AI in design idea development: A workshop on creativity and human-AI collaboration

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AI in design idea development: A workshop on creativity and human-AI collaboration

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Abstract: In a fast-paced society, AI systems can prove to be reliable teammates alongside human agents during the early stages of the design process, capable of helping to manage the increasing complexity of projects. Therefore, the introduction of AI systems into the design process is analysed according to the implications on the designer's creativity and the kind of human-AI collaboration that is established, highlighting trust balance and the new role played by the designer. The main aspects covered by the study were tested in a workshop, in which *continuous* and *discontinuous* human-AI collaboration were compared. In the case of continuous collaboration, the results show that AI assumed the role of a bossy groupmate, leading to an AI-driven creative process. In the second case, AI took the role of an expert capable of generating variance outside the team, leading to a human-driven creative process.

Keywords: design process; artificial intelligence; human-AI collaboration; creativity

1. Introduction

The advent of the digital age has pushed the world into continuous and urgent changes, in which major social, cultural, and technological shifts can occur in short periods. In this fast-paced and always-evolving environment, designers are asked to find new solutions to deal with the increasing complexity of their projects. Among others, this paper focuses on those tools driven by artificial intelligence (AI) and employable in the early phases of the design process. Indeed, the value and usability of AI in the initial creative phases are still unexplored and opaque (Stoimenova & Price, 2020), meaning that the potential of AI systems applications in design thinking practices is still largely unknown (Cautela et al., 2019). Exploring the implementation of this technology within the initial phases of the design process means assessing the AI's impact on the designer's creativity and the process outputs, considering that the most polarizing design decisions are usually made here (Wang et al., 2002).

2. AI as a human creativity enhancement

The main difference between a traditional computational tool and an AI system is that the latter is increasingly similar to a person's mental apparatus and less to a mere tool (Stoimenova & Price, 2020). Even though AI systems are often perceived as a replacement for human work, their potential is fully disclosed if considered in a human-AI relationship of complementarity, in which humans and machines cooperate to make up for each other's deficiencies and improve the final quality of the output (Wilson & Daugherty, 2018). This shift in the relationship, where AI from an instrument becomes an almost-equal partner, generates a continuous exchange between the parts involved. Yannakakis et al. (2014) refer to this new collaboration as *mixed-initiative co-creativity*, defining it as creating artefacts through the interaction of a human and a computational initiative.

> "Through the mixed-initiative perspective we assume an autonomous computational system that explores the possibility space in its own ways as guided by human lateral decisions during the creative process, realising and fostering human-machine co-creativity" (Yannakakis et al., 2014, p. 8).

Therefore, the non-human agent (i.e., AI) assumes inductive and deductive behaviour towards problem-solving, capable of inspiring, triggering, suggesting, and even evaluating choices and actions. In other words, a scenario is now possible where a human agent and a non-human agent both proactively contribute to the solution of a problem that, consequently, can no longer be ascribed exclusively to either the human or the machine but always to both (Liapis et al., 2016).

AI systems, in particular, are highly functional in providing the designer with random stimuli (Beaney, 2005) during the creative process. A random stimulus is defined as a foreign and unforeseen conceptual element that can break designers' prejudices and already-existent patterns of reasoning, therefore triggering lateral thinking and curiosity (Beaney, 2005; Yannakakis et al., 2014). In conclusion, Liao et al. (2020) suggested a shift into the *knowledge-driven principle* perspective, meaning that the outcomes generated by AI could be a new form of design knowledge that is exploitable by designers in new and original ways.

3. AI applications in the design process early phases

3.1 Research phase

Through the digital world, which includes social networks, blogs, digital newspapers, IoT, and many more, society generates more than 2.5 quintillions (10^{18}) bytes of data each day (Wu et al., 2014) that are ready to be analysed and implemented into the design process. Although relevant for collecting certain kinds of information, the traditional design research methods are not comparable with the AI-driven ones regarding data size, heterogeneity, and analytical skills (Tuarob & Tucker, 2015). Hence, AI can improve the designers' idea development with a more complete and profound level of knowledge regarding their projects, a much larger user pool to draw from, and an overall reduction in costs and resources employed. In addition, AI's ability to gather and recognise people's emotions and behaviours (Xue & Desmet, 2019) through quantitative data (Kern et al., 2016) could play a key role in predicting possible future scenarios, an issue of significant relevance considering the widespread uncertainty of today's society (Cooper, 2019). Adopting this new generation of AI-driven research tools (Tucker & Kim, 2011; Pan et al., 2017) would mean empowering the designers' capability of gathering useful knowledge for the design process.

