity to enhance the creation of novel ideas. Results from studies using the tools in a design task show that computational tools with a medium level of contextuality and a higher level of interpretability can positively influence the creation of new ideas. Discussions about the role of computation in the early phases of the design process suggest that tools with higher levels of creative agency can contribute to the designer’s creative agency and become a more natural partner in these activities.

Keywords: Computational design tools; artificial intelligence; creativity

1. Introduction

Renowned designer Kenya Hara (2007) writes that “creativity is to discover a question that has never been asked”. This is especially true in the early phases of the design process—those of discovery and defining—where exploring new information and considering it in new, non-obvious ways helps designers to reveal new meanings and associations (Mendel, 2012). Particularly in these early explorations, using design tools that embrace less literal analogies and allow for ambiguity and serendipity (Gaver & Dunne, 1999; Mothersill & Bove, 2017) can provoke new ideas that cross over the boundaries between existing conceptual schemas (Gero & Maher, 2013). These creative leaps can help designers break through to that moment of inspiration (Cross, 1997) which guides the development of the design in the latter phases.

Computation is increasingly being integrated into the tools used throughout the creative process. While currently better suited to the more well-bounded deductive process of the latter phases of the design process (Bernal, Haymaker & Eastman, 2015), Computer Aided Design (CAD) tools are starting to be used in these earlier, more abstract explorations. Technologies such as genetic algorithms and machine learning programs use statistical mathematics to repeatedly generate, evaluate and optimise design solutions (Sjoberg, Beorkrem & Ellinger, 2017), as well as navigate us through the

multitude of online content that can inspire our new creations. At the very core of these intelligent technologies is an equation called the ‘cost function’; the average of the error between the expected and actual data, calculated over and over again. It is from minimising this average that we are quickly guided to converge on a few specific, quantitatively better solutions, but is this the best approach for tools used in the earlier, more abstract explorations of the design process?

These computational tools are undoubtedly better than humans at quickly generating a multitude of different design options (Steinfeld, 2017), but when it comes to discovering the radical inspiration needed for creative breakthroughs these technologies have their limitations. The ‘intelligent’ tools we are increasingly using to find inspiration for our new designs, such as Google and Pinterest, do not always provide the diversity of information and images that we need to guide our research in the early phases; information that helps prompt us to question concepts in different ways, reveal new insights or inspire unexpected ideas (Fulton Suri, 2008). Artificial intelligence can indeed help us find huge amounts of data very quickly, but if we are not careful these technologies can also pull us down very creatively problematic, average-driven, algorithmic rabbit holes (Carter & Nielsen, 2017).

Perhaps we don’t always need these intelligent tools to be that ‘smart’ or provide us with such optimised, unambiguous responses. The ambiguity provided by imperfect technologies and randomness delivered by ‘dumb’ AIs can actually augment our human smartness, and potentially even our creativity (Shirado & Christakis, 2017; Mothersill & Bove, 2018). This paper explores this seeming paradox and asks: how can design tools that use ‘dumb’ computation and purposeful ambiguity influence the creative process in the early phases?

2. The limitations of average

What is the best way to Larissa? This is the question that Plato imagined his teacher Socrates and the Greek general Meno discussing (Plato). Since Meno was born in Larissa, he knew very well how to get there from previous travels. An inexperienced traveler could also use a map to make the journey most efficient. Or, as a tourist, he might wish to see the sites along the way and therefore take a less direct, but potentially more satisfying route. The more adventurous soul might just head out in the general direction and let chance guide her actions along the journey. The core of this dialogue is to question what knowledge is, but it also relates to an important consideration for any research into developing new computational design tools: how should they guide us? This question has been considered extensively in the field of cybernetics and provides useful insights into the challenges for integrating automated computation into the design process (Dubberly & Pangaro, 2015).

Cybernetics comes from the Greek word *kybernētēs* (κυβερνήτης) meaning "to steer, navigate or govern". At its most basic, a cybernetic approach takes feedback from a system to understand how to reach a goal in the most efficient way. Building on Plato’s analogy, as a crow flying over the mountains of Athens, we could navigate our way to Larissa using compass bearings along the most direct route, modifying our movements to get to our end goal. Or applied to the design process, computational systems that use these approaches can help us answer questions such as “what possible solutions fit these goals & constraints?” (Case, 2018).

Our computational design tools are increasingly relying on these intelligent statistically-driven approaches or ‘technologies of the average’. By optimising the average at the core of the cost function described above to quickly converge on a few specific, quantitatively better ‘answers’, computational tools such as genetic algorithms and machine learning programs can help us quickly diagnose a medical condition (Mukherjee, 2017), generate thousands of designs for a chair (Rhodes, 2016), or create a ‘new’ work of art by an old Master painter (Korsten, 2016).

While these technologies can help us find huge amounts of content in search engines or quickly generate designs from sets of data, the efficiency-based approach to analysing information used by these systems means we are only presented with the average of this material. Googling ‘chair’ may not bring you images to inspire new ideas; you might just get a collection of pictures that look similar. Pinterest boards are often becoming collections of homogeneously sleek designs; so much so that designers suggest that we have reached the “Pinterest singularity” and are shunning it in an attempt to not create average-looking designs (Gong, 2018).

Integrating the notion of the average into the design process is not new (Rose, 2016): from its original application to understand the diversity in human sizes (leading to the Body Mass Index), to its use in the field of scientific management (or Taylorism) to operationalize the processes of factory workers, to integrating it into standardized ergonomic measurements to design mass-consumable objects (Dreyfuss & Dreyfuss, 1967). But just as its applicability was questioned when it was discovered that none of over 4000 pilots matched all of the 10 average body dimensions that cockpits were being designed for (Daniels, 1952), perhaps we should be questioning the suitability of technologies that rely on an efficiency approach used in the early phases of the creative process.

