Creative Collaboration with the "Brain" of a Search Engine: Effects on Cognitive Stimulation and Evaluation Apprehension

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Abstract. Artificial Intelligence (AI) is rapidly becoming part of how we do creative work. This to the extent that commonly used AI-powered systems, such as search engines, are already routinely used to support our day-to-day creative tasks. However, surprisingly little is known about how creative collaboration with the "brain" of a typical search engine compares to creative collaboration with other people. We propose that exploring this requires a cognitive and a social perspective. Firstly, the output of a search engine might influence cognitive stimulation differently than human collaborative forms, i.e. the degree to which output by another inspires more and more novel associations. Secondly, evaluation apprehension, i.e. not sharing all your ideas due to a fear of being evaluated negatively, might be reduced when collaborating with such AI-powered systems due to their limited perceived social agency. Thirdly, a user's attitude towards AI might moderate this effect, e.g., due to fears about what such systems do with the user's data. An experiment ($n = 139$) was conducted where participants were instructed to collaborate with an AI powered by a search engine, or with another person, during a divergent thinking task (in reality these collaborations were scripted). The results indicated that 1) collaborating with another person increased cognitive stimulation, 2) collaborating with the AI decreased evaluation apprehension, and 3) people's general attitude towards AI did not moderate its effect on evaluation apprehension. Herewith, the study contributes to an emerging body of work on creative collaboration with AI.

Keywords: Co-creative AI · Cognitive stimulation · Creativity · Divergent thinking · Evaluation apprehension · Search engines

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1 Introduction

Artificial intelligence (AI), as science, aims to create artifacts that exhibit some form of intelligence, with achieving human-level creativity as one of its hallmark challenges [1]. Along with other recently achieved AI milestones, such as DeepMind's AlphaGo beating the Go world champion Lee Sedol [2] people professionally engaged in domains that are historically associated with creativity are now starting to compete with AI algorithms [3]. Generated by a neural network and developed by artist Collective Obvious AI & Art, the Portrait of Edmond de Belamy sold for $432,500 at the world-renowned auction house Christie's on October 25th, 2018 [4]. Alongside this ongoing development of (collaborative) creative AI systems, one could state that AI has already permeated our day-to-day creative activities via another route.

As AI-driven hardware and software have become omnipresent, the possibilities of running excessively large trained neural network algorithms have increased. Neural networks mimic the semantic network of the human brain to better reason, classify, and understand received input, and to produce suitable output [5]. This has not only sparked the further development of creative AI [1, 3] but has also led to the further optimization of search engines used on the web, for example Google's reverse image search [6]. The "brains" of these search engines are the semantic networks that emerge from the search engine's neural networks, vectorization techniques, and other algorithms (e.g., content analysis, meta-data, and ranking models), from which it draws its associations. Recent work suggests that creatives, from laypersons to professional artists, routinely rely on these search engines to provide them with input to support their creative activities [7]. For example, a fine artist might search for images to inspire new ideas, or a layperson might seek inspiration for what to cook for dinner. Therefore, one could claim that AI has already permeated our day-to-day creative work, via our reliance on search engines to support our creative thinking. Despite this, relatively little is known about how our collaborations with the "brains" of these search engines affect creative task performance [7].

In light of these developments, we propose that taking both a cognitive and a social perspective could provide a useful starting point for further investigation. A cognitive perspective is relevant because differences in the semantic networks of search engines and human collaborators [8] may directly affect cognitive stimulation, i.e. the degree to which output by another person or system inspires more and more novel associations [9]. Specifically, it is an open question whether the output of search engines increase or decrease cognitive stimulation when compared to the output of other human beings [5]. A social perspective is relevant because of a common tendency to anthropomorphize AI systems as a collaborator or teammate [5]. This raises novel questions about whether effects on creative task performance might be explained by the mitigation of issues that commonly arise during creative collaborations among people, such as evaluation apprehension [10], i.e. not sharing ideas due to a fear of being evaluated negatively [11]. This due to the technology's limited perceived social agency [12]; or alternatively whether a user's attitude towards AI technologies might also elicit technology-specific forms of evaluation apprehension, e.g., due to fears about what such systems do with their data [13].