3.2 Concept phase

Once the divergent phase of the research is concluded, the designer should converge into a limited number of design ideas. During this phase, each designer, according to their educational background, experience, and sensitivity, develops their modus operandi, which can be personal and unique (Cross, 2011). Thus, AI should not be understood as a tool that standardises and flattens design individualities but as an impressively versatile instrument capable of preserving and enhancing them. Given this extraordinary variety in the approach to idea development, potentially useful AI systems also have a wide range of applicability. We have categorised them into five groups based on literature, distinguishing the kind of tasks performed (figure 1).
The five categories are described as follows:

1. **Image generators.** AI can act as a powerful medium for enhancing human creativity, especially when it plays the role of visual stimulus, either intended or random, from which the designer can draw inspiration. (Chai et al., 2018; Chen et al., 2019; Dosovitskiy et al., 2017; Gatys et al., 2016; Isgrò, 2020; Karras et al., 2019; Park et al., 2019; Quan et al., 2018; Reed et al., 2016; Schmitt & Weiß, 2018; Zhang et al., 2018)
2. **Sketching assistants**. AI systems can be an ally in this core creative action, comparable to how a teammate brings her vision to the project by generating a pair dialogue consisting of a continuous exchange of information. (Davis et al., 2016; Fan et al., 2019; Ha & Eck, 2018)
3. **Model generators and modifiers**. When developing an idea, AI-generated 3D models become additional systems at the designer's disposal as they provide unique final outputs and, therefore, unique information such as the one obtainable from sketching. (Autodesk, n.d.; Oh et al., 2019)
4. **Facilitators**. AI systems aimed at streamlining and simplifying the number of actions the user needs to perform, such as Adobe Sensei.
5. **Concept evaluators**. AI-concept benchmarking systems, capable of analysing many design proposals, evaluating them according to the parameters of *novelty* and *level of detail*, and ranking them accordingly from best to worst. (Camburn et al., 2020)

