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Short Paper

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Abstract

Human creativity is a crucial factor in developing innovative ideas. Many ideas are being generated, but only a few receive feedback, as creating feedback is a costly and time-consuming effort in innovation. While feedback promises higher idea quality, previous work requires human experts with domain expertise. Generative AI could provide automated feedback and is expected to transform creative work. This short paper presents an experimental series in which we let humans collaborate with generative AI to develop ideas. Based on dual-coding and media synchronicity theory, we conceptualize numerical and visual feedback to overcome cognitive barriers. We manipulate feedback modalities and timing to personalize the interaction. Our contributions provide evidence on when and why specific co-creative arrangements between humans and generative AI are favorable.

Keywords: Generative AI, Idea Development, Feedback

Introduction

Creativity and innovation drive long-term growth for business (Andriopoulos, 2001). Individuals and their creativity are important factors in innovation, as they contribute ideas by ideating (Kornish & Ulrich, 2014). The goal of ideation is to create creative ideas that should be both novel and useful (Mehta & Dahl, 2019). While creativity is required to innovate (Shalley & Gilson, 2004), innovation extends ideation by implementing the ideas (Amabile, 1996). In larger innovation contexts, the person ideating is typically not responsible for implementing the idea, such as crowdsourcing platforms (Blohm et al., 2016) or employee suggestion schemes (Lasrado et al., 2016). The ideation process in innovation consists of three phases (Clegg et al., 2022; Kornish & Ulrich, 2014): (1) generation of new ideas, (2) further development of the generated ideas, and finally, (3) evaluation of the developed ideas. In this process, research is focused on (1) idea generation (Anderson et al., 2014; Paulus & Brown, 2007) and, to a lesser extent, (3) idea evaluation (Blohm et al., 2016; Dahlander et al., 2023). Idea development aims at increasing the quality of initially generated ideas (Clegg et al., 2022), with feedback being a crucial factor (Piezunka & Dahlander, 2019). Developing generated ideas promises increased idea quality as feedback can lower cognitive barriers (Nijstad et al., 2002) and lead to higher motivation (Zhu et al., 2019). However, creating adequate feedback is a costly and time-consuming effort in innovation (Ashford & Cummings, 1983) and a bottleneck in the process.

To address this problem, artificial intelligence (AI) could be a potential creative collaborator that can provide personalized feedback on ideas automatically and almost immediately (Rezwana & Maher, 2022). Deep learning has empowered AIs to support human creativity in various ways (Nguyen et al., 2015). ChatGPT can help users improve their business plans (Taecharungroj, 2023), and tools like Midjourney create art based on user input (Oppenlaender, 2022). These tools, which are gaining momentum, share the same interactive process. In turn, users prompt creative input to the AI, which returns creative output or textual feedback. The ability of generative AI to react to previous inputs allows humans to take turns with the machine. As the creative process requires iterations to support trial and error (Puccio et al., 2010), using generative AI to support human creativity is promising. This interactive process can be defined as augmented creative turn-taking, a co-creative process in which the technology acts as a collaborator that augments human creativity (Bouschery et al., 2023). Co-creative systems augmenting human creativity are focused on creating creative output in a planned fashion with little communication of the AI back to the human (Rezwana & Maher, 2022).

In this work, we explore co-creative arrangements of human and generative AI. This technology is impacting the work of many professions, especially creative labor (Eloundou et al., 2023). Therefore, we investigate how generative AI can be employed in a new form of technology-enabled work in creative turn-taking. The AI could create images based on an idea, write text to ask questions about the idea, or calculate a numeric score to evaluate it. Following two theories, these affordances target different processes. Based on dual-coding theory (Paivio, 1990), we argue that feedback on creative work should target both verbal associations and imagery. Additionally, we build on media synchronicity theory and distinguish feedback by symbol variety (Dennis & Valacich, 1999). In total, we conceptualize two kinds of feedback on ideas that AI can create automatically: (1) numeric feedback, like a quality score with low symbol variety targeting verbal associations, and (2) visual feedback with high symbol variety targeting imagery. Following the dual-coding theory, numeric feedback is processed as verbal information and visual feedback by sensory imagery in distinct channels (Paivio, 1990). While we expect AI to be able to create such feedback, the effects of AI-generated human creativity could be manyfold. Positive effects of constructive feedback can include higher motivation when the feedback is constructive (Zhu et al., 2019), humans leaving the path-of-least-resistance (Nijstad et al., 2002), or steering of attention to good ideas and crucial aspects by lowering fixation effects (Ezzat et al., 2017; Jansson & Smith, 1991). However, also negative effects of feedback can be expected. It can lead to satisficing as ideators perceive from feedback that their idea is "good enough" (Kaufman, 1990). Directed feedback can reduce the variance of idea quality and, therefore, reduce the quality of exceptional ideas (Wooten & Ulrich, 2017), in which the value of ideation is concentrated (Blohm et al., 2016). In light of the potential positive and negative effects of AI-generated feedback, we investigate boundary conditions and potential arrangements of collaboration between humans and generative AI by answering the research question: How does numeric and visual AI-generated feedback affect creative performance?