In comparison to this current computational approach that prioritises efficiency, the early phases of the design process need a less logical exploration full of experiments and questions (Schön, 1983); we are the adventurers who prefer the richness of the scenic route to Larissa! Especially when dealing with the often ill-formulated ‘wicked problems’ that we are designing for today (Churchman, 1967), the beginning of the design process feels like aiming at a shifting target where we often don’t fully understand the problem, let alone have a defined goal (Rittel, 1988). Appreciating this flexibility in the early phases of the design process is very important because, just as “we shape our tools and, thereafter, our tools shape us” (Culkin, 1967), the inspiration we can obtain to guide our designs is being shaped by the algorithms that rule the machines we use to search for new ideas (Lynch, 2016). The argument for integrating these efficiency-based approaches into our design tools is one of convenience (Carter & Nielsen, 2017). But can outsourcing our creative tasks to these overly ‘user-friendly’ interfaces contribute to cognitive inertia? While part of the creative process can indeed benefit from the competence and efficiency that these intelligent tools can provide (Steinfeld, 2017), radical breakthroughs come only from considering concepts more abstractly (Fulton Suri, 2008) and challenging the existing principles in our fields (Nielsen, 2016).

3. Alternatives to the average

It is often in the early phases of the design process—those of discovery and defining—that creative leaps can lead to radical breakthroughs (Cross, 1997). Activities in these phases include ‘gathering disparate information’, ‘generating hypotheses’ and ‘identifying novel directions’ (Mothersill & Bove, 2018); activities where a wide variety of information is explored and considered in non-obvious ways to hopefully reveal new meanings and associations. These activities involve the often serendipitous creative challenges that humans are very good at: considering different contexts, embracing ambiguity and using analogy to find new interpretations and associations (Bernal et al., 2015).

These elements of the creative process were championed by creativity researchers Edward de Bono and William Gordon. De Bono developed the practice of lateral thinking, which utilised the fact that the human mind is very efficient at recognising patterns; if we are presented with information which does not immediately seem relevant, we naturally try to ‘make sense’ of it. Lateral thinking welcomes chance intrusions, irrelevance, and ambiguity in order to provoke different patterns and create new ideas (Bono, 1970). This strategy was also embraced by Gordon in the practice of

synectics—literally meaning ‘the joining together of different and apparently irrelevant elements’—where ‘perfect’ ideas are rejected in favour of the non-rationality that can generate more evocative metaphors and seeds of inspiration (Gordon, 1961).

When compared to the certainty offered to us through the technologies of the average described above, the early phases of the design process often follow a less logical and predictable path (Mitchell, 1993) and so potentially require different approaches. Purposely integrating noise into the very predictable and controllable systems we are so familiar with, such as through ambiguity and chance intrusions, can “create a margin of error in which creative interpretation and misinterpretation might thrive” (Bernes, 2017). If we are open to exploring these moments of creative reinterpretation, we might discover entirely new approaches to a design problem and invent “ways of thinking which haven't yet been invented” (Nielsen, 2016).

If ambiguity and openness to chance interventions are important aspects of the early phases of the design process that can help us discover new ideas, then we believe they should also be integrated into the tools we use in those design activities. In contrast to the drive for quantification, optimisation and ‘intelligence’ in current technologies (Sjoberg et al., 2017), we are exploring how the more serendipitous principles of creativity—those of seeming irrelevance and ambiguity—can be used as an approach for creating new computational tools. The following sections describe the ‘Beyond Average’ approach we have taken to develop two computational design tools and the evaluations carried out to understand how they can be used to generate new ideas.

4. A ‘Beyond Average’ approach

Building on these serendipitous principles of creativity present in the early phases of the design process, we propose the following design space dimensions to guide the development of computational tools that can contribute to the activities where new ideas are discovered:

Contextuality

This dimension assesses the amount of contextual information—or seeming irrelevance—that the tool uses to guide the collection, generation and reviewing of inspirational information and design outputs. This dimension can also relate to the ‘smartness’ of the tool. A tool with a high contextuality integrates a lot of advanced computation such as the machine learning analysis of extensive data sets to calculate a contextually ‘optimised’ and relevant response, e.g. as used in a search engine such as Google. In contrast, a tool with low contextuality is one that uses much simpler algorithms such as randomness, hence doesn’t generate recommendations learned from previous uses and can often provide seemingly irrelevant responses.

Interpretability

This dimension determines how direct or ambiguous the information or creative guidance provided by the tool is; is it a prescription or a provocation? This dimension can also relate to the agency that the user has when using the tool. Examples of tools with low interpretability are search engines like Google where a user enters a specific request and the tool returns very directly related information that requires little additional interpretation; the user is very active in choosing a specific concept to explore but more passive when interpreting the information. An example of a tool with a higher level of interpretability is Eno and Schmidt’s (1975) Oblique Strategies card deck that does not require the user to choose an initial concept but relies on their active perception and imagination to ‘make sense’ of the more ambiguous information.

These dimensions create a framing through which to consider how computational design tools can influence the creation of new ideas in the early phases of the design process. Figure 1 shows our proposed positioning of the ‘Beyond Average’ tools (described in the next section) on the design space dimensions, with Google included as a benchmark of current tools.