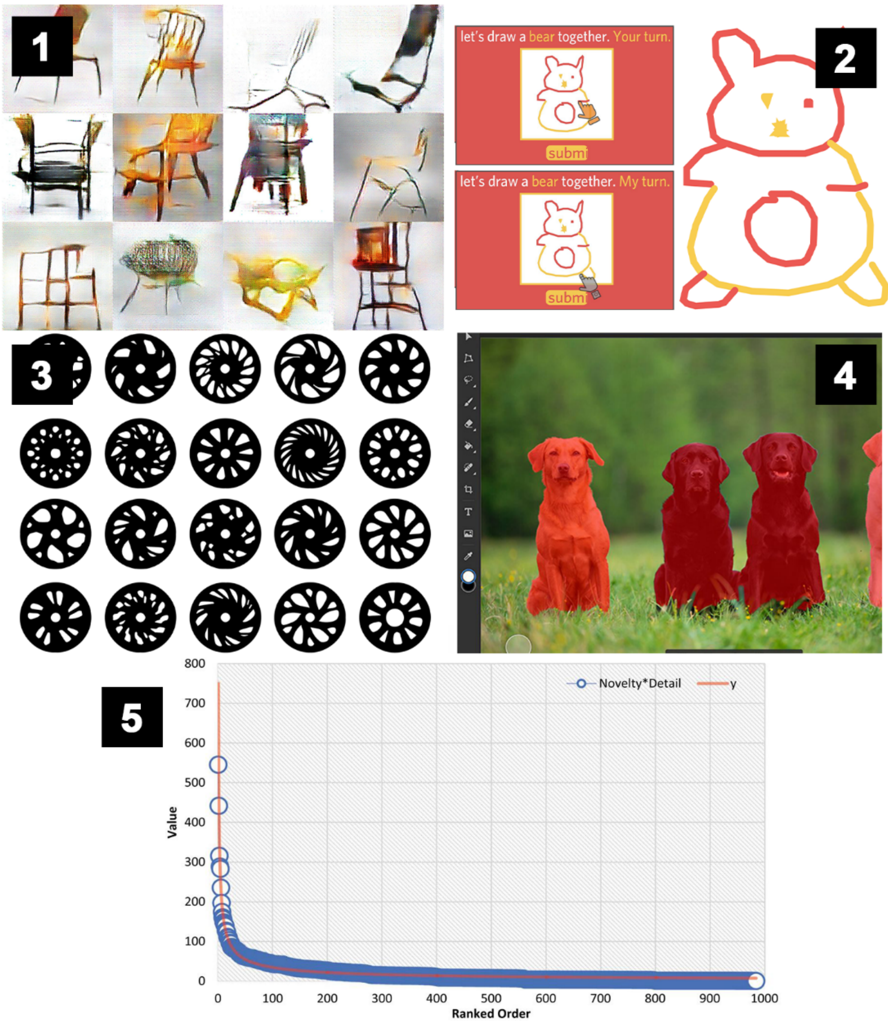

Figure 1. From 1 to 5: (1) examples of image generator (Schmitt & Weiß, 2018); (2) sketching assistant (Fan et al., 2019); (3) model generator and modifier (Oh et al., 2019); (4) facilitator (Adobe Sensei); (5) concept evaluator (Camburn et al., 2020).

4. Human-AI collaboration

4.1 New team dynamics

As mentioned above, the capabilities of AI systems suggest that collaborative technologies are shifting away from the nature of a performance-enhancing tool toward that of a teammate (Seeber et al., 2020). Thus, designers and AI could establish a human-machine relationship that is strikingly similar to the human-human relationship (Krämer et al., 2012). From this perspective, design practices assist in a transition from groups composed only of humans to groups consisting of both humans and machines, which results in new and still largely unknown teamwork dynamics. Therefore, given how critical is the social and emotional functioning of groups for the success of a project (Barsade & Gibson, 2007), a study on the impact of AI in the design process would be incomplete without considering the implications on design teams and human-AI collaboration. In particular, while there is an active debate about how machines should collaborate with humans and adapt to their

needs, the same cannot be said for the reverse situation: a knowledge gap exists regarding humans' ability to facilitate the integration of the machine into their work. As AI systems advance in their capabilities, humans also need to relate to the machine and progressively optimise teamwork.
In this respect, Pandya et al. (2019) and Zhang et al. (2021) have shown in their studies that, so far, Human-AI collaboration is most successful (i.e. leads to better outcomes) when the machine has more developed capabilities compared to the human, while it is likely to become counterproductive if the machine has lower or equal capabilities compared to the human. We named this principle *AI>Human* rule, intending that the Human-AI collaboration is most productive when AI is more performative than the human agent on a specific task. Based on the literature, we identified three primary consequences of the AI>Human rule.

1. **The acknowledgment of the AI's predisposition to performing repetitive and straightforward tasks** (data screening, generation of images, prevention of CAD errors, etc.), in which computers usually excel, enables a redistribution of tasks within the design process, streamlining alienating activities from the human's duties and thus allowing her to concentrate on enhancing other strategic activities (Rajpurohit et al., 2020);
2. **The recognition of complementarity in Human-AI collaboration** discloses that a critical phase for work success is allocating tasks based on the distinct competencies displayed. (Wilson & Daugherty, 2018)
3. **The tendency of AI to improve the work quality of low-performing teams**, expanding the possibilities and frequencies of use of the machine. In these cases, AI can compensate for the team's shortcomings. On the contrary, AI should be employed carefully in a high-performing team as the current state of the technology might worsen the team's overall performance. (Pandya et al., 2019; Zhang et al., 2021),

Accordingly, it is recommended to plan who will carry out a given activity: only the AI system if the human agents could hinder it; only the human agents if the AI system could slow it; both if combining efforts would lead to greater efficiency and better results (figure 2).