The study presented in this paper aims to shed more light on these conjectures by answering the following research question: *How does creative collaboration with the "brain" of a search engine affect creative task performance?* The paper is structured as follows: first, the rationale introduced above is developed in more detail, based on which three hypotheses are conjectured. Second, the methodological details of an experiment (n = 139) that was developed and conducted to test the hypotheses are presented. Third, the results of the experiment are explained. Fourth, the results and key limitations are discussed and future work is proposed.

2 Creative Collaboration with the "Brain" of a Search Engine

Creativity can be defined as the creation of novel yet useful ideas, problem solutions, or products [14]. Whether it is laypeople or professional artists, the general process by which they arrive at a creative outcome tends to be similar [15]: People undertake activities to understand a problem, generate ideas, evaluate these ideas, and (iteratively) revise and test these ideas to arrive at a revised version of their idea, problem solution, or product [16]. *Divergent thinking*, the ability to produce variation [17] contributes to the creative process at various stages [18]. The assumption is that unrestricted quantity in some parts of the creative process will ultimately lead to quality in other parts [19]. This depends in part on the organization of a person's semantic memory [20] and the ease and semantic distance which associations can be retrieved [21, 22]. Faster retrieval of associations from semantic memory enables people to generate more options to develop a creative solution from within a limited time frame, whereas the semantic distance of the retrieved associations correlates with the likelihood that these associations enable novel outcomes of the creative process [20–22]. For example, having many novel associations can benefit the early stages of understanding a problem, by generating a diverse set of perspectives on a problem [23]; and during idea generation, generating many novel candidate solutions increases the chance of developing a truly creative revised idea, solution, or product in the remainder of the creative process [24]. As such, divergent thinking can be viewed as an indicator of creative task performance and divergent thinking tests are often used to assess creative potential [17, 18].

It is well known that collaboration with other people can benefit divergent thinking due to *cognitive stimulation* [9]. Output by others may contain semantic categories that enable an individual to make new associations faster, which would otherwise require them to engage in an increasingly time-consuming search in their semantic memory [25]. Output by others can also contain semantic categories with a more semantic distance than the categories that are immediately accessible by a person [26] due to the idiosyncrasies of how an individual's semantic memories are organized [27]. A person can therefore benefit from others' output by increasing the number and semantic distance of the associations they are able to make themselves, beyond what they are capable of alone, which positively influences divergent thinking [26, 27]. However, it is common that the semantic categories contained in the output from a collaborator might not be so different from the associations that an individual would make on their own [26] or that the categories contained stimulate having common associations or verge towards the useful at the cost of novelty [27] with a negative influence on divergent thinking.

Therefore, the quality of the output during collaboration can affect cognitive stimulation positively or negatively, and by extension divergent thinking. Extending this *cognitive perspective* to our day-to-day reliance on search engines for creative work [7] suggests that creative task performance is affected in the same way. However, it is not known whether the quality of the output generated by a typical search engine in 2021 causes more or less cognitive stimulation, than say, an averagely creative human being.

The literature appears to be ambiguous on this topic. On the one hand, AI systems in general learn and organize their semantic networks differently than humans do [8]. In theory, these systems could retrieve more, more efficient, and more apt associations from its semantic network than people can, due to the unimaginably extensive database they could be based on [28]. The information retrieved by the AI is different from what another person is likely to provide, sometimes to the extent that an AI's retrieved information violates human expectations and is characterized as weird [29]. Possibly, weird stimuli entail novelty by prompting the generation of semantically distant associations [30] thereby positively influencing divergent thinking [26, 27]. Thus, one could be tempted to conclude that the output of search engines might be more cognitively stimulating than the output of an averagely creative human being. On the other hand, researchers have also voiced concerns about the limits of search engines in particular in this regard, citing the argument that search engines are often designed to retrieve data based on similarity [5]. This would suggest that our ubiquitous but everyday reliance on search engines [7] may negatively influence cognitive stimulation, and subsequent divergent thinking [26, 27]. As such, the available literature suggests that cognitive stimulation is likely to be affected, but it is not clear whether this effect is positive or negative. Therefore, the following non-directional hypothesis is proposed:

H1: Creative collaboration with the "brain" of a search engine, compared to creative collaboration with an averagely creative person, influences divergent thinking due to its effect on cognitive stimulation.

A *social perspective* might provide additional insight into how creative collaboration with the "brain" of a search engine compares to creative collaboration with another person. *Evaluation apprehension*, i.e. not sharing ideas due to a fear of being negatively evaluated [10] is a key example of how social interactions among people may affect creative task performance negatively [11]. A reduced willingness to share ideas directly affects the amount and diversity of information shared with others due to self-imposed constraints about what is "safe" to share or not. A direct consequence can be a reduction in the number and diversity of responses shared between collaborators and possibly also generated during the ideation process. Although evaluation apprehension can have several causes [9] it is well known that often social anxiety underlies evaluation apprehension [31]. People regularly do not share ideas because they fear the negative social consequences they might incur from others in response to the information they share. Past experimental research, for example, suggests that a fear of being evaluated negatively reduces the number of ideas when interacting with other people. This effect is mitigated when working alone [31]. We propose that creative collaborations with AI systems in general might reduce evaluation apprehension due to their limited social agency and could consequentially positively influence divergent thinking.

Even though there is a common tendency to anthropomorphize AI systems as a collaborator or teammate [5] this does not mean that people attribute the same level of social agency to creative AI systems as they do to other people [12]. Even when AI systems are specifically designed to increase (the illusion of) social agency, e.g., by endowing them with the ability to detect and send social signals [32] people do not attribute the same social abilities to these technologies they also attribute to other people [12]. Social robots, for example, tend to be seen at best as in between an anthropomorphic being and a technological object. Previous work suggests that interacting with these technologies can reduce social anxiety (a common cause of evaluation apprehension), when compared to interacting with people, due to the limited social agency users attribute to these technologies [33, 34] (but see [10] for an alternative finding). Therefore, we conjecture that people are less likely to expect social repercussions from any kind of AI system than from another person. In terms of social repercussions there is little to fear from an AI. Thus, another way in which creative collaboration with the "brain" of a search engine might affect creative task performance, is social in nature: Collaborating with an AI might reduce evaluation apprehension and its negative effects on divergent thinking. Based on these conjectures, we propose the second hypothesis:

H2: Creative collaboration with the "brain" of a search engine, compared to creative collaboration with an averagely creative person, positively influences divergent thinking due to a negative effect on evaluation apprehension.

As previously suggested, evaluation apprehension can have many causes [9]. When AI technologies are cast into an anthropomorphic framework of collaborators and teammates [5] we cannot expect that people forgo any mistrust they might have about the type of technology they are interacting with, simply because these technologies allude to something more human-like than other similar technologies [13]. Despite the positives that come with using search engines [6] and AI more broadly [8] people are often concerned about whether they can trust using the output of an AI [35] or have privacy or other concerns about how search engines use their data [36]. Thus, speculatively, when people do not view AI systems positively [13] it is possible that this might introduce another cause of evaluation apprehension that is specific to creative collaboration with these kinds of technologies. A user's *attitude towards AI* might thus moderate the expected effects on evaluation apprehension and divergent thinking expressed in H2 because it introduces another cause of evaluation apprehension. Based on these speculations, the third and final hypothesis is proposed:

H3: The effects of creative collaboration with the "brain" of a search engine, compared to creative collaboration with an averagely creative person, on divergent thinking via evaluation apprehension, is moderated by a person's attitude towards AI.

3 Method

To test the hypotheses an online experiment was conducted with a between-subject design.

3.1 Participants

A total of one hundred forty-one participants were recruited. One participant did not sign the informed consent and one did not finish the experiment. The data from these two participants were therefore removed from the data set. Data from the remaining one hundred thirty-nine participants ($M_{age} = 22.54$, $SD_{age} = 3.70$) were used in the analysis. Eighty-four of these participants self-identified as females and fifty-five participants self-identified as male. The participants were recruited by convenience sampling using the researcher's network (n = 52) and the human subjects pool (n = 87) of the Department of Communication and Cognition, Tilburg University. All participants were previously or currently engaged in a higher education program. The Research Ethics and Data Management Committee of the Tilburg School of Humanities and Digital Sciences approved the study.

3.2 Materials and Measurements

3.2.1 Experimental Manipulations

Participants were randomly instructed to collaborate on a divergent thinking task [25] with either an AI (referred to as AI collaborator, for the sake of brevity in the following sections), which was powered by a search engine, or with another person (referred to as human collaborator). In both conditions participants were asked to generate as many creative associations with either a depiction of a flower or a rocket as they could (also randomly assigned; Fig. 1). Two objects were chosen to reduce the chance that any results could be attributed to the specifics of one object. Collaboration entailed that while the participants were generating and typing in associations, they saw the associations generated by the other in real-time while thinking that the other also read their associations (Fig. 2). This was emphasized by asking participants to press the ENTER key after each association to "share" their associations with the collaborator. In reality, however, these collaborations were scripted. Using a scripted collaboration made the data collection feasible. The scripted collaborations entailed that participants were presented with associations that were previously collected. The associations by the collaborator were presented in a simple text output window in both conditions. This was done to avoid confounding variables that might be introduced by differences in, e.g., seeing another person while collaborating versus using the GUI of a search engine. The AI collaborator's associations were collected by uploading the rocket and flower image into Google's reverse image search. The first fifty images retrieved were manually translated into a word and stored. Google search was chosen because it is one of the search engines that is routinely used in everyday creative tasks [7]. As Fig. 3 shows, the related associations given by Google's reverse image search were also images. Therefore, a human translation of these images into words was necessary as the associations were later presented to the participants via a text-output field in both conditions. The human collaborator's associations were collected by asking eight people from the researcher's network to do the divergent thinking task for the flower and the rocket image. The associations were pooled and redundant associations were removed. Then, fifty of their responses were randomly selected for the rocket and flower image and stored. These eight people represented an "averagely creative person" as indicated by their scores on Runco's

Ideational Behavior scale ($M = 3.10$, $SD = 0.27$) [37]. In the AI collaborator condition, each participant was presented over time with 21 out of 50 randomly selected associations obtained from the search engine. In the human collaborator condition, participants were presented with 21 of 50 randomly selected associations obtained from the collected human associations. To realize a sense of real-time collaboration, the interval at which associations were presented mimicked the human divergent thinking process (0–30 s= 3.33 sec interval, 31–60 s = 5 sec interval, 61–90 s = 7.5 sec interval, 91–120 s = 15 sec interval) [25].

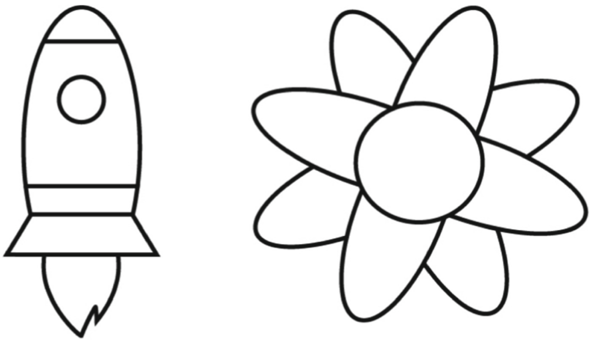

Fig. 1. The rocket and flower stimuli used in the divergent thinking task.

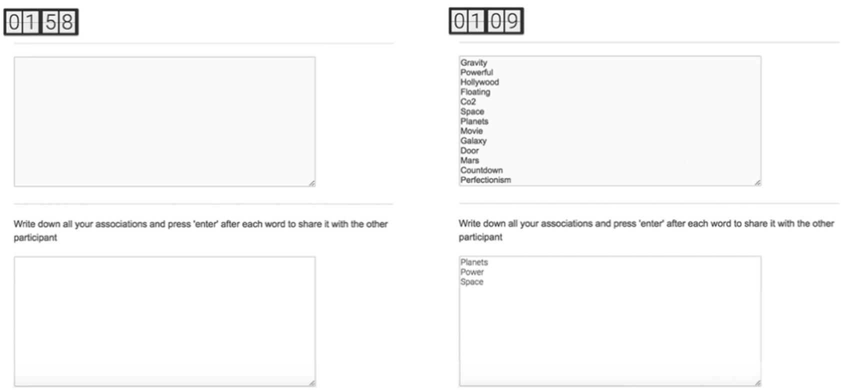

Fig. 2. Textual interface through which associations were shared by the collaborator (top), and where the associations were entered by the participant (bottom).

3.2.2 Assessing Divergent Thinking

Divergent thinking performance was assessed with 1) fluency, i.e., the number of associations produced, counted by the researchers [25] and 2) the average semantic distance between the associations and the rocket or flower, calculated with the SemDis software tool [38]. SemDis was previously shown to have good criterion validity as a divergent thinking performance measure [38].

Fig. 3. Google's reverse image search associations with the rocket (left) and flower (right).

3.2.3 Assessing Cognitive Stimulation, Evaluation Apprehension, and General Attitudes Towards AI

Cognitive stimulation was assessed with a self-developed six-item five-point Likert scale (1 = strongly disagree, 5 = strongly agree). The items asked participants about whether the collaboration simulated their divergent thinking (e.g., "The input of the collaborator helped me to think creatively"). Cronbach alpha suggested acceptable reliability, $\alpha =$ .74. Evaluation apprehension was assessed with a seven-item five-point Likert scale (1 = strongly disagree, 5 = strongly agree) developed by [39]. The scale was adapted to suit the present study better, e.g., "I felt nervous to share my ideas with the group" was rephrased as "I felt nervous to share my associations with my collaborator". Cronbach alpha suggested good reliability, $\alpha = .85$. The participants' general attitude towards AI was assessed using a twenty-item five-point Likert scale (1 = strongly disagree, 5 = strongly agree) developed by [13]. Cronbach alpha suggested good reliability, $\alpha = .83$.

3.3 Procedure

The experiment was conducted online using Qualtrics. There, participants were asked to read the study information, to sign informed consent, and were randomly assigned to one of the conditions. Information that could reveal the deceptions in the experiment was withheld at this point such as participants assuming that collaboration was done in real-time. The participants were asked to fill in demographic information and the general attitude towards AI scale. After this, they received the divergent thinking task instructions, and were presented with an example to aid in their understanding: "If the illustration depicts a 'Cow' you could answer with: 'Milk, 'Grass', …"). They were randomly assigned to either the instruction that they would be collaborating with an AI, which was powered by Google's reverse image search, or with another person. Subsequently, they were presented with their stimulus and started the divergent thinking task. Important to note is that even though the experiment was held in English, participants were allowed to respond in their native language (Dutch) whenever they experienced a language barrier to allow for fluency of the associations spilled by the participants. Participants were instructed to write down all their associations for the next two minutes, to press ENTER after every association in order to share their association with the collaborator, to use the received input from the collaborator to think of other associations related to the concept, to answer in single words, and to answer either in English or

Dutch. After finishing the task, the participants filled in the cognitive stimulation and evaluation apprehension scales, were fully debriefed, and thanked.

4 Results

To provide insight into the general characteristics of the data the descriptive statistics and correlations were calculated. Visual inspection of the histograms suggested that the data distribution of the variables evaluation apprehension and fluency deviated from normality. Therefore, the non-parametric Kendall's tau-b correlation coefficients were reported. These are presented in Table 1.

Table 1. Means and standard deviations (between parentheses) and Kendall's tau-b correlations (two-tailed). Note. † $p < .100$, * $p < .050$, ** $p < .010$.

	Experimental manipulations		Correlations				
	AI collaborator	Human collaborator	1	2	3	4	5
1. Cognitive stimulation	3.00 (.65)	3.50 (.57)	–				
2. Evaluation apprehension	1.89 (.57)	2.14 (.68)	−.144†	–			
3. Fluency	16.67 (.6.14)	15.88 (5.69)	.137	−.072	–		
4. Semantic distance	.78 (.05)	.76 (.07)	.085	−.067	.283**	–	
5. General attitude towards AI	3.51 (.51)	3.59 (.37)	.269**	−.344**	.093	.103	–

To test whether creative collaboration with the "brain" of a search engine, compared to creative collaboration with an averagely creative person, positively influences divergent thinking due to its effect on cognitive stimulation (hypothesis 1), two mediation analyses were conducted using Hayes' bootstrapping method [40]. This method is robust against deviations from normality. The model terms were both specified with collaboration type as the independent variable (human collaborator coded: 0, AI collaborator coded: 1) and with self-reported cognitive stimulation as the mediator. Model 1 was specified with fluency as the dependent variable, and model 2 with semantic distance as the dependent variable. Assumption checks suggested heteroskedasticity in both models, which was tested by visually inspecting the distribution of the studentized residuals plotted against the standardized predictor values [41]. Therefore, Huber-White heteroscedasticity consistent standard errors were used to calculate the test statistics for both models [42]. The models and unstandardized coefficients are presented visually in Figs. 4a (model 1) and 4b (model 2), whereas the indirect and direct effects are presented in the text below.

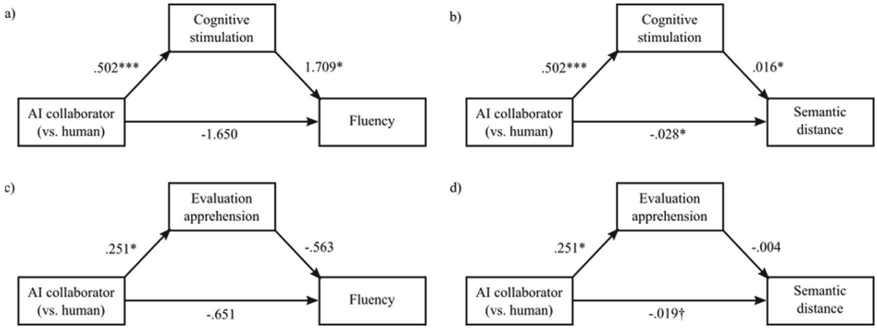

Fig. 4. a) Mediation analysis of the effects of collaborating with the AI on a) cognitive stimulation and subsequent fluency (model 1), and b) semantic distance (model 2), and c) mediation analysis of collaborating with the AI on evaluation apprehension on subsequent fluency (model 3), and d) semantic distance (model 4). Data are unstandardized coefficients. † $p < .100$, * $p < .050$, ** $p < .010$, *** $p < .001$.

These mediation analyses showed a significant indirect effect of human collaborator, compared to the AI collaborator, on the relationship of cognitive stimulation with fluency, $b = -.858$, $se = .487$, 95% CI[.040, 1.976] and with semantic distance, $b = .008$, $se = .005$, 95% CI[.001, .018]. These indirect effects were characterized by a significant positive effect of collaborating with a human on cognitive stimulation, $b = .502$, $se = .104$, 95% CI[.296, .707] and of cognitive stimulation on fluency, $b = 1.709$, $se = .786$, $p = .031$, 95% CI[.155, 3.264] and semantic distance, $b = .016$, se $= .008$, $p = .034$, 95% CI[.001, .031]. In contrast no significant direct effect was found on fluency, $b = -1.659$, $se = 1.116$, $p = .142$, 95% CI[−3.857, .558]. However, the results did show a significant negative direct effect on semantic distance, $b = -.028$, $se = .011$, $p = .013$, 95% CI[−.049, −.006]. This finding suggests that creative collaboration with the "brain" of a search engine, compared to creative collaboration with an averagely creative person, negatively influences divergent thinking due to its effect on cognitive stimulation. As such, this finding confirms hypothesis 1 in the sense that there is an influence, and it adds that this influence is negative.

To test whether creative collaboration with the "brain" of a search engine, compared to creative collaboration with an averagely creative person, positively influences divergent thinking due to a negative effect on evaluation apprehension (hypothesis 2), two more mediation analyses were conducted using Hayes' bootstrapping method [40]. Again, the model terms were both specified with collaboration type as the independent variable (human collaborator coded: 0, AI collaborator coded: 1), but now with self-reported evaluation apprehension as the mediator. Model 3 was specified with fluency, and model 4 with semantic distance, as the dependent variable. Assumption checks suggested heteroskedasticity in model 4 [41]. Therefore, Huber-White heteroscedasticity consistent standard errors were used to calculate the test statistics for model 4 [42]. No further corrections were thus applied to model 3. The models and unstandardized coefficients are presented in Figs. 4c (model 3) and 4d (model 4). The indirect and direct effects are presented in the text below.

The results of these tests showed no significant indirect effect of the human collaborator, compared to the AI collaborator, on fluency, $b = -.141$, $se = .237$, 95% CI[$-.656$ .329] nor on semantic distance, $b = -.001$, $se = .002$, 95% CI[$-.006$, .004] that was mediated by its effects on evaluation apprehension. Furthermore, no significant direct effects were found of the human collaborator, compared to the AI collaborator, on fluency, $b = -.651$, $se = .972$, $p = .504$, 95% CI[-2.573 1.272] nor on semantic distance, $b = -.019$, $se = .011$, $p = .099$, 95% CI[$-.041$ .004]. Note, however, that the results did show a significant positive effect of the human collaborator, compared to the AI collaborator, on evaluation apprehension in model 3, $b = .251$, $se = .108$, $p = .021$, 95% CI[.038 .464] and in model 4, $b = .251$, $se = .105$, $p = .019$, 95% CI[.043, .460]. These findings suggest creative collaboration with the “brain” of a search engine, compared to creative collaboration with an averagely creative person, negatively affects evaluation apprehension, as expected. However, there is no subsequent effect on divergent thinking. As such, these results only partially confirm hypothesis 2.

The results from models 3 and 4 also suggest no significant moderation of a person’s general attitude towards AI of the effects human collaboration, compared AI collaboration, on the fluency and semantic distance of the associations produced by the participants, that was mediated by evaluation apprehension (hypothesis 3). That is, given that no mediation effect was found, there is no effect to moderate. However, because the results from models 3 and 4 did suggest an effect of AI collaboration, compared to human collaboration, on evaluation apprehension, we can test whether this effect is moderated by a person’s general attitude towards AI. To this end, a regression model was calculated with collaboration type, the general attitude towards AI, and the product of these two variables (interaction) as the independent variables, and self-reported evaluation apprehension as the dependent variable. The results showed no interaction effect of collaboration type and general attitude towards AI on evaluation apprehension, $b = .200$, $se = .236$, $p = .398$, 95% CI[$-.267$ .667]. These findings suggest that the effects of creative collaboration with the “brain” of a search engine, compared to creative collaboration with an averagely creative person, on divergent thinking via evaluation apprehension, is not moderated by a person’s attitude towards AI. As such, these results do not confirm hypothesis 3.

5 Discussion

The presented study was conducted to take a first look at how creative collaboration with the “brain” of a search engine affects creative task performance in comparison to creative collaboration with the averagely creative person.