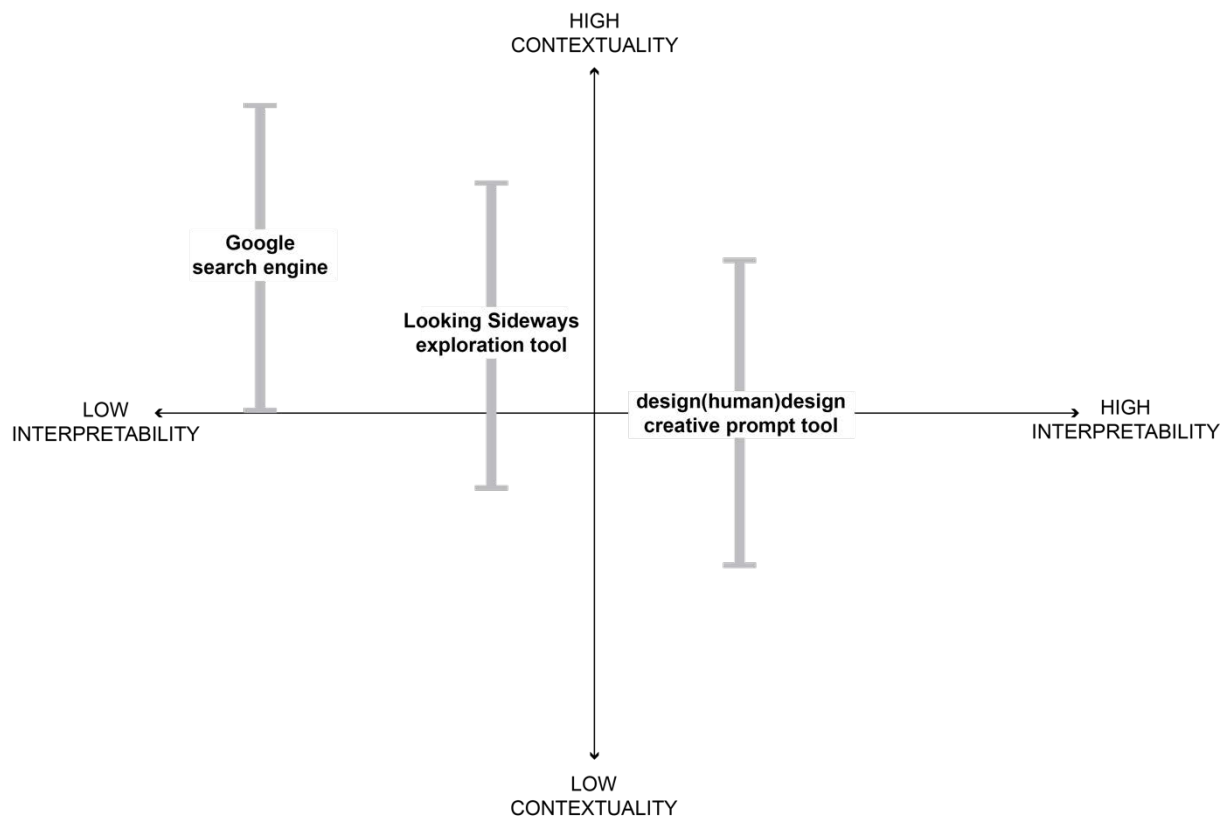


Figure 1. Existing and ‘Beyond Average’ tools proposed mapping onto design space dimensions

5. ‘Beyond Average’ design tools

5.1. design(human)design creative prompt tool

design(human)design is a computational creative prompt tool that provokes new associations between concepts in a user’s project (<http://reframe.media.mit.edu>). Using text from a designer’s own notes and readings, design(human)design presents a randomised prompt, helping to juxtapose concepts in new ways (Figure 2). This tool was developed in response to findings from field research at design consultancy IDEO; that tools offering ‘structured serendipitous inspiration’ could help provoke new interpretations and ideas (Mothersill & Bove, 2017).

As shown in Figure 1, we propose that the design(human)design tool has medium interpretability and, at its simplest state, a low-to-medium level of contextuality. If the text corpus is modified to include information only related to a certain topic or personal data set, the level of contextuality becomes medium-to-high.

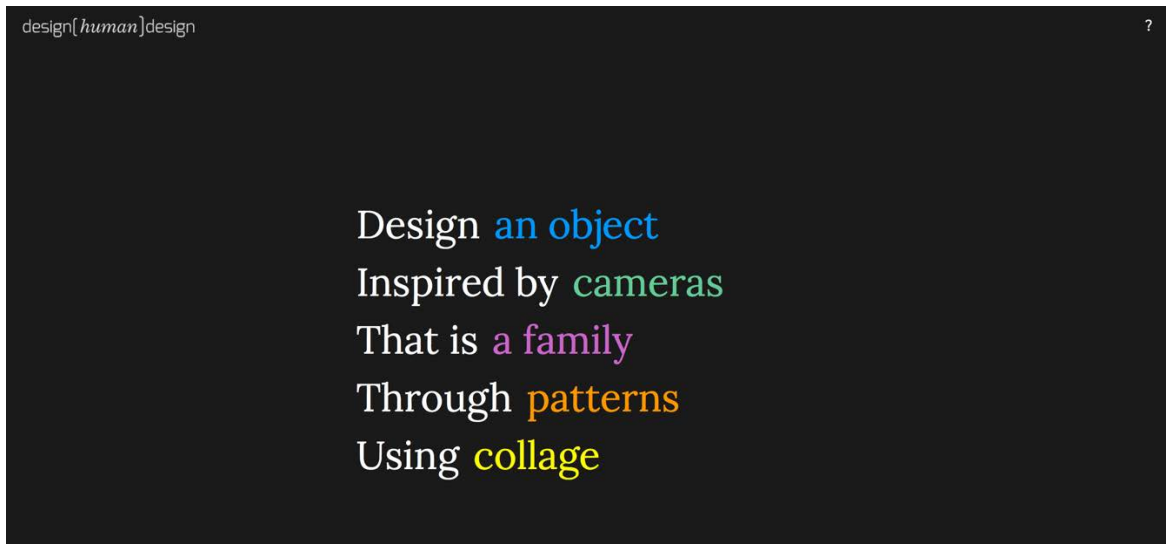


Figure 2. Screenshot from design(human)design creative prompt tool

5.2. Looking Sideways inspiration exploration tool

Looking Sideways (<http://sideways.media.mit.edu>) is an online exploration tool that seeks to provoke unexpected inspiration and create new associations by providing users with a selection of semi-randomly chosen, loosely related, diverse online sources from art, design, history and literature for every search query (Figure 3).