This research-in-progress paper presents an approach to answering this research question and preliminary results. First, we present related literature on feedback during idea development and the possibilities of generative AI to create feedback. Next, we derive our research framework and hypotheses from theory. Further, we present our approach to test these hypotheses in an experimental series. We offer preliminary results from a pre-study and discuss opportunities for further research. Last, we outline our planned contributions and how they might affect the research streams on idea development.

Conceptual and Theoretical Foundations

Conceptual Background: Feedback in Innovation & Generative AI

Feedback and reward systems can motivate users to innovate, especially on digital platforms (Dahlander & Piezunka, 2014; Hofstetter et al., 2018). However, a lack of feedback can demotivate users as they could infer that a lack of attention is associated with their idea's quality (Beretta et al., 2018). This could lower the willingness to contribute more ideas (Zhu et al., 2019). Generating adequate feedback is a time- and cost-intensive task. (Ashford & Cummings, 1983). Other users could contribute feedback in online settings, but only a few ideas receive community-based feedback (Dellarocas & Wood, 2008). Wooten and Ulrich (2017) have investigated the role of feedback on idea quality in an innovation contest. They observe that even random feedback encourages participants to contribute more (Wooten & Ulrich, 2017). In their field study, Wooten and Ulrich (2017) point out the high effort involved in providing daily feedback. Ezzat et al.

(2017) explored the role of live feedback, which guided participants toward exploration paths to prevent fixation effects. Ezzat et al. (2017) trained a human for the task using a data set of previous ideas to provide guidance. Both examples show the potential of providing feedback but require manual effort that could be automated. Generative AI can learn from large amounts of data and be used for various use cases with little training (Brown et al., 2020). It can augment the innovation process by giving access to knowledge (Bouschery et al., 2023) and creating feedback (Lund & Wang, 2023). While the works of Bouschery et al. (2023) and Lund and Wang (2023) are focused on text applications, creative processes require different modalities (Wang & Nickerson, 2017). Wang and Nickerson (2017) argue that systems supporting creativity should target various cognitive associations to support a variety of factors and aspects. Therefore, we will explore modalities like numeric or visual feedback beyond textual feedback.

First, numeric feedback can be indicated by a rating (Wooten & Ulrich, 2017). Ideas are usually rated during the idea evaluation phase (Blohm et al., 2016; Dahlander et al., 2023). After receiving submissions, expert panels evaluate and choose winning ideas (Blohm et al., 2016). Challenges are the high number of generated ideas, unbalanced datasets as only a few ideas are actually good, and the high costs of implementing bad ideas (type-1 errors) and missing blockbusters (type-2 errors) (Blohm et al., 2016). Automated solutions try to predict idea quality based on its text and other features (Rhyn & Blohm, 2017). However, no labeled data for the idea competition is usually available during idea development, making transfer learning (Torrey & Shavlik, 2010) required for the process. Generative AI is a technology capable of text understanding and transfer learning (Brown et al., 2020). It could learn from a labeled set of idea competitions and their submitted ideas to predict the quality of previous unseen ideas in new competitions. Implementations could range from training a deep neural network based on transformer-based language models to utilizing a pre-trained model with in-prompt fine-tuning (Brown et al., 2020). Deployed in an online setting, a generative AI would require the text of an idea competition and the idea itself and return a prediction of the idea in the form of a rating (e.g., 0-1) that can be used as numeric feedback.

Second, visual feedback can help the creative process by providing dynamic stimuli based on the idea (Moreau & Dahl, 2005). Stimuli in creativity face the challenge of being inspirational but also fixating (Cardoso & Badke-Schaub, 2011). Hofstetter et al. (2021) show that seeing other ideas can harm creative performance. Instead, the visualization could target the idea, allowing personalization but limiting fixation through abstraction (Finke, 2014). Generative AI can generate images based on prompts (Oppenlaender, 2022) and can be accessed via APIs. Again, in an online setting, a generative AI could return an image as visual feedback based on the idea and a prompt (e.g., “Visualize feedback on the following idea: “).

