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Switching perspectives: enhancing generative artificial intelligence's creativity, by humans, with design

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Abstract

The rise of ChatGPT and Generative Artificial Intelligence (GenAI) has stimulated discussions on their potential to enhance human creativity. However, the fixation effect, a well-known barrier to creativity, studied by psychologists and design scientists, remains unexplored in the context of GenAI. To address this gap, we propose leveraging the literature in design creativity and creativity management to understand the fixation effect with GenAI tools. Our approach involves two steps: first, a qualitative exploration with design theory experts to formulate hypotheses, second, an experimental setting to validate them, based on the egg task, a recognized creativity assessment. Our findings reveal that while GenAI tools increase idea generation, they do not eliminate fixations, on the contrary they tend to reinforce them. Moreover, defixating techniques, known to work with humans, have a mitigated effect with GenAI. These results emphasize the importance of a co-creative approach involving both humans and GenAI, expanding our understanding of fixation effect in this domain. They also highlight GenAI potential in creative endeavors, suggesting practical applications for these tools.

Keywords

Generative AI, Creativity, Human-AI interactions, Design, Fixation Effect, Idea Generation

Introduction: leveraging the creative power of GenAI tools

“Generative AI is the most powerful tool for creativity that has ever been created”, said Elon Musk, the famous founder of Tesla. Yet this quote calls for some clarification, especially on what is generative artificial intelligence (GenAI) and creativity. First, creativity is a long-discussed notion, with varying definitions depending on authors but can here be understood as the ability to produce original ideas, adapted to the constraints of a given task (Amabile, 1996). On the other side GenAI is a challenging notion to define, but it can be understood in comparison to artificial intelligence (AI). Whereas AI is the science of understanding and construction of human intelligence, GenAI is known as “the science which studies the (fully) automated construction of intelligence” (van der Zant et al., 2013). The subtle difference lies in the supposed ability of the model to generate itself intelligence, thus the hope of a generative power. As such, GenAI tools with their supposed creative power are at the origin of many hopes and opportunities, especially to address today’s grand challenges. On the other side, they are at the origin of many fears and challenges, whether technical, ethical or legal. With respect to human creativity, a well-known challenge is the fixation effect that hinders creativity (Jansson and Smith, 1991). This fixation effect has been studied and some techniques, often based on design theories, have been derived in order to overcome the fixation effect. This has not yet been studied in the context of GenAI whereas it is of major interest: since the creative power of such models attracts lots of attention, it is of great interest to study whether they show fixations and whether they can help humans in overcoming them. This is what this research aims to explore, in line with recent work that proposes to shed light on the generative power of such models (Bordas et al., 2024).

The paper is structured as follows. The next section will provide a literature review which will position design theories as a relevant framework to understand creative issues of GenAI models. Section II will post the research question, and the third section will explain the research design based on an experimental setting. The end of this third section will also propose analysis of the experiments conducted, leading us to formulate the results obtained in section IV. The fifth section will propose a discussion with the literature and will draw both theoretical and managerial perspectives, before concluding the whole paper.

I. Literature: GenAI and design theories for creativity

1. The creative power of GenAI tools

Creativity has for long been considered as a major asset for companies and organisations, the creative outcome leading to innovations when successfully implemented (Amabile, 1996) and in the end firm performance (Dul and Ceylan, 2014). That is why a vast literature looked at how creativity can be enhanced within companies at different levels of the organisation (Mumford et al., 2012).

On the other side and very recently, artificial intelligence (AI) in the first instance, has reshuffled the cards of creativity, authors putting forward the potential of AI in creative endeavours (Amabile, 2020), whether at the individual, collective or organisation level (Grilli and Pedota, 2024). It is expected that the latter GenAI tools could be used to foster the creative process in organisations. Indeed, many works have had a look at how GenAI tools can be leveraged to enhance and augment human creativity. To mention only some of them, (Doshi and Hauser, 2023) study how these tools can help in enhancing individual creativity for writing short stories. The authors show participants who had access to ChatGPT wrote more stories, whereas, in the meantime, the stories generated were more similar than the stories generated by participants that did not employ GenAI tools. Overall it shows that using GenAI

tools in a creative endeavour tend to homogenise the creative level. (Eapen et al., 2023) consider that GenAI has the ability, among others, to foster divergent thinking and “help overcome biases such as design fixation”. With the example of crab-inspired toy concepts, the authors show that resorting to already known defixation techniques can foster imaginative ideas. Yet it is important to note that this defixating effort is guided by humans, what lead the authors to conclude that “GenAI’s greatest potential is not replacing humans; it is to assist humans in their efforts to create hitherto unimaginable solutions.”