As shown in Figure 1, we propose that the Looking Sideways tool has a lower level of interpretability than the design(human)design tool due to the user’s more active engagement with it. At its most simple state, it has a medium level of contextuality, however if the databases that the tool is searching are customised to a certain topic or personal ‘creative watering holes’, the level of contextuality can become quite high.

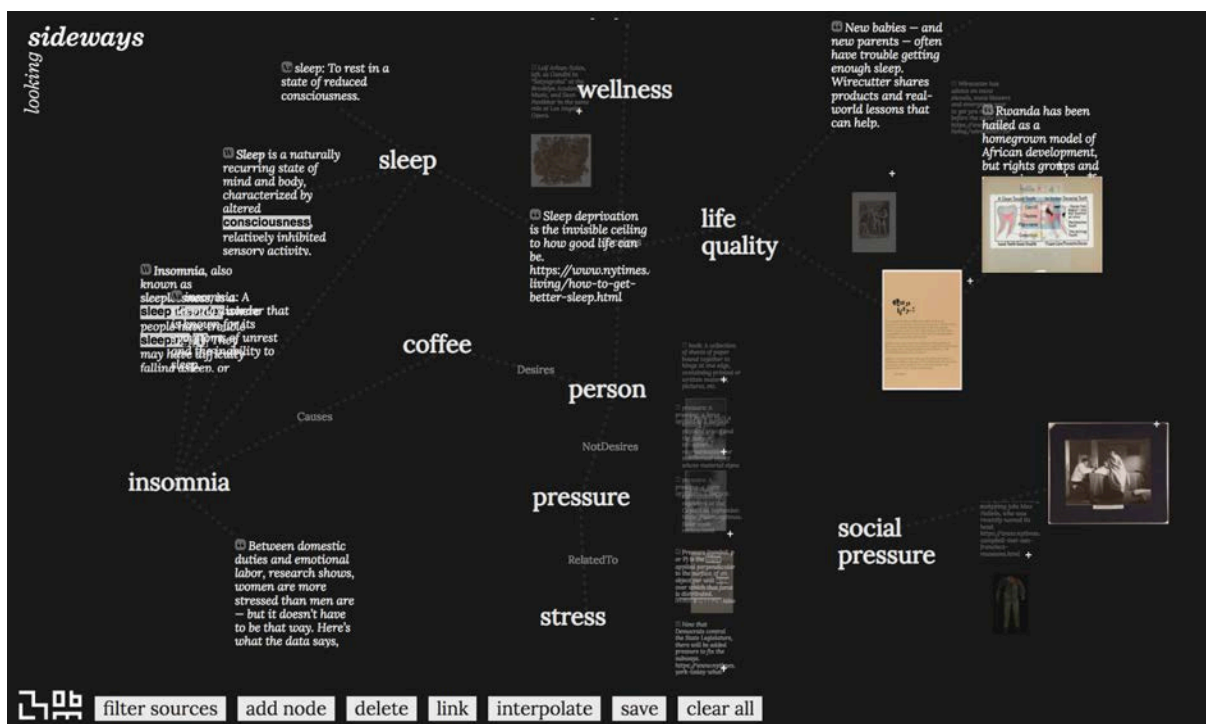


Figure 3. Screenshot from Looking Sideways inspiration exploration tool

6. Evaluation methodology

To evaluate the creative potential of these tools, we carried out studies with both professional and student designers. 18 participants (10 men, 8 women) took part in an observed study where they were asked to generate creative responses to one of two themes (“automated systems (in the home, work, city etc.) that we trust” and “the future of wellness (in the home, work, city etc.) that is integrated”) using the Beyond Average tools to provide inspiration. The text corpus that the design(human)design tool drew from was customized for each theme using words from relevant Wikipedia pages and articles. The results pages (including images, news, shopping etc.) from Google’s search engine was used as a control tool. The participants had 10 minutes to use each tool to explore the themes and generate ideas based on the inspiration they provided, noting down any ideas or sketches using pen and paper. As learning from previous tools was inevitable, the order of the tools was randomised across participants. Finally, participants completed a survey that asked questions related to the potential of each tool to provide unexpected creativity (<https://bit.ly/2FkvMEU>).

Shah & Vargas Hernandez’s (2003) metrics for measuring ideation effectiveness—novelty, variety, quality, quantity—as well as metrics relating to de Bono’s (1970) analysis of lateral thinking—whether ideas are of immediate usefulness, areas for further exploration or new approaches to problem, and if they are vertically or laterally related—were integrated into questions that participants rated on a 5 point Likert scale. Overall comments about how the tools influenced the participants’ generation of new ideas, how the tools could integrate into their creative practice and any suggestions for modifications were also collected.

