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Article

Human-Machine Creativity – How AI Can Influence Human Creativity in Open Innovation

Marketing Review St.Gallen

Provided in Cooperation with:

Universität St. Gallen, Institut für Marketing und Customer Insight

Suggested Citation: Clegg, Melanie; Hofstetter, Reto; Blohm, Ivo; Bravin, Marc (2022) : Human-Machine Creativity – How AI Can Influence Human Creativity in Open Innovation, Marketing Review St.Gallen, ISSN 1865-7516, Thexis Verlag, St.Gallen, Vol. 39, Iss. 6, pp. 40-47

This Version is available at:

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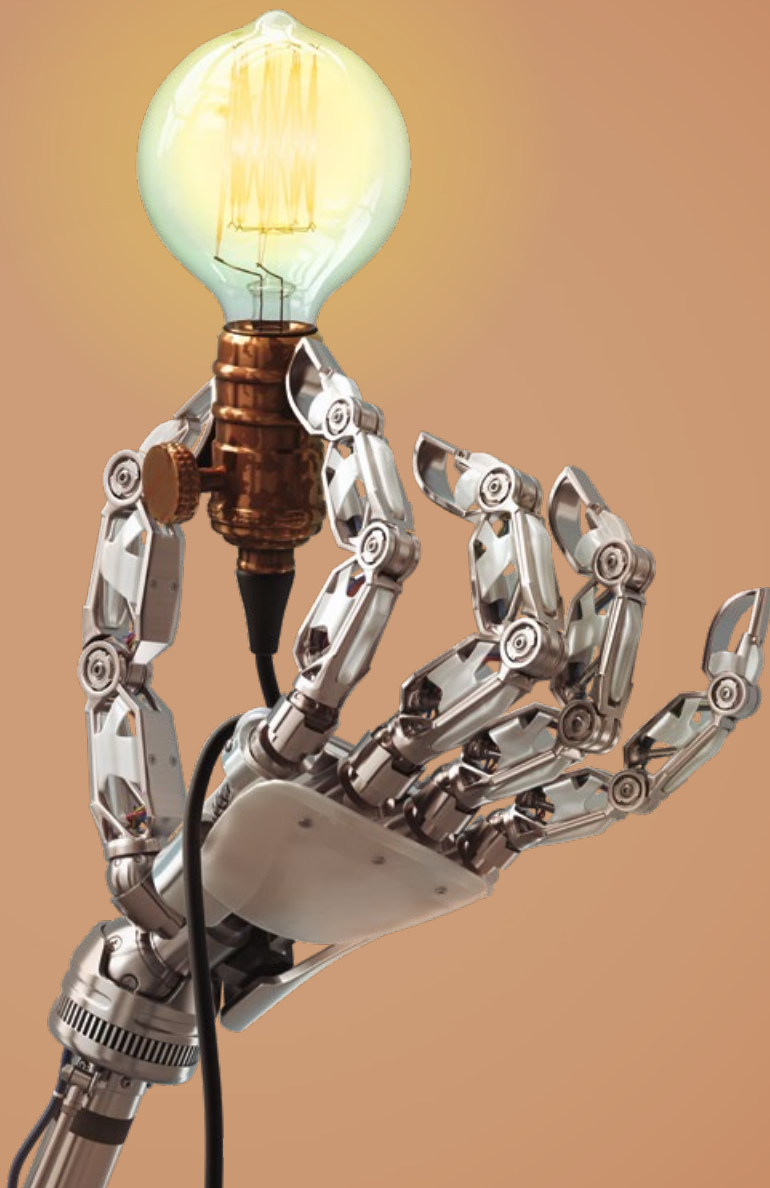
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Marketing Review

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Open Innovation
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Human-Machine Creativity

How AI Can Influence Human Creativity
in Open Innovation

Innovation platforms are powerful instruments for harnessing crowd creativity. Yet, platform users still struggle with cognitive barriers when looking to unfold their creative potential. This conceptual article identifies three barriers from innovation literature and outlines how artificial intelligence can help users overcome these barriers.

Dr. Melanie Clegg, Prof. Dr. Reto Hofstetter, Prof. Dr. Ivo Blohm, Marc Bravin, M.Sc.