2. Design theories for creativity issues

On the other side, design theories have specialised over the years on understanding and fostering generativity and creativity in several directions (Cascini et al., 2022). First, scholars developed numerous design theories, among them is C-K theory, that emphasises the crucial interplay between two spaces, one of concepts and one of knowledge, to foster creativity in design processes (Hatchuel and Weil, 2008). This theory has especially been used to shed light on the creative process (Hatchuel et al., 2017) and also to develop students’ creativity. In the same direction, it is to be noted that other design frameworks have been leveraged to foster the creative process, such as design thinking (Lee et al., 2019) as well as the role of generative design tools in the context of product design (Barbieri and Muzzupappa, 2024).

More formally, they also showed that human creativity depends on the access to new and relevant knowledge, formalising the need for knowledge to respect the “splitting condition” (Le Masson et al., 2016). On the contrary scholars have shown the existence of creativity-limiting factors, such as the fixation effect (Jansson and Smith, 1991) and studied techniques to overcome this effect, like the negation of categories of ideas (Ezzat et al., 2020) or giving them expansive examples (Agogué et al., 2014) as such helping people to gain in creativity. On top of these developed methods and techniques to foster creativity, tools have also been developed (Gero, 2020) and the notion of co-creativity when several creative minds are involved has been formalised (Candy and Edmonds, 2002), what is started to be discussed in the specific context of GenAI (Bouschery et al., 2023).

II. Research question: humans-GenAI collaborations for creative endeavours

The literature review highlights the creative power of GenAI tools even though some authors mention creative-hindering effect, such as the fixation effect. On the other side, design theories long relevant in creativity studies, provide a framework to analyse it.

Therefore, this work hopes to capitalise on the expertise of design theories for creativity issues, but in the context of GenAI, to study:

how can design theories be leveraged to enhance humans-GenAI collaborations in creative endeavours?

III. Research design: a conceptual framework to be tested experimentally

To study this research question of humans-GenAI creative collaborations, we propose a two-step methodology:

- i. First, we will make use of C-K theory (Hatchuel and Weil, 2008) and previous design-based techniques to foster human creativity to propose a conceptual framework so as to foster the creative endeavour of the duo humans-GenAI.
- ii. Second, we will conduct an experiment to validate the relevance of the proposed framework.

1. A design-based framework for humans-GenAI collaborations

i. C-K theory for understanding design creativity

C-K theory is one of the last design theories that intend to shed light on the design reasoning; It has been introduced by (Hatchuel and Weil, 2008) and states the existence of two disjunct spaces in every design process, the crucial point being the interplay between these. Namely a knowledge space, made of propositions whose logical status is known, and a concept space, made of propositions without a logical status. In other terms, the knowledge space is made of propositions that are supposed to help the designer in the design process, whereas the concept space is made of propositions to be explored. According to this theory, a design process starts with an initial concept and is made of four main operators that allow circulating between the knowledge and concept spaces (as illustrated on Figure 1):

- $C \rightarrow K$: knowledge expansion from concept exploration
- $K \rightarrow C$: concept exploration from knowledge
- $K \rightarrow K$: knowledge creation thus expansion
- $C \rightarrow C$: concept exploration.

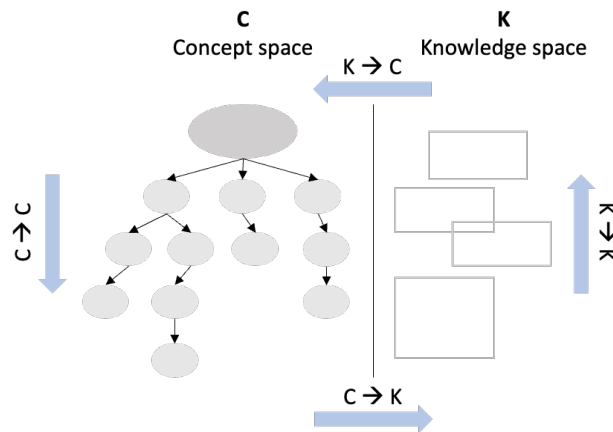


Figure 1 - Illustration of C-K theory and the four related operators of design.