7. Findings

While we did collect numerical data about the creativity metrics and design space dimensions described above, we acknowledge that it is hard to draw generalisable quantitative findings from these types of subjective, not easily repeatable creative interventions, especially with our relatively small sample size. Therefore, here we will present general trends indicated by the quantitative data and extend the analysis of these insights with the qualitative feedback also collected. As both of the themes tested provided similar responses (most ratings were within one Likert point), we have combined the data into a single average used in the results below. There did appear to be some effects due to the different order of the tools shown to the participants, but those will be discussed further in the next section.

To understand if the participants had a similar experience using the tools as we expected, Figure 4 shows the participants ratings of how contextual and ambiguous they considered responses generated by the tools (Low contextuality/interpretability = 1; high contextuality/interpretability = 5). The participants generally agreed with our hypothesis for where these tools sit within the design space dimensions: Google was considered to give very direct, highly contextual responses, design(human)design was considered to have the most interpretability and medium contextuality, and Looking Sideways was considered to give mediumly ambiguous and contextual responses (slightly lower than our expectation, likely due to technical limitations with the prototype).

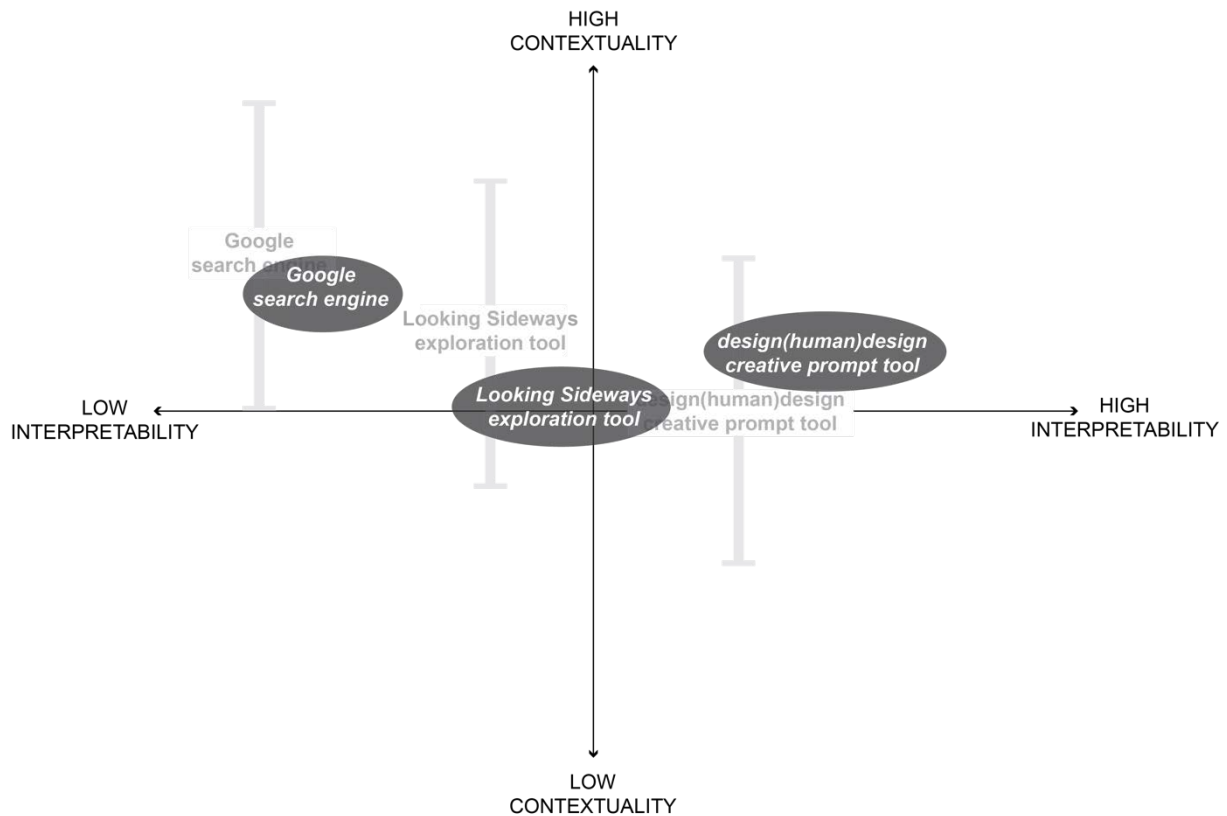


Figure 4. Existing and ‘Beyond Average’ tools mapping onto design space dimensions by participants compared with proposed mapping

Reviewing the data mapped against the design space dimensions individually reveals some larger trends about how the levels of contextuality and interpretability affect creative output. Figures 5 and 6 show the ratings for each of the tools for the metrics described above mapped along the design space dimensions. Lines have been added between the discrete data points to indicate trends in how the creativity metrics might vary as a design tool includes more or less contextuality and interpretability. Quantity of ideas is not included as all tools generated similar results (1-2 ideas), probably due to the short time allowed for the task.

7.1. The influence of contextuality on the creative process

Figure 5 shows that Google—the tool with the highest contextuality—had the lowest ratings for most of the metrics (between 2.33 and 3.83). Despite participants’ familiarity with using Google to gather a large quantity of information on a theme, its high contextuality meant this knowledge was situated in terms of what other people have done and thought before; the “generally accepted ‘norm’ answers”. While this helped some participants identify common features or trends, it led others to feel there was “too much priming in the wrong direction.” The high contextuality of Google was considered beneficial when the participant has already “honed in on something narrow” and is “thinking about framing their enquiry”, but was “not useful for deeply assessing where [their] ideas were situated” and therefore not the right tool for coming up with new ideas.