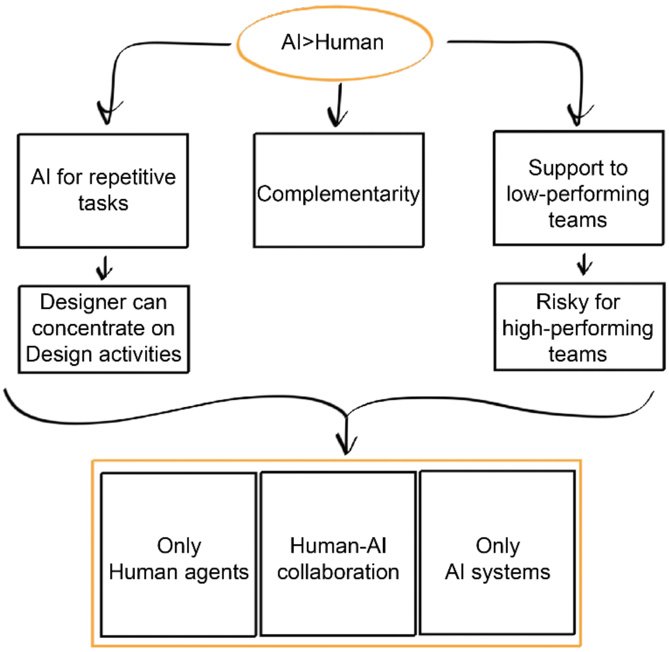

Figure 2. The primary AI>Human rule consequences.

We define these criticalities of Human-AI collaboration as *technical*. However, also it is essential to consider another set of criticalities, more subjective and nuanced, hard to be framed in absolute rules and therefore more challenging to manage. We named these criticalities as *sensitive* and identified three main types.

1. **Predisposition criticalities** derive from the person's predispositions and manifest mainly as biases. (Lopez et al., 2019)
2. **Perception criticalities** are due to the reduction in the number of actions performed by human agents. If the human's overall knowledge of the project tasks decreases, their ability to evaluate it is also likely to be altered once the work is completed. (Zhang et al., 2021)
3. **Communication criticalities** are caused by the AI working as a *black box*, in which the human agent is only capable of knowing the inputs and the outputs, not the reasoning process in between. (Liao et al., 2020; Bansal et al., 2021)

These sensitive criticalities can lead to harmful imbalances in the relationship of trust between humans and AI, alimenting two opposite phenomena. On one side, they increase the risk of the *over-trust* of humans towards AI agents, eventually leading to misuses and costly mistakes. On the opposite side, imbalances might cause *under-trust* of humans toward AI, possibly causing disuse (de Visser et al., 2020).

4.2 The designer's role

These modifications also affect the designer's figure and work, forcing her to adopt a new role within the design process, with new priorities, tasks, and skills. Given the current state

of the technology, human-AI collaborations are not infallible, and consequently, it is up to the designer to evaluate the machine's work and choose whether to consider its output or discard it. When increasingly operational tasks are assigned to AI, the designer assumes a privileged position within the design process, focusing more on management and supervision of tasks. We named this emerging role of designers *designer arbiter*, intending that the designer becomes responsible for evaluating and making choices rather than executing tasks. This role is aligned with designers' distinctive qualities, such as the maintenance of the general direction of the project, the understanding and framing of the problem analysed, the coordination of AI systems (Verganti et al., 2020), and the contribution of their sensitivity, intuition, and know-how into the design process (Cross, 2011).
The designer arbiter is a figure with solid evaluation skills, capable of understanding the project and the AI systems deeply. In this way, designers can significantly maximise the human-AI collaboration to expand the design process's potential and final output.

5. Workshop

5.1 Workshop design

The main dynamics of a human-AI collaboration were tested during a workshop with 16 design students, focusing on changes in creativity and the trust relationship.

The 16 participants worked in pairs, thus forming eight groups, split into two distinct types that we defined as *simultaneous* and *delayed* groups. Simultaneous groups worked throughout the whole duration of the workshop alongside their respective AI system. Instead, delayed groups alternated between an initial period, per each phase, without the help of AI system, followed by a period with it. For instance, simultaneous groups had 20 minutes to develop their research phase using Google search engine, while delayed groups started their research without it and were asked to use the search engine only in the last 10 minutes. Our aim was to compare continuous and discontinuous human-AI collaboration and verify divergences, repercussions on the creative process, and participants' perception of the different working conditions.