These four operators are central to understand the design and consequently the creative process. Accounting for this reasoning logic in design processes, C-K theory has been used to understand and foster creativity issues, what we shall describe hereunder.

ii. Design-based techniques to overcome fixations

The literature in design creativity has formulated several methods and tools so that humans can gain in creativity and especially overcome fixations, in particular in a leadership logic. We summarise these main techniques that we will test thanks to an experimental setting. As seen in the literature review, there exist three main design-based techniques to defixate a human in a creative process, that are represented on Figure 2 and detailed here with the famous example of the egg task:

Technique 1- Consists in giving a defixating example, outside the initial explorations, for example on the egg task, it means to propose training an eagle to catch the egg during its fall.

Technique 2- Consists in negating a whole category of propositions, thus indicating several potential new concepts, for example it means proposing to consider devices that are not made to cushion the egg's fall.

Technique 3- Consists in indicating new and orthogonal knowledge from what has already been explored, for example it means proposing to look at what would be learned from cocoa beans that could be useful.

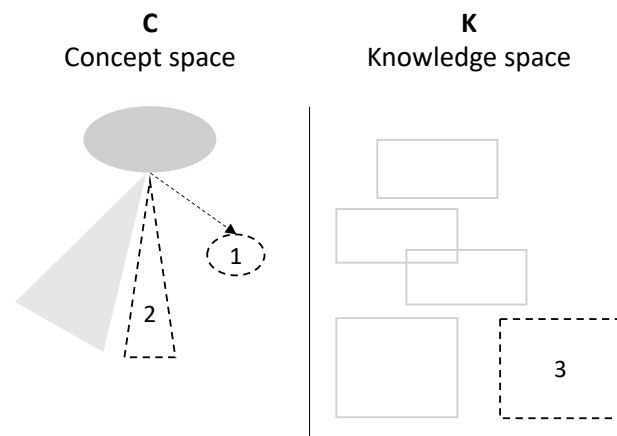


Figure 2 - Illustration of the various design-based techniques to defixate a human.

2. An in-depth qualitative study to formulate hypotheses

The aim of this subsection is to explicate the qualitative study conducted by design-theory experts, leading to the formulation of several hypotheses that will be experimentally tested. Precisely, we gathered three experts of design theories, especially well versed in the design-based techniques to overcome fixations described in ii and asked them to generate “as many original ideas as possible to ensure that a hen’s egg dropped from a 10m height does not break” with the help of ChatGPT 3.5. After qualitatively analysing their discussions with this GenAI tool and interviewing them, we were able to formulate the three following hypotheses.

First, experts recognised that using ChatGPT allowed to have a greater number of ideas, which is in line with what the literature has already identified, especially (Doshi and Hauser, 2023). Hence this leads to the first and not so surprising hypothesis:

Hypothesis 1: The mean number of ideas generated with the help of GenAI tools is greater than the mean number of ideas generated without.

Second, experts tried to estimate whether the fixations are the same for the duo human-GenAI than what they are when only a human is dealing with the egg task. Regarding this question, it appeared very quickly that the primary responses given by the GenAI tool are in the traditional fixated categories. As an example, the vast majority of the first responses gave ideas such as an “egg parachute”, an “airbag protector” or a “shock-absorbing gel”. Moreover reading the rest of the discussion with ChatGPT and interviewing experts revealed that further ideas developed fell into these categories of “egg protection” or “fall reduction” but with more original ideas such “egg spiderweb” or “magnetic fields” for instance. Hence this leads us to formulate the second hypothesis:

Hypothesis 2: The fixation effect of the creative duo human-GenAI is similar to the fixation effect of a human only.

Third, as design experts they tried to use this GenAI tool to overcome this fixation effect and have more original ideas, outside the fixations. To do so, they tested the various design-

based defixating techniques described in ii. However, they concluded that these techniques tend to have a similar efficiency as the one they have with humans. Yet it seems that they show more originality within the fixation. In other terms, it appears that ChatGPT is very efficient to provide surprising ideas within the fixations. One example that arose for all of them was the “eggshell reinforcement inspired by woodpecker”, very original in the sense that no human spontaneously think to draw inspiration from woodpecker’s bone structure, yet it remains with the fixated category of “egg protection”. Hence the third hypothesis:

Hypothesis 3: Defixating techniques show a similar efficacy for the duo human-GenAI than for humans only.

These three hypotheses being based on a very small sample of design experts, we shall now test them with a bigger sample, in order to account for the diversity of GenAI tools’ users within organisations.

3. An experimental setting to validate the framework

The objective of this subsection is then to explicate the experimental setting adopted to study and test the relevance of the three hypotheses formulated above and based on the defixating techniques described in ii.

i. Participants

First, the set of participants is composed of a diversity of profiles, precisely: engineering students, PhD students and executives from a French healthcare company. Regarding industrial participants, they were from various levels of seniority as well as various departments of the company, thus allowing to prevent us from having people specialised in design and creative issues.