The results suggested that creative collaboration with the “brain” of a search engine, compared to creative collaboration with an averagely creative person, influenced divergent thinking due to its effect on cognitive stimulation (hypothesis 1). Specifically, the results indicate that this is a negative effect, meaning that participants who interacted with the AI collaborator, experienced less cognitive stimulation, and produced fewer associations, with a lower average semantic distance, when compared to participants who interacted with the human collaborator. Speculatively, general search engines, such as Google’s reverse image search, may retrieve information that is different or weird "in the wrong way" [29] or perhaps just too similar [5]. What stands out, however, is that our routine reliance on AI-powered search engines [6] for our day-to-day creative tasks [7] in 2021, may negatively affect cognitive stimulation and subsequent divergent thinking when compared to creative collaboration with an averagely creative person [26, 27]. Creatives, from laypersons to professional artists, might therefore need to be careful when considering the source of their inspirations. Choosing these types of AI technologies over people for creative collaboration may thus harm creative task performance. At least, from a cognitive perspective.

The results also suggested that creative collaboration with the "brain" of a search engine, compared to creative collaboration with an averagely creative person, negatively influences evaluation apprehension. However, these effects did not subsequently enhance divergent thinking (hypothesis 2). Despite people's common anthropomorphization of AI technologies as collaborators and teammates [5] it was conjectured that AI collaboration would reduce evaluation apprehension. The underlying reasoning was that the limited perceived social agency of these types of technologies would mitigate a common cause of evaluation apprehension, social anxiety [11]. Although confirmation of this particular mechanism is outside the scope of this paper, the results, for now, suggest this might be the case. One possible explanation could be that AI-powered systems might serve as psychological safety net that helps people to be less socially pressured [43–45]. Thus, from a social perspective, these types of human-technology interactions might benefit creative task performance via a reduction of evaluation apprehension. Though note that the former could not be confirmed.

Furthermore, the results did not show that effects of creative collaboration with the "brain" of a search engine, compared to creative collaboration with an averagely creative person, on divergent thinking via evaluation apprehension, was moderated by a person's attitude towards AI (hypothesis 3). Also, further testing confirmed that the effect of collaboration type on evaluation apprehension was not moderated by a person's general attitude towards AI. Thus, in the present study, we could not confirm our speculation that a person's general attitude towards AI introduces a different cause of evaluation apprehension.

The study leaves several unanswered questions that merit future research, partly due to the study's limitations. The basic form of collaboration with the "brain" of Google's reverse image search, e.g., normally happens via its graphical user interface (GUI) [6] whereas we presented its retrieved associations via a text-output field. Interacting with Google's AI via its GUI may affect divergent thinking differently [7]. For example, the associations generated by Google's reverse image search might have been biased in some way as the images were manually translated into words to avoid confounding variables in a later state of the experiment. Yet this might have influenced the original process of interpreting the AI-generated associations by participants. Additionally, the effects on evaluation apprehension might differ from situations that are socially richer than the present study. Although low social richness helped to reduce confounds, because the associations could be presented similarly in both experimental conditions, it also removed the (non-)verbal expressions of others that may worsen evaluation apprehension [11, 31]. Indeed, the average scores on the questionnaire suggested low evaluation apprehension, possibly too low to affect divergent thinking [10]. Future work could therefore focus on the effects of social cues on evaluation apprehension and subsequent divergent thinking, by comparing face-to-face creative collaborations between people and socially rich AI systems such as social robots [10]. Finally, the positive direct effect of creative human-AI collaboration on semantic distance observed in model 2 (Fig. 4b) requires further investigation. It may be that the quality of the associations of information that general purpose AI systems retrieve [8] can stimulate divergent thinking but is not perceived as cognitively stimulating, or its effects may be best explained by other key psychological mechanisms that affect creative collaboration between people, such as social loafing or social disinhibition [9]. This should also be the subject of future research.

Herewith, the present study contributes to an emerging body of work on the efficacy of creative human-AI collaboration by showing that creative collaboration with the "brain" of a search engine, compared to collaboration with an averagely creative person, reduces cognitive stimulation but also evaluation apprehension, and that a person's general attitude towards AI does not introduce a novel form of evaluation apprehension.

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