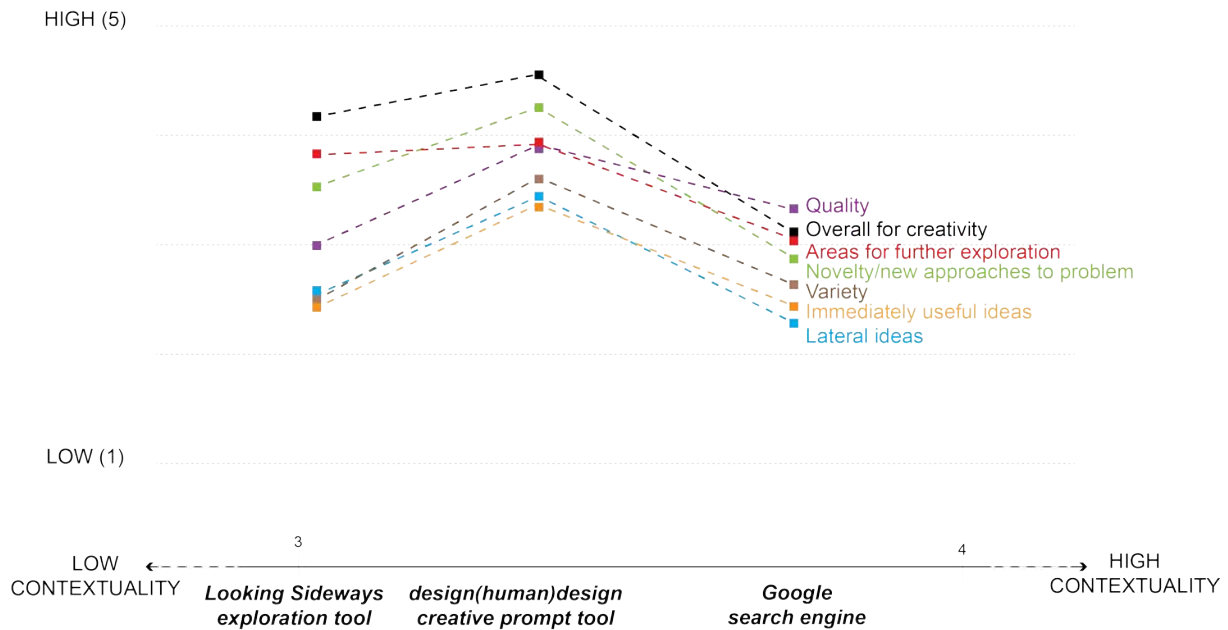


Figure 5. Map of creativity metrics against the level of contextuality in each of the tools studied

In contrast, the design(human)design tool (medium contextuality) was rated highest for all metrics (between 3.17 and 4.67). The lower level of contextuality was found helpful in liberating the participants from their own preconceptions. Being primed with text related to the two themes allowed the tool to easily provide many simple but different “relatively stable starting points” from which ideas could be constructed. However, due to the format of the tool, some participants felt that the prompts often fell into more project-based tasks rather than general inspiring concepts, limiting their boundaries of thought. Another participant also commented that while “arbitrariness can be very powerful for lateral thinking...sometimes it can feel forced or difficult to draw connections” and that “knowing when to skip and when to ponder” a seemingly irrelevant connection requires consideration, and potentially guidance.

Helping to see links between ideas was one of the features that participants liked in the Looking Sideways exploration tool; adding a level of contextuality to seemingly unconnected concepts. This ability to visually map how random concepts intersect “provided nice tangents” to open up their existing idea domain. As participants controlled the context of the exploration by entering their own search terms “some connection to the goal is there” which guided one participant “into a headspace that is comfortable and that I feel authoritative in, but is new territory.” Despite this feedback, participants still rated the tool as fairly low contextuality and it did not score as highly as the design(human)design tool in terms of creativity (between 2.56 and 4.11). In general, participants liked that the search results were not defined by popularity such as on Google, but due to limitations in the number of content sources in the current prototype, there wasn’t a large enough amount of information available to explore a concept deeply—as Google provides—or consider many new perspectives—as the design(human)design tool provides.

Overall, it appears that tools which provide more highly contextual responses, i.e. Google, are good for exploring a narrow subject once design parameters (or search terms) are known but the focused range of similar information limits the ability to generate new ideas or connections. Tools that have a lower contextuality—design(human)design and Looking Sideways—can provide tangentially associated responses that prompt participants to reconsider how concepts could be interpreted and connected, providing them with interesting “starting points” for new ideas to explore further.

7.2. The influence of interpretability on the creative process

Mapping the same results onto the interpretability axis, Figure 6 shows a clear trend towards greater creativity with higher levels of interpretability. For Google (low interpretability) participants are relied upon to come up with interesting search terms, hence the responses can only be “as creative as your own mind essentially allows you to be.” This improved with higher levels of interpretability in the Looking Sideways tool as its ability to connect random user-defined concepts provided fresh, unexpected input that “encouraged momentum and outgrowth” and “a way to riff out from where I already am”. Presenting the responses in a more visual, unorganised manner also allowed for the participants to “make a mess”, inspiring less literal connections and more varied interpretations because they can find their own sense in the content.

The tool that provided the most varied and new connections was the design(human)design tool (high interpretability). Participants found that when they allowed themselves to let go of controlling the tool and consider the often ambiguous responses in a more flexible way, the random juxtapositions of concepts challenged them to take on “a more non-structural thinking” that prompted “new and very different points of views on my ideas”; a feeling that several participants described as being rare in comparison to other computational design tools today. However, while many participants enjoyed the possibility to quickly iterate through a high number of ambiguous prompts as it helped them get into a different mindset, a few considered the juxtaposition of even two of the often very broad concepts required a lot of time to think deeply about the potential connections between them.