Name of the cohort	Number N	Training level
Engineering students	4	2 nd year engineering school students
University students	2	PhD students in engineering management
Industrial executives	18	Diverse (mainly engineering and business schools)

Table 1 - Statistics on the set of participants to the experiment.

As the Table 2 below shows it with some descriptive statistics regarding the participants, there is a rather equal repartition of men and women, most of them (65%) were familiar with ChatGPT in the sense that they had already used it at least once and only less than a third of them (30%) were familiar with the creative task given.

Descriptor	Value
Total number of participants	23
Average age	32,1
Number women	14
Number men	9
Average professional experience (in years)	5,9
Number already familiar with the creative task	7
Number familiar with ChatGPT 3.5	15

Table 2 - Descriptive statistics on the set of participants.

ii. Creative task given

The creative task given is the egg task, particularly relevant in this context because it has already been widely used for creativity studies, thus giving us access to all the fixations and the accessible categories of solutions, as summarised on Figure 3 (Agogu e et al., 2014). Precisely, participants were asked to use ChatGPT 3.5 in order to come up with “as many original ideas as possible to ensure that a hen’s egg dropped from a 10m height does not break”.

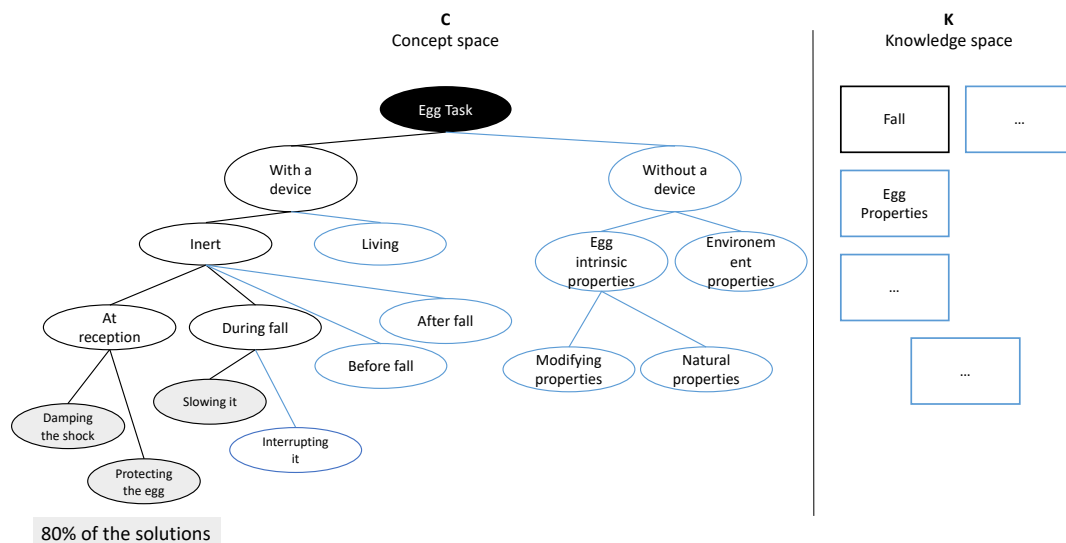


Figure 3 - Illustrative summary of the C-K referential and the accessible categories of solutions of the egg task.

iii. Detailed protocol followed for the experiments

As a summary of the method adopted, Table 3 below gives a stepwise and detailed view of the protocol adopted, which can be broken down into three main steps.

Protocol steps	Description
Step 1 – 5 min	
General explanations	Explain participants the context and what they will be asked.
Step 2 – 15 min	
Participants experiments	Give participants the creative task “with ChatGPT’s help find solutions so that a hen egg thrown from 10 m height does not break”.
Step 3	
Data gathering and analysis	Recover, for each participant, a number of control variables, all the ideas generated during the experiment and the whole discussion with ChatGPT for the egg creative task.

Table 3 - Detailed steps of the protocol followed.

4. Analysis of the experiments

With this experimental design in mind and the gathered data, we will now provide several analyses in order to test each one of the three hypotheses formulated in 2.

i. Hypothesis 1: Number of ideas generated by participants during the experiments.

The very first analysis we provide here is a counting of the number of ideas generated for each participant. Figure 4 provides the occurrences of the number of ideas generated by participants, for instance 4 participants generated 9 ideas during the whole experiment. The average number of ideas generated by participants in our context is $m = 8,0 \pm 3,3$, which appears greatly superior (+110%) compared to the number of ideas generated by adults in the experiment conducted by (Cassotti et al., 2016), that precisely was $m_0 = 3,8 \pm 2,3$. To compare these means, a Z-test is conducted, whose value is $z = 1,4E - 09$, confirming that the mean number of ideas generated with the help of GenAI tools is greater than the mean number of ideas generated by humans only.