Digital open innovation platforms have experienced dramatic growth in recent years. Firms increasingly involve individuals in innovation processes via such platforms to develop new products, advertising campaigns, or business strategies (Bayus, 2013). Platform users typically post ideas, allowing firms to draw on crowd creativity. These ideas can be a response to a particular innovation challenge posed by a firm, such as PepsiCo's contest for new iced tea flavors for their Lipton beverage brand on the platform Eyeka (Eyeka, 2016). Some firms including Starbucks or LEGO even host their own platforms, where users can either take part in contests or freely submit ideas for novel products (e.g., a Starbucks drink recipe, a LEGO product design). Ideation challenges can also involve image-based ideas for brand logos (a typical design challenge on the platform 99designs), or ideas for complex problems (e.g., create "a better food future for everyone, everywhere" posted on Openido, 2021). All of these platforms share the goal of enabling organizations to reach for innovative ideas beyond what is already known by taking advantage of the creative potential of multiple platform users.

Crucial to the success of such digital innovation processes is the creativity of each individual contributing to the process (Kornish & Ulrich, 2014). Users contribute to the innovation process by generating ideas, further developing these ideas, and evaluating the ideas of others. However, the static one-size-fits-all architecture of such platforms can pose major barriers that prevent users from unleashing their full creative potential, including a fixation on previously suggested ideas, a lack of motivation to develop more and better ideas, and a bias against highly novel ideas.

In this article, we argue that machine learning (ML) and artificial intelligence (AI) can help users overcome these human barriers by automating and customizing processes to support

human creativity. Here, AI is defined as a collection of ML instruments that allow a system to interpret, learn from, and adapt to data (Syam & Sharma, 2018). AI tools on innovation platforms allow the targeted presentation of ideas, automate providing feedback, and optimize presenting ideas for evaluation. Yet, the integration of these approaches into the creative process remains a major challenge to companies and providers of innovation platforms. Hence, our research aims to answer the following overarching question: *How can AI tools increase individual creative performance on innovation platforms?*

Digital Open Innovation Platforms

Given the high potential of digital open innovation, a great deal of research has focused on drivers and barriers to creative performance on digital open innovation platforms. Examples are the impact of user interactions or the visibility of ideas submitted by other users on creative performance (Hofstetter et al., 2018a, 2020; Stephen et al., 2016). Moreover, several papers addressed how feedback or reward structures on innovation platforms should be designed (Hofstetter et al., 2018b; Kosonen et al., 2014; Piezunka & Dahlander, 2019; Toubia, 2006) or how innovation challenges should be formulated to improve the creativity of users (Luo & Toubia, 2015). Another branch of research has focused on efficient ways for companies to evaluate and identify the most promising submitted ideas (Beretta, 2019; Blohm et al., 2016; Hoornaert et al., 2017; Kruff et al., 2019; Magnusson et al., 2016). While this research stream made great progress in improving the quality and quantity of the obtained ideas, user comments, and evaluations, certain limitations remain. For instance, the state-of-the-art is limited by the assumption that these principles are equally and universally effective for every user, which provides ample opportunity for AI tools to improve the current



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platform design. Machine learning-based AI tools allow for a personalized intervention at the user level and could thus be programmed to foster user performance during the creative process. Yet, to the best of our knowledge no research has systematically addressed how AI tools should be designed to foster individual human creativity on innovation platforms.

Artificial Intelligence and Creativity

AI technologies are increasingly entering the creativity domain, yet researchers have typically focused on AI as a creative machine independent of humans. Indeed, AI can be stunningly creative: New AI developments, such as generative adversarial networks (Goodfellow et al., 2014), allow machines to create original art, text, music, or products (Aiva Technology, 2021; Yang et al., 2017; Yu & Chen, 2018). Consider Botnik, an AI program that can write its own Harry Potter chapters (Towsen et al., 2020), or the deep neural network DALL-E that creates images such as avocado armchairs based on text input (Ramesh et al., 2021). Another use of AI tools is the prediction of similarity/novelty as proxies for creativity. Similarity measures based on ML have been

used to predict the popularity of songs (Berger & Packard, 2018), the success of video files (Wei, 2020), the likelihood of funding for crowdfunding projects (Wei et al., 2022), the impact of scientific papers (Uzzi et al., 2013), and the value of patents (Youn et al., 2015). As can be seen, the majority of current AI-creativity research aims to develop tools that may *replace* human input rather than *support* human creative performance (some exceptions are Toubia & Netzer, 2017 for idea generation; or Blohm et al., 2020 for idea evaluation). In what follows, we present a framework making suggestions for AI support instead of replacement.

Human–Machine Creativity Along the Innovation Process

We define creativity as the ability to create an idea that is both original and useful (Mehta & Dahl, 2019). Creativity is a precondition for innovation (Shalley & Gilson, 2004) but differs from innovation in that innovation also refers to the implementation of ideas (Amabile et al., 1996). We structure our research along the normative stages of the innovation process in which users of innovation

platforms participate (