The groups were asked to design in an hour a frog-sofa that, being uncommon and deliberately vague, was chosen as an element of surprise, thus encouraging participants to generate their interpretation and explore unique and personal solutions.
The workshop was structured to simulate, in a simplified way, a design process up to the definition of one or more concepts through three typical creative phases: research, sketching, and colour selection. A specific AI system was provided for each phase to support the participants during their design activity: the search engine Google; the sketching assistant Sketch-rnn; and the colour palette builder Coolors (figure 3). These were chosen because of their ease of use, affinity with the corresponding design phase, and capacity of establishing different Human-AI relationships. Furthermore, it was in our interest to select already commonly used tools to raise awareness by showing participants that AI algorithms

are often hidden behind seemingly simple systems.
The data were collected with a qualitative approach by analysing: (1) the participants' responses to two different forms, given respectively before and after the workshop; (2) the workshop outcomes provided by the groups; (3) the collective focus group run by two facilitators at the end of the design activity.

A detailed and complete account of the Workshop's results can be found in the recently published book "Artificial intelligence in the design process: The Impact on Creativity and Team Collaboration" (Figoli et al., 2022).

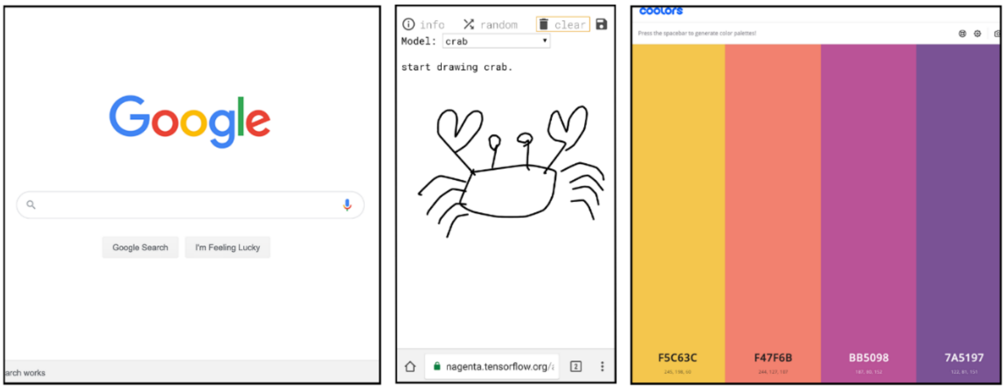

Figure 3. AI in the workshop: Google, Sketch-rnn, and Coolors.

5.2 Discussion on the workshop outcomes

The participant's responses to the initial form show their neutral position towards the introduction of AI systems in their profession but also demonstrate an overall welcoming attitude towards AI. After the workshop, 10 out of 16 participants substantially changed their opinion. Of these 10, five altered to a more favourable position and five to a more contrarian one, including slight and drastic shifts. The type and extent of the shifts are not explicitly related to being the respondent in a simultaneous or delayed group.

Observing the outcomes of the three design phases emerged the AI capability of supporting the designer's work by providing a significant volume of information in a short period and by facilitating numerous tasks performed during the design process. When employed, Google, sketch-rnn and Coolors speeded up the design phases, allowing the groups to generate new information and variance with ease. At the same time, they decreased the risk of blockage and fixation, as demonstrated by the number of outputs obtained using AI exceeding those obtained without AI.

The simultaneous groups, which performed each project phase alongside the AI systems, generated a workspace environment marked by continuity. This continuity resulted from humans and AI sharing the workspace rules from the beginning of each phase. Participants did their research within Google workspace, their sketches within Sketch-rnn, and their colour selection within Coolors. Even if the shared workspace rules allowed continuity in work, they resulted from participants' one-way adaptation to the AI interfaces. Since it was not possible to pursue a free creative process, the participants addressed the design problem exclusively from the point of view of the AI system (figure 4). As a result, the final outputs of the simultaneous groups often resemble each other and are somewhat deficient in uniquely human creative impulses, leading to foreseeable design solutions. In this scenario, Google, Sketch-rnn, and Coolors could be seen as *bossy* group members, meaning that human agents must adapt excessively to AI systems.

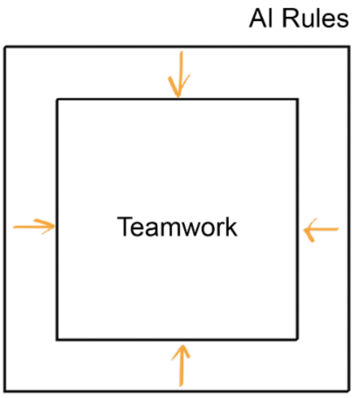

Figure 4. AI forces its constrictions on the simultaneous team.