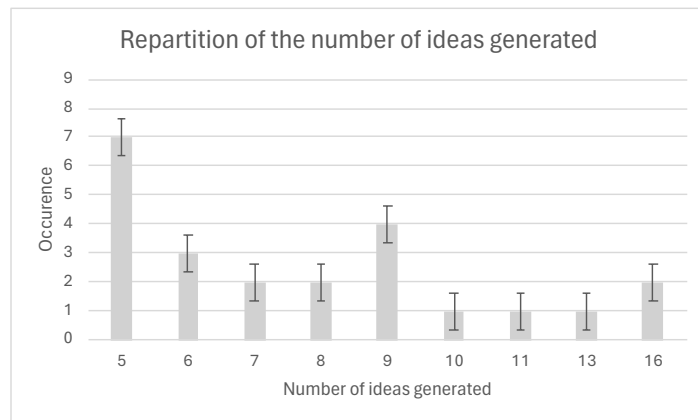


Figure 4 - Repartition of the number of ideas generated by participants.

ii. Hypothesis 2: Repartition of the ideas in the known categories of solutions

The second analysis we provide here is aimed at testing whether the distribution of obtained solutions by the duo human-GenAI is similar to the one obtained when only humans perform the egg task. To do so we read each of the solutions given by the participants and

assign them to one of the categories of solutions, as given in the seminal work by (Agogu  et al., 2014). Table 4 then gives the corresponding statistics with the number of ideas falling in each category, the subsequent percentage as well as an aggregated percentage to account for the main fixated categories. The last column gives the original percentage of occurrence, as obtained by the aforementioned authors when the experiment is carried out by humans only.

To compare the fixation effect, we run a test of proportion to compare the empirical percentage 87,8% to the theoretical one of 80%. The resulting decision variable equals $T = 2,37$ leading to reject the null hypothesis. Meaning that the fixation effect, in addition to being similar for the duo GenAI-human, is even stronger than the one highlighted in the human only context.

Category description	Number of ideas generated	Percentage	Aggregated percentage	Original percentages (human only)
Egg protection	54	36,5%	87,8%	26%
Fall reduction	46	31,1%		21%
Shock reduction	30	20,3%		33%
Environnement modification	6	4,1%	10,8%	3%
Catching	4	2,7%		7%
Egg properties	3	2,0%		5%
Machine	3	2,0%		3%
Simulation	2	1,4%	1,4%	2%
Total	148	100,0%	100%	100%

Table 4 - Number and percentage of ideas generated by the participants in each of the categories of solution.

iii. Hypothesis 3: Efficacy of the design-based defixation techniques

This third analysis aims to elucidate whether the defixating techniques used for humans only are also efficient for the duo human-GenAI in the context of the egg task. To do so, we read the discussions with ChatGPT, categorised each of the defixating techniques and evaluate the rate of success. More precisely, we assigned each of the prompts made to one of the three defixating techniques explicated in ii and studied whether the subsequent response of ChatGPT is defixated or not. This allows us to compute the percentage of success for each defixating category, defined as the proportion of responses that are effectively defixated. These proportions are depicted in Table 5, where the last columns represent the percentages of success of each defixating category for humans only (Agogu  et al., 2014; Ezzat et al., 2020).

To compare the distributions of the percentage of success, the value of the χ^2 -test is computed: $\chi^2 = 0,0345$. A F -test is also conducted in order to test the variances of these two distributions $T = 0,2854$. Consequently, the p-value of the χ^2 -test being smaller than 0,05, it reveals that neither distribution is similar, and the value of the T test similarly reveals that both distributions have a low probability that their variances are not significantly different.

Defixation technique	Number of uses	Percentage of success	Original percentages (human only)
Defixating example	17	29,4%	29,4%
Category Negation	9	44,4%	21%
Orthogonal K	10	80,0%	8%

Table 5 - Number and percentage of efficacy regarding defixation techniques for ChatGPT.

IV. Findings: insights towards a co-creativity with GenAI

This work aimed at understanding how design theories can be leveraged in order to gain in creativity for GenAI models, especially ChatGPT. The experiment described in the previous section above allows deriving several results, what this section shall describe.