Overall, there seems to be a clear trend that higher levels of ambiguity in the responses provided by the tools—something we could also describe as a higher level of creative agency on the machine’s part—allowed for more variety of interpretations within the information presented and therefore a greater possibility for new connections and ideas to be made.

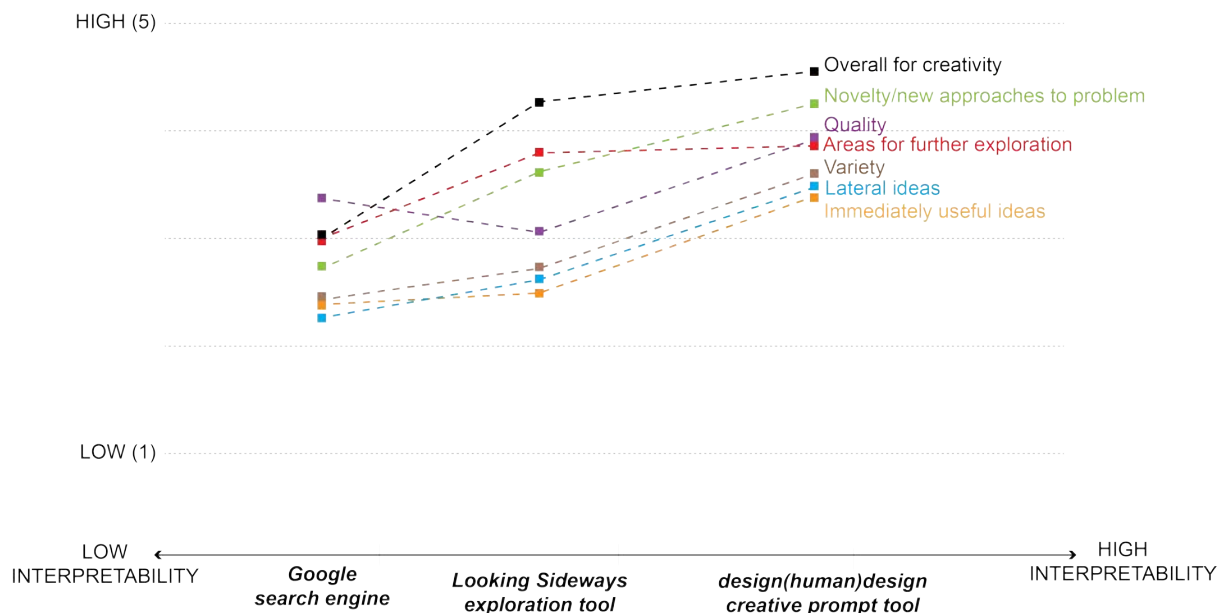


Figure 6. Map of creativity metrics against the level of interpretability in each of the tools studied

7.3. The roles of the Beyond Average tools in the design process

From the results discussed above, we suggest that computational tools with a medium level of contextuality and a medium-to-high level of interpretability can positively influence creativity in the early phases of the design process. The lateral responses to search queries and somewhat random

provocations enabled by higher levels of interpretability allow participants to have some agency over the direction of explorations but also be provoked to rethink how something seemingly irrelevant could be contextual; responses that make *just enough* sense and provide a high *potential* contextuality for participants to generate relevant but novel ideas.

Figure 7 shows this quadrant of the design space dimensions was also rated the most desirable for inspiring new ideas, supported by the design(human)design tool being rated favourite by most participants (11 out of 18). However, one participant commented that desiring tools in this quadrant of the design space seemed like a paradox. This relates to how participants felt Google—and the general trend for efficient search tools—had conditioned them to think in a logical way and using the Beyond Average tools helped them embrace more ambiguous, non-deterministic approaches.