AIs ability to generate numeric and visual feedback is expected to increase collaboration between AI and humans for creative tasks, as creative writers are likely to face high exposure to generative AI (Eloundou et al., 2023). Empirical studies have investigated human-AI collaboration to investigate how to utilize both strengths (Ren et al., 2023). Jia et al. (2023) identified that high-skill workers collaborated more successfully with AI while having more freedom. Besides task or domain knowledge, beneficial collaboration with AI increases when the worker has appropriate knowledge about AI and knowledge about the AI capabilities to support the task at hand (Lebovitz et al., 2022). However, it remains unclear if the patterns observed can be transferable to other domains, such as creativity and work contexts like creative labor (Ren et al., 2023).

Theoretical Background

Creativity theories consider creativity as being composed of different factors and based on associations (Wang & Nickerson, 2017). This makes systems supporting creativity dependent on individual users and personalization, a lack in current research, according to the literature review by Wang and Nickerson (2017). We build on dual-coding and media synchronicity theory to conceptualize how feedback should be given to foster creativity.

Dual-coding theory states that information is represented by both sensory imagery and verbal information (Paivio, 1990). Mental codes respond to these representations and process the information in distinct channels within the human mind. Dual-coding theory suggests that having both text and imagery information helps students recall information (Paivio, 1990). Appearance, sounds, or smells could target imagery. In this paper, we provide feedback through numeric scores as text to target verbal information. On the contrary, visual feedback in the form of images targets sensory imagery. While a score itself is a quantitative measure, a number is part of verbal information (Mix et al., 2005). We enrich it with contextual understanding by labeling scores higher than the median score on our test set with "well done" and below with "keep trying" (Viswanathan & Childers, 1996).

Media synchronicity theory describes communication processes and different mediums' abilities (Dennis & Valacich, 1999). First, communication processes are distinguished between their synchronicity, e.g., the current engagement of communication participants. A face-to-face meeting has high synchronicity, allowing for convergence towards an agreement, whereas e-mail communication has low synchronicity, giving participants time to convey and process information (Dennis & Valacich, 1999). Second, following media synchronicity theory, mediums have a set of abilities such as transmission velocity – how quickly the message transfers from a sender to a receiver – or symbol sets – how much room leaves the message for interpretation (Dennis & Valacich, 1999). This work uses media synchronicity to present AI-generated feedback in two mediums to explore how AI-human communication affects creative collaboration (Rezwana & Maher, 2022). First, numeric feedback is a medium with low symbol variety, as a score leaves little room for interpretation. It can be transmitted fast thanks to its size of only a few bytes and little required computational effort. Conversely, visual feedback communicated as an image medium leaves room for interpretation due to its high symbol variety. Furthermore, its creation requires higher computational effort and increased transmission length.

Hypotheses

We believe the two kinds of feedback influence the creative performance of the ideas (MacCrimmon & Wagner, 1994). Numeric feedback, like a quality score, can be optimized, leading to incremental innovation, while we expect the targeted imagery of visual feedback to allow radical innovation (Silk et al., 2019). Therefore, we hypothesize that presenting feedback (numeric vs. visual vs. both) increases the creative performance of individuals. In greater detail, we propose:

H1a/b/c: Numeric/visual/numeric and visual AI-generated feedback improves the creative performance of individuals.

As individuals take turns with the AI developing their idea collaboratively (Rezwana & Maher, 2022), we expect them to feel more motivated and more likely to leave the "path of least resistance" (Nijstad et al., 2002; Zhu et al., 2019). Therefore, we hypothesize (H2) that the positive feedback of presenting feedback is mediated by increased turn-taking.

H2a/b/c: Creative turn-taking mediates the effect of numeric/visual/numeric and visual AI-generated feedback on creative performance such that higher turn-taking leads to higher creative performance.

Last, the positive effect could be moderated by increased creative self-efficacy (Tierney & Farmer, 2011). Providing automated feedback could evoke a sense of external control harmful to creative performance (Deci & Ryan, 2000). Self-controlled feedback is expected to be more helpful (Chiviacowsky & Wulf, 2002), and a personalized symbol variety can improve performance following the media synchronicity theory (Dennis & Valacich, 1999). Therefore, we hypothesize (H3) that the positive effect on turn-taking is moderated by the opportunity to control the timing of the feedback. Our research framework for investigating the moderating and mediating effects on creative performance is depicted in Figure 1.