First, we show that this GenAI tool suffers the fixation effect and that defixating techniques are not as efficient as they are with humans. Second, with this work we characterise the unequal ability of ChatGPT with the four operators of design as given by C-K theory.

1. Conclusion regarding the three hypotheses

This first subsection of the results proposes a summary, given in Table 6, of the findings regarding validation of the hypotheses made in 2.

Hypotheses	Validation
Hypothesis 1 Number of ideas of the duo GenAI-human	The duo GenAI-human does have, on average, more ideas than human only
Hypothesis 2 Fixations of the duo GenAI-humans	The duo GenAI-human does have similar fixations, even stronger than humans only
Hypothesis 3 Defixating the duo GenAI-human	Defixating the duo GenAI-human is not similar to defixating human only

Table 6 - Summary of the results regarding validation of the formulated hypotheses.

The first hypothesis looked at the number of ideas generated by the duo GenAI-humans and our experiment showed that, on average, it is more efficient to generate ideas than what humans only do. This is not surprising as long as GenAI are considered as tools aimed at fostering a creative endeavour.

However, the second hypothesis looked at the fixation effect and intended to measure whether the vast number of ideas generated suffer from it or not. Our result shows that the duo ChatGPT-human has the same overall fixations as humans, if compared to previous experiments done and published in academic journals (Cassotti et al., 2016). It even appears that the fixation effect is stronger since the three main categories of solutions represented 80% of the ideas generated by humans, whereas in our context, where ChatGPT is involved, they represent almost 88%.

Finally, the third hypothesis looked at whether defixating techniques known to be efficient for humans only are as efficient when GenAI is involved. Our result shows a mixed efficacy of these techniques.

Let us briefly deep dive in this mixed efficacy. Overall, it appears that defixating examples are as efficient as they are with humans but for different reasons. In the human context, the focus has to be made on examples outside of the fixation zone in order to be defixated. Yet, in the context of ChatGPT, the model often proposes a feasibility assessment of the example provided or proposes a reformulation of the concepts it has already given, but breaking down the knowledge associated with the defixating example for each of them. For example, with the eagle example, ChatGPT often proposes new solutions that still fall in the fixation category of fall reduction (“collapsible wings” for instance) or egg protection (“feathered suit” for instance).

On the other side, the second technique that consists in negating a category of example appears as more efficient, with greater efficacy than on humans. Yet it should be noted that in some situations the model proposes more original solutions that still fall in the traditional fixation categories (for instance “anti-gravity” or “magnetic field” that still belong to the category of fall reduction).

The third main technique of defixation is the orthogonal knowledge one, which appears to give surprisingly high levels of efficacy (80%) for ChatGPT. Still, it should be noted that in all the solutions the model proposes it has a tendency to break down the new knowledge brought to him in the already mentioned categories of solutions. This indicates that there might exist conditions on the orthogonal knowledge brought to ChatGPT in order to allow for efficient defixation, what this research setting has not allowed us to study precisely.

2. GenAI capacity with the four operators of design

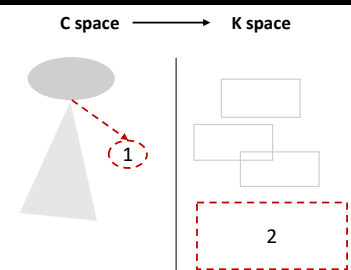
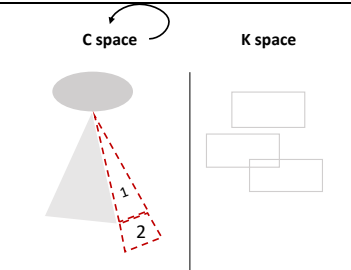
As discussed in the methodology section, it is of great interest to understand the ability of a designer (or a group of designers) with the operators of design, as given by C-K theory. This theory highlights the interplay between two spaces, concept and knowledge, thus putting forward four operators at the heart of design creative processes (Hatchuel et al., 2004). Quantifying the capacity of the duo ChatGPT-human for each of these operators then gives an idea of its creative capacity, what we propose to present in this subsection. The Table 7 provides a summary of the ability of ChatGPT-human duo with these operators and calls for some comments. We provide some illustrations of what happens in the fourth column of this table that we shall explain here. The grey shapes on the figures refer to the existing situation, the red shapes correspond to what is added. The numbers 1 in the red shapes represent the use of one of the defixating techniques by the humans and the numbers 2 represent what the GenAI tool response provides.