On the other hand, the delayed groups generated a highly discontinuous working environment. Discontinuity required a necessary realignment between the previous work carried out without AI, therefore outside the rules of the machine, and the machine itself (figure 5).

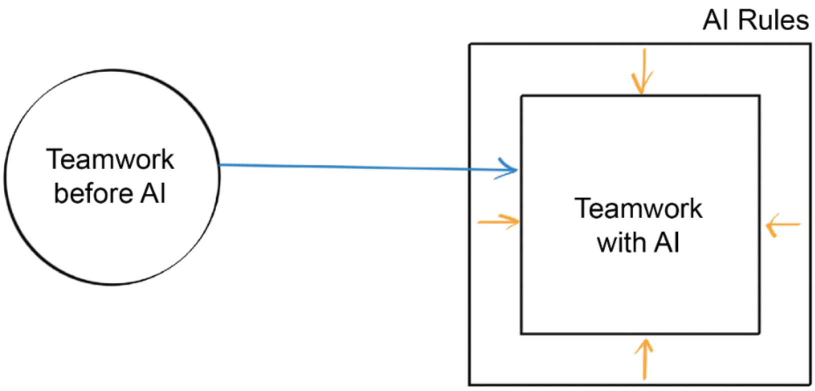

Figure 5. Process of realignment in delayed teams.

We divided the critical moments of realignment observed in delayed groups into three recurrent types (figure 6).

1. **Simple and relatively harmless realignment** occurred when the task (i.e., research, sketching, colour selection) initially developed by human agents alone

was conducted, either by planning or by coincidence, in conformity with the machine rules.

2. **Complex realignment** occurred when the task (i.e., research, sketching, colour selection) initially developed by human agents alone did not conform to the machine rules, hence needing modifications to integrate the AI system in the collaboration. This type led to delays, which might, in professional contexts, determine additional costs.
3. **Impossible realignment** occurred when the task (i.e., research, sketching, colour selection) initially developed by human agents alone was in no way re-adaptable to the machine rules. This generated a fracture that did not allow the collaboration between the parts to go any further except with significant readjustment measures.

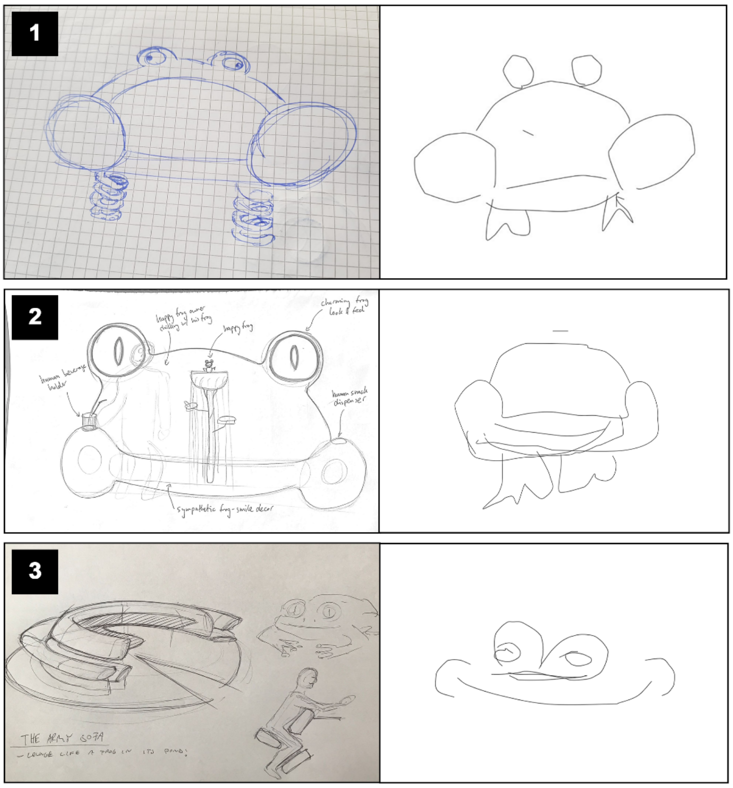

Figure 6. Three types of realignment observed in delayed groups between prior Human-alone sketches (left side) with later Human-Sketch-rnn ones (right side). (1) Simple realignment – Human sketch is already aligned with AI rules. (2) Hard realignment – Human sketch is too detailed and needs simplification to realign with AI rules. (3) Fracture – Human sketch is a "sofa that makes you sit like a frog", in contrast to the AI rule "a sofa that looks like a frog".