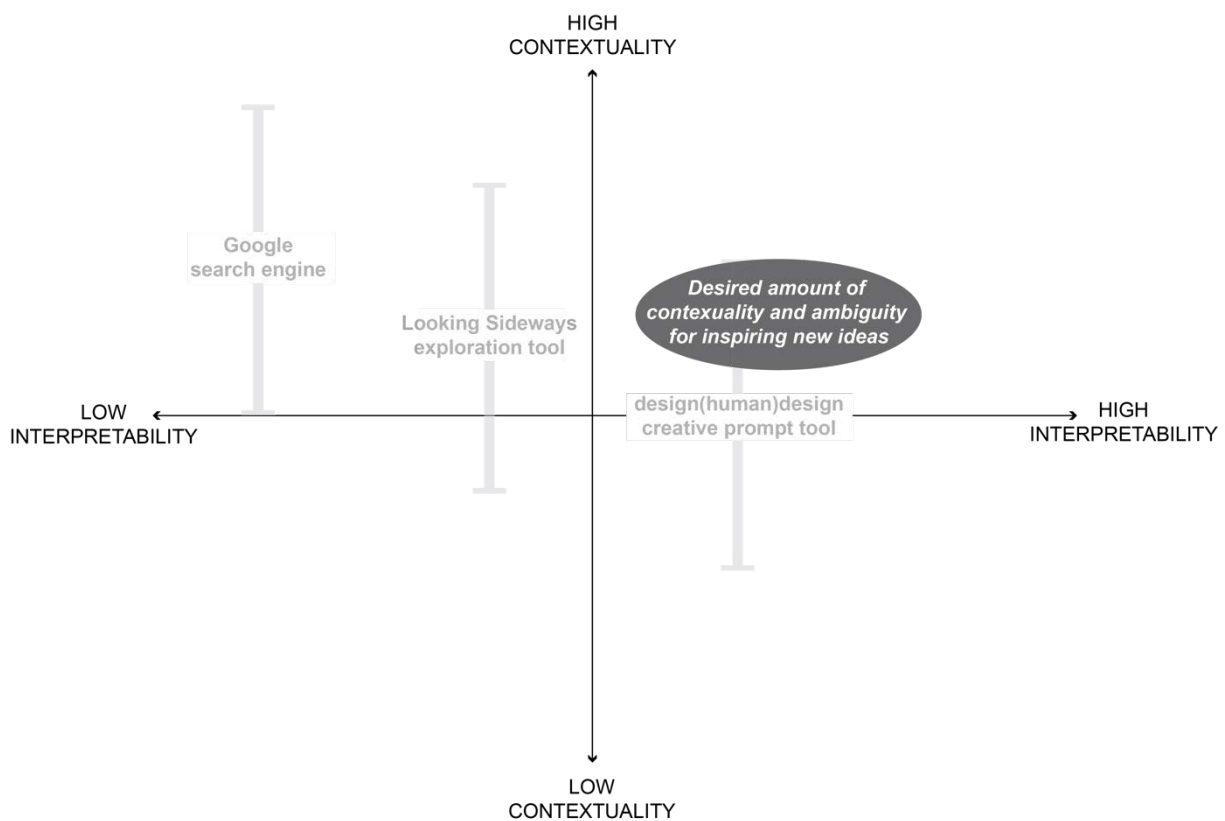


Figure 7. Proposed mapping of existing and ‘Beyond Average’ tools onto design space dimensions compared with desired amount of contextuality and ambiguity rated by participants

The effect of these different approaches was noticeable through the order effects that emerged. When the Beyond Average tools were tested first, participants started to consider how they could use Google more creatively, with mixed success due to its more efficiency-oriented search approach.

The fact that these tools can influence each other is an exciting finding. While some participants did distinguish the tools for separate design activities, e.g. design(human)design for brainstorming and Looking Sideways as a mapping tool to document their creative process, most thought they would be useful as a suite. Using a mediumly contextualised version of the design(human)design tool was considered a useful creative ‘ice breaker’ for seeding interesting new directions for further exploration, followed by the Looking Sideways tool to suggest lateral connections between concepts and Google to gather more focused information to further frame their ideas. Integrating information related to key concepts explored in Google and the Looking Sideways tool back into a more contextualised version of the design(human)design tool was suggested as a way to further generate novel but more focused ideas related to the participant’s emerging themes and design parameters.

This imagined role of the tools in the design process indicates a somewhat cyclical need for high levels of contextuality and interpretability in exploration and ideation activities. When using computational tools with very high levels of contextuality, e.g. Google, the creative agency is determined by the human; the search terms are determined by the designer, often through some non-computational means such as brainstorming. When the computational tool can have creative agency as well, e.g. through using higher levels of interpretability as the design(human)design and Looking Sideways tools do, the computer can contribute to the designer's creative agency and become more of a natural partner to guide the early phases of the design process.

7.4. Future research

These results have highlighted exciting opportunities for us to pursue. Modifications to the tools include: automating the customisation of the text corpus in the design(human)design tool to generate more contextually specific provocations, expanding the number of content sources in the Looking Sideways tool, and fixing several user interaction issues. Extending the Looking Sideways tool, we are also developing the Design Daydreams table and post-it note; a low-tech augmented reality tool that can project the digital content explored onto objects in the real world (Figure 8).



Figure 8. Design Daydreams augmented reality viewers (as part of a larger augmented drafting table)

Acknowledging that observed studies are limited when investigating the design process, we are also carrying out longer unobserved studies to further analyse the tools. In these less structured studies, we imagine there might be a greater hesitancy to embrace the serendipitous logic of the Beyond Average tools, especially in real-world projects when productivity demands are higher. We aim to investigate this apparent limitation of the tools' effectiveness by exploring how the responses provided can be the right balance of disruptive randomness and efficient relevance. Through understanding how to better frame the benefits these tools can provide within different design activities, we aim to stimulate purposeful moments of unexpected creative reinterpretation for designers, as well as slowly broaden their attitudes about the different ways computational tools can guide us to be 'productive' in the creative process.

8. Conclusion

In the early phases of the design process, embracing chance intrusions, seeming irrelevance and ambiguity can lead to considering concepts in different ways and provoke new ideas. However, the computational tools we are increasingly using in these phases value efficiency over serendipity; technologies whose foundations are an average. This paper explored how developing computational design tools that embrace seeming irrelevance and ambiguity could influence the creative process in the early phases.

The 'Beyond Average' approach defined two design space dimensions: contextuality—how 'smart' responses from the tool were—and interpretability—how ambiguous the responses were. Situated at different positions along these dimensions are two tools developed by the authors: the design(human)design creative prompt tool and the Looking Sideways exploration tool. Results from studies using these tools to provide inspiration to participants as they attempted to generate new ideas around a theme (with Google as a control) showed that computational tools with a medium level of contextuality and a higher level of interpretability can positively influence the creation of new ideas.

Imagining these tools used as a suite in their design process, participants suggested jumping between the tools when they needed different levels of contextuality and interpretability; using the very ambiguous design(human)design tool to provoke new seeds of ideas that they can deeply explore in the more situated Google search engine and Looking Sideways tool. Extending this discussion to consider the role of computation in the early phases of the design process, we suggest that tools with higher levels of creative agency—those with high levels of both contextuality and interpretability—can contribute to the designer's creative agency and become a more natural partner in these activities.

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