H3a/b/c: Self-controlling feedback positively moderates the mediation effect of numeric/visual/numeric and visual AI-generated feedback on creative performance via creative turn-taking; the stronger the level of self-control, the stronger the mediation effect.

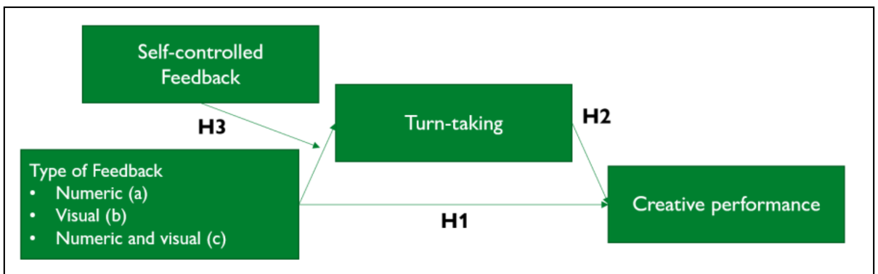

Figure 1. Research Framework Used

Methodology

We plan to test our research model by a series of experiments. Study 1 focuses on the main effect and tests hypotheses H1a to H1c. We conduct a 2x2 experimental design and show no feedback, provide numeric feedback, visualize the idea as feedback, or both kinds. After users have submitted their ideas, we show the feedback of the AI and ask them to revise the idea based on the feedback. In Study 2, we conceptually replicate study 1 but focus on the provided visual feedback. While in study 1, our AI has directly visualized the provided idea, in study 2, we want to predict feedback prompts for visualization using transformer-based language models (Brown et al., 2020). Using these prompts, we will again visualize that feedback. The visualization should preserve the positive effects of more fitting feedback based on an extended knowledge space of the language model (Bouschery et al., 2023) while limiting fixation effects (McCaffrey, 2012). Finally, in study 3, we investigate the creative turn-taking process with our AIs and test H2 and H3. Therefore, we extend the platform to allow users to request feedback at will or provide feedback automatically every minute. Each feedback condition (numeric, visual, or both) is extended with the opportunity to self-control feedback (or not), resulting in a 3x2 experimental design.

We have developed an online platform that can provide numeric and visual feedback. Our platform features two AIs that we have trained utilizing a large-scale ideation dataset to (1) predict idea quality as a numeric score and (2) provide visual feedback as an image. We employed a large-scale ideation dataset for the numeric feedback condition and trained a DistilBERT classifier pre-trained with cased text in German (Sanh et al., 2019). The dataset was collected from innovation challenges from an innovation platform over eight years. A total of 23,863 users contributed 149,455 ideas and 72,815 comments. Each idea in the set was binary labeled by the contest provider. Only 4.6% of all ideas were awarded. We trained the model to classify ideas based on the contests' title, text, and criteria in combination with the ideas' title and text. We removed the innovation challenge used in the experiments to simulate a real-world scenario from the training dataset. As participants request feedback, their idea's text and title are concatenated to the contest's text information and evaluated by our model. It will return a probability of the idea being awarded, which is displayed to the user as numeric feedback. For the visual feedback condition, we utilize the DALLE 2 API by OpenAI (Ramesh et al., 2022). We use a basic prompt prefix for study 1 ("Visualize feedback for the following idea: "), but will extend the prompt in study 2 as described above. The visual feedback is created by combining our prefix with the participant's idea to a prompt, requesting an image with default hyperparameters from the DALLE 2 API, and displaying the image.

We investigate the role of feedback in an experimental setting, asking participants to contribute ideas to a real-world ideation challenge from our large-scale ideation set. The selected challenge asks: "*What would you improve in a crowded commuter rail to make the ride more enjoyable from boarding to alighting?*". As criteria, the contest provider named "suitable for the masses", "feasible", "technically and financially not a luxury", and "sustainable". During the contest, 302 ideators contributed 638 ideas and 468 comments. Afterward, the contest provider awarded 28 ideas (4.3%) as "winning ideas". The innovation challenge seems reasonable for the experimental setting, as participants are familiar with potential problems in public transport and require no prior knowledge. Participants were asked to contribute ideas to the innovation challenge, making the task representative of tasks in crowdsourcing.