The result is a Human-AI collaboration widely unbalanced in favour of the human agents. In the most extreme case of a delayed group, the human-AI collaboration did not happen since the human agents remained particularly attached to their idea, entirely rejecting AI suggestions. In other words, the risk of human agents' fixation was more marked and evident in delayed groups.

Regarding the AI>human rule, the results show that it is verified in the case of Google and Coolors and not verified in the case of Sketch-rnn. Google and Coolors proved to be efficient partners, capable of improving the design process of the groups both as teammates and stimuli for the human agents. On the other hand, although Sketch-rnn is a cutting-edge system, it can only generate suggestions following its paradigms. Thus, it is still limited in its ability to support a designer in sketching ideas beyond its range of scope. Consequently, the human-AI collaboration established presents a high risk of slowing and worsening the group's performance. Nevertheless, the AI capacity of providing random stimuli remains valid regardless of the AI>Human rule.

In addition to this, the Human-AI relationship must consider the balance of trust between the parts involved. During the workshop, participants followed Google and Coolors's suggestions more frequently than Sketch-rnn ones, showing how groups have adopted a more or less open stance towards the three AI systems used. The main factors identified that can significantly affect the balance of trust in a collaborative human-AI relationship are (figure 7):

1. **The evaluation of the machine's outputs**. The human agent receives and evaluates the AI system's work repeatedly and gradually increases her understanding of the machine. Throughout this process, the designer develops a judgment about AI competence, which affects the trust placed in the machine. An example of this phenomenon is the participants' progressive rejection of Sketch-rnn's suggestions during the workshop, as it was increasingly considered an incompetent teammate.
2. **Designer lack of knowledge and expertise**. If the human lacks knowledge on a specific task, she will be more likely to rely on the machine's outputs. This might lead to AI-driven decision making, in which the human has reduced agency. An example of this phenomenon is the participants' confidence in Coloors due to their scarce knowledge in colour theory and application.
3. **Familiarity**. When the human agent is familiar with the AI system due to frequent interaction, she develops consolidated trust patterns. In this scenario, specific collaboration's dynamics aimed at verifying the machine's competencies are possibly unconsciously repressed or avoided. An example of this phenomenon is the low level of critical evaluation by the workshop participants of the results displayed by Google search.
4. **The AI accessibility**. The human agent is inclined to follow with greater acceptance the machine's output if she can view and intervene through editable parameters. AI systems generally operate as *black boxes*, where it is possible to know only of the final output and not of the intermediate process, thus

providing incomplete information to human agents. The designer might develop an under-trust attitude if the machine is wholly shadowed or provides poor communication, as in Sketch-rnn. Oppositely, designers might over-trust the system if it displays a high level of communicability. For instance, Google and Coolors parameters control foster human confidence in the AI system.

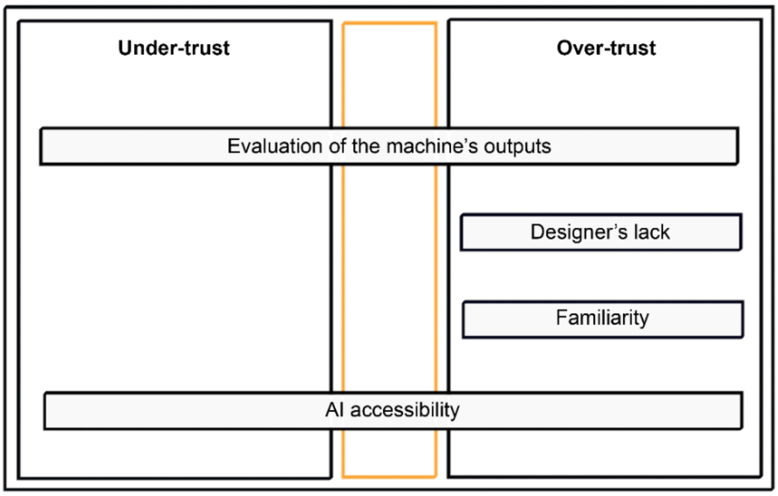

Figure 7. Main discriminating factors that can significantly affect the balance of trust in a Human-AI collaboration related to under-trust and over-trust attitudes. The orange section represents an ideal trust balance, led by the designer's critical judgment.