Firstly, and not surprisingly, such a GenAI model is unable to expand its own knowledge base (operator $K \rightarrow K$), as has already been mentioned by the literature, it is trained to represent the state of human knowledge (Bordas et al., 2024) and cannot provide causal reasoning (Gao et al., 2023). Yet, it is important to note that considering the situation of the duo GenAI-human, the GenAI tool does have the ability to expand the knowledge base of the involved human. This is typically what happens when the GenAI tool comes with knowledge regarding the bone structure of the woodpecker, a knowledge base largely inexistent for most humans.

Second, on the contrary, is the excellent ability to find new knowledge (when referred to the involved human knowledge base). This can also be observed with the very precise and extensive knowledge ChatGPT can provide on the woodpecker and its bone structure when given the defixating eagle example.

Regarding the operator of concept expansion, it has been shown that ChatGPT rather provides an ability for refinements. This is for instance what has been observed on magnetic levitation: when asked to expand from this concept, the model rather give a precise feasibility assessment, sometimes even explicating the design parameters (strength and angle of the magnets among others).

Concerning the last operator of disjunction, that is to say concept expansion from knowledge, an uneven efficiency has to be acknowledged. However, it should be noted that once again, this GenAI is particularly efficient to develop tree depth instead of breadth. This is what has been observed with biomimetics knowledge indications: ChatGPT appears particularly efficient to spread this pocket of knowledge across all the categories of concepts already uncovered. To illustrate this effect let us mention that when human mention birds, the GenAI tools quickly proposes feathered parachute, that simply appears as a specific bio-inspired kind of parachute, thus remaining in the fixating category “fall reduction”. Yet it has to be noted that with appropriate and close human guidance, this GenAI can reveal itself efficient to open new concepts from unexpected knowledge.

Operator	Description	ChatGPT's capacity	Illustration
<p>C→K <i>conjunction</i></p>	<p>Ability to look for relevant knowledge in front of a new concept</p>	<p>Excellent</p>	 <p><i>Figure 5 - The red shape n°1 corresponds to the defixating concept given by the human, what leads ChatGPT to propose associated relevant knowledge (red shape n°2).</i></p>
<p>C→C <i>concept expansion</i></p>	<p>Ability to partition and derive new concepts from a given concept</p>	<p>Rather concept refinements than expansion</p>	 <p><i>Figure 6 - The red shape n°1 corresponds to the defixated category proposed by the human, what leads ChatGPT to propose refinements (red shape n°2).</i></p>

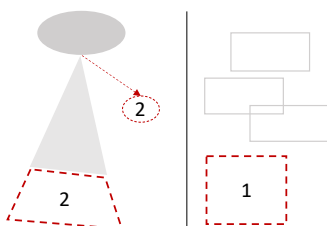
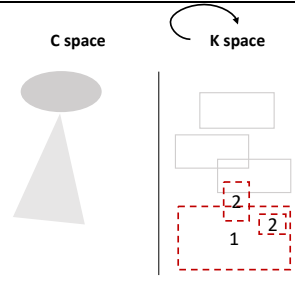
K→C <i>disjunction</i>	Ability to use knowledge to partition and create new concepts	Unevenly good	 <p data-bbox="1021 459 1380 672">Figure 7 - The red shape n°1 corresponds to the orthogonal knowledge proposed by the human, what leads ChatGPT to propose refinements (red shape n°2) with sometimes new concepts (light red shape n°2).</p>
K→K <i>knowledge expansion</i>	Ability to create new knowledge from existing ones	Inability to create new knowledge	 <p data-bbox="1021 974 1380 1153">Figure 8 - The red shape n°1 corresponds to the orthogonal knowledge proposed by the human, what leads ChatGPT to propose associated knowledge (red shapes n°2).</p>

Table 7 - Summary of GenAI (here ChatGPT) capacity with the four operators of design. The illustrations are to be understood as described each one of them.

V. Discussion and implications: a precise idea of GenAI creativity to clarify interactions and use case

The aim of this research was to study the fixations and defixation techniques of the duo human-GenAI. The results presented above are twofold: first even when using GenAI the same category of fixations tend to stand out, and second the known design-based defixating techniques show a mixed efficacy.

1. Precising what GenAI can and cannot do

The literature, especially in innovation management has been fertile over the past few years in studying the impact and opportunities of GenAI models, especially ChatGPT. Many authors report successes and explain that GenAI tools are a great resource in many creative and design situations, showing an increased creative power compared to humans (Eapen et al., 2023). Let us note that this wish to enhance human creativity with artificial intelligence is not so new since it has been discussed some years ago (Colton and Wiggins, 2012) in the field of computational creativity. Yet it is to be noted that, on the other side, some scholars show GenAI underperform the best humans in specific situations (Koivisto and Grassini, 2023).

This stream of research implicitly supposes that there are no interactions between humans and the GenAI models to be able to compare the efficiency of each of them. In contrast, our

work rather proposes to put back in the spotlight the interactions at stake between humans and GenAI, in a co-creative framework (Davis, 2013). This is in line with (Rafner et al., 2023), the authors suggesting incorporating psychological and creative sciences in the studies of GenAI, therefore leading to enhance the synergies and collaboration between humans and GenAI.

Behind indications on the creative power of GenAI, our work sheds light on the relevant use cases for GenAI such as ChatGPT. For instance, such GenAI tools are really efficient to act as encyclopaedias, in other terms “democratising knowledge access” (Kanbach et al., 2024). Moreover, our results shows their high efficiency when it comes to refining concepts, whether when given knowledge to do so or when given a concept to develop it even more, as has been noted also recently by (Eapen et al., 2023)

2. Theoretical implications

In terms of theoretical implications, two levels can be distinguished. First, for creativity and innovation management, this work extends the work on creative leadership. These works focused on human-human interactions, in other terms, how a human can help another human gaining in creativity. Therefore, here we extend it to the context of human-GenAI interactions. As a consequence. This work could also give very first insights on the impacts of GenAI on people’s work and to what extent such models could change people both jobs content and meaning (Gmyrek et al., 2023).

This work could also complement a more mathematical stream of literature by providing research avenues for machine learning scholars. For instance, we saw that regarding the concept space, the tree is rather deep than wide; thus it might be of interest to parametrise this capacity within the model.

3. Managerial implications

This research has several implications for organisations and practice of GenAI by humans, especially indicating where humans can be of help to such models.

First, we saw that the concept expansion capacity of ChatGPT appears limited and can benefit from human guidance, while the disjunction capacity can only be done by humans, as well as the knowledge expansion capacity. Consequently, it appears that designing with ChatGPT cannot be automatised, as it is sometimes promised. Rather the contrary it indicates a crucial role of humans in the loop, especially for certain creative tasks requiring precise formalisation of new concepts. In terms of use case within organisation, it means that GenAI models such as ChatGPT are of better use for

- i. finding and summarising knowledge giving a concept or an idea,
- ii. giving first imprecise concepts, rather thoughts, to allocate specific and known characteristics on also know artefacts (biomimetic example of the woodpecker).

Second, in terms of managerial implications, it indicates at least two required competencies to design with ChatGPT: a good knowledge of design theories in order to be able to identify the models’ fixations and a good knowledge of design-based techniques of defixations to help ChatGPT overcome its own fixations. In that sense, it indicates a defixating leadership capacity (Ezzat, 2017) for humans that want to efficiently leverage GenAI tools such as ChatGPT for creative endeavours.

4. Limits and perspectives

Some limits still have to be acknowledged for the research conducted here. The first limit concerns the size of the considered sample that could be extended, especially in order to have an even greater diversity of profile among participants. Another experimental limitation concerns the use of ChatGPT 3.5, whereas a more recent version is now available. In the same direction, it could be of interest to replicate a similar study with other GenAI tools that are not based on the same family of model: what would fixations and defixating techniques give on diffusion-based or generative adversarial networks give?

More theoretically speaking, we saw that there seem to be conditions on the structure of the orthogonal knowledge brought or the defixating example given so that it really helps in defixating the model. Yet our research setting has not allowed us to study that, therefore, it could be of interest to complement this study in this direction. Still from a theoretical point of view, rather for the machine learning community, it could be interested to understand what would be the modifications to make in the architecture in the model so that it is able to itself gain in creativity or maybe recognised its own fixations.

VI. Conclusion

To conclude, this research had for objective to look at the creative power of GenAI tools, in our experimental context specifically ChatGPT. In a parallel setting to what was done for human creativity, we looked at the fixation effect and the defixation techniques for GenAI. Working with the well-known egg task in creativity, we showed that the categories of fixations for GenAI appear similar as for humans, and even stronger. However, the efficiency of the three defixating techniques is not similar. Overall, this work also allowed us to understand the capacity of GenAI tools such as ChatGPT with the four operators of design, therefore allowing refining the relevant use cases with such tools.

Consequently, we shed light on the vast issue of creativity in the context of GenAI, by leveraging design creativity theories and creativity management. As such, we show how design theories, initially formulated in the context of human-human interactions is relevant and fruitful to understand and foster the creative endeavour in the context of human-GenAI interactions. Moreover, it opens rich research avenues that could enrich the corpus of both design creativity and creativity management.

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