Across all three studies, we operationalize creative performance using Amabile's Consensual Assessment Technique (Amabile, 1996), similar to Blohm et al. (2011). Besides, we assess the following controls: (1) self-reported creativity by Bruner et al. (2013), and perception of the feedback (not asked in control) with scales: (2) originality, (3) imagination, and (4) inspiration, also by Bruner et al. (2013). Last, we ask all participants their perception of the creative task with scales: (5) competence, (6) autonomy, and (7) enjoyment by Bruner et al. (2012). Our large-scale ideation set mostly features German ideas from innovation contests conducted in German. Hence, we require a German-speaking sample for all studies, which we ensured by screening for German native speakers. Requiring participants to have a high acceptance rate of 95%, at least 20 submissions on the platform and correctly answering two attention checks ensures data quality in the sample. We do not further screen the sample to be able to investigate creativity with various controls, e.g., knowledge of innovation or self-assessed creativity.

Preliminary Results

The pre-study was conducted online, with 20 (Mage = 32.0; SD = 9.74; 25% female) participants recruited from Prolific. As the dataset contains German ideas, we pre-screened participants to speak fluent German as their first language and to live in the DACH region. They needed a median time of 10:44 minutes to complete the experiment. After signing up for the study, participants indicated their ability to speak German and knowledge of innovation using a 5-star rating. Participants indicating three or fewer stars saw a short explanation of innovation contests. Before explaining the task, we assessed self-reported creativity to make the assessment independent of the task or manipulation. We then introduced the task and split participants into four treatment groups: a "control" group not receiving feedback, a "visual feedback" group, a "numeric feedback" group, and a fourth group, "numeric and visual feedback". Participants were presented with the innovation competition and its criteria on our experiment platform. Each participant had to submit at least one idea. To be able to submit an idea, participants in the three treatment groups had to request at least one feedback by clicking "Get numeric (/visual) feedback". Participants in the treatment groups generated 21 ideas during the experiment and received 14 visual and 12 numeric feedback. The control group generated five ideas. After submitting at least one idea, participants were free to leave the experiment platform at any time. In a post-survey, we asked participants in the treatment conditions how they perceived the feedback. The scales reached sufficient Cronbach's alpha (Tavakol & Dennick, 2011): originality 0.78, imagination 0.83, and inspiration 0.89. While statistical results must be treated with caution due to the low power of the study, we observe significantly higher perceived originality for visual feedback ($t=4.39$, $p=0.003$) and a weak increase in imagination ($t=1.64$, $p=0.14$).

Next, we asked for the perception of the creative task, again reaching sufficient Cronbach's alpha: creative task enjoyment 0.93, creative task autonomy 0.7, and creative task competence 0.76. Participants in the "visual feedback" group reported higher task competence ($t=2.97$, $p=0.019$). Additional access to numeric feedback weakened this effect in the "numeric and visual feedback" group ($t=2.15$, $p=0.064$). We observe increased task enjoyment and creative autonomy with having access to numeric or visual feedback but cannot report statistical significance. Lastly, we asked which feedback was present on the experiment platform as a manipulation check, which all participants answered correctly. Due to the nature of the pre-study, we only tested the scales, infrastructure, and manipulation but did not test the hypotheses. Therefore, the idea quality was not assessed.

Next Steps and Intended Contributions

This paper aims to explore how AIs can provide feedback in the human creative process. We want to investigate how humans collaborate with feedback-providing AIs in a turn-taking fashion. Our platform allows us to generate AI feedback in real-time during the experiment instead of providing "mock-up" feedback. Additionally, we can observe user behavior on our platform, allowing further research on human-AI collaboration in creative tasks. We contribute to the research stream of augmented innovation (Bouschery et al., 2023) to investigate how digital technologies like generative AI influence how humans innovate and work creatively. Currently, the stream is focused on text generation due to technological developments of transformer-based language models, which limit modality and creative potential (Wang & Nickerson, 2017). Therefore, we extend the research of feedback on innovation by creating visual and numeric feedback using generative AI. Numeric feedback allows us to contribute to the field of idea evaluation, as we can explore the assessment of ideas during idea development without requiring the idea contest to be finished. Additionally, our developed AI could be transferred to other contests, a limitation of current approaches. Visual feedback contributes to the research stream of visual stimuli (Cardoso & Badke-Schaub, 2011; Hofstetter et al., 2021) as we explore how images generated by AI fixate or inspire humans.

Furthermore, we explore how humans and AI can collaborate and how the level of creativity influences the use of AI and the reception of its feedback. We contribute to the empirical research on human-AI collaboration (Ren et al., 2023) by investigating creative labor, which is characterized by high uncertainty and openness to workers from diverse domains. In the next step, we plan to expand our research model and platform to include a third modality: textual feedback. This enhancement is possible due to the latest advancements in transformer-based language models.

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