5.3 Conclusion

The workshop experience significantly impacted how participants perceived AI systems' introduction in the design process. It is observed that the participants are likely not to have any deep-rooted prejudices about the issue. Still, being design students, they are currently in a delicate phase of evolving thinking and experimentation that will eventually establish their position towards AI in design. Consequently, an individual's first experience of collaboration with AI systems may be determining for shaping her future human-AI relationships, including the generation of potentially dangerous biases that may lead to over-trust or under-trust attitudes toward the machine. The importance of providing a proper and gradual introduction to disruptive technologies, including AI, to designers is thus recalled.

Regarding human-AI collaboration, both technical and sensitive criticalities were verified in the workshop. In particular, Google and Coolors, which complied with the AI>Human rule, allowed a functional and positive partnership. On the contrary, Sketch-rnn showed a high risk of hindering the groups' creative process. Moreover, participants showed both under-trust and over-trust attitudes, mainly caused by the AI's level of competence against the human ones, the human's familiarity with the AI system, and the AI accessibility.

AI, as already stated, displayed its capability of supporting the designer's work by providing knowledge and variance, functional to inspire creativity and counter fixation. In addition to this, to clarify better the role that AI can assume within the group, we synthesised three guideline points:

1. If the AI>Human rule is respected, **AI can assume the role of a teammate**, meaning that is capable of assisting the designer proactively in problem-solving and idea development.
2. If the rule is not respected, **the designer arbiter progressively needs to adjust the machine's contribution** to the project or, if necessary, to exclude it.
3. **AI as an external stimulus to designers**, useful to inspire and generate variance while also preventing fixation, remains valid whether the AI>human rule is respected. In the current state of technology, this role is to be considered the most constant and safe for AI in the idea development stages of the design process. However, the stimulus offered by AI is still subjected to the perception and evaluation process of the designers.

Considering a design process where designers and AI agents might alternate moments of collaboration with moments of autonomous work, simultaneous and delayed groups operated with two different approaches. In the simultaneous groups, characterised by continuous human-AI collaboration, the AI assumed the internal role of a bossy groupmate, leading to an AI-driven creative process. On the other hand, in the delayed groups, AI assumed the external role of an expert capable of generating variance, leading to a human-driven creative process. Furthermore, even if both cases highlighted issues, the ones displayed in the delayed groups are far more complex to solve because they need to deal with a process of realignment every time an AI system is introduced in an ongoing creative process. Thus, a detailed work planning must be considered to make the human-AI collaboration more stable.

5.4 Limitations

Although an attempt was made to compose heterogeneous working groups by diversifying them in terms of gender, culture, and education, the sixteen participants are all students at the Politecnico di Milano in the Design & Engineering Master of Science, thus considerably narrowing down the profiles participating in the workshop.

Another limitation concerns the AI systems used during the workshop (i.e., Google, Sketch-rnn and Coolors), as they were suitable for the purpose but very general. Indeed, each AI system fostered different human-AI relationship dynamics and allowed the researchers to observe them. However, these general systems possibly did not generate particularly complex or singular scenarios during the work, hence not exhaustively simulating all the possible aspects of a human-AI collaboration within the design process.

We should perform further studies with new modalities to verify how much the findings are caused by the workshop set-up rather than the use of AI.

5.5 Future developments

The paper presented an analysis of the implementation of AI systems into the early stages of the design process.

The implementation of AI systems into the design process is a critical issue, still largely unexplored. Aspects that could hinder the efficiency of the human-AI collaboration, such as teamwork dynamics, AI applicability, applications, and ethics, should be investigated further. This research represents a first attempt to study human-AI interactions within collaborative design tasks qualitatively and provides insights into how humans' trust dynamics affect the inclusion of AI systems as team members. In general terms, the paper aims to contribute to the debate around the use of AI systems in design and open the way for possible future developments. Future studies might provide frameworks to understand human-AI design collaborations and investigate further the design arbiter role to prepare new professionals to deal with such technologies. Indeed, this knowledge is key to fostering proper and safe relationships in human-AI collaborations by guaranteeing efficiency for the design and well-being of the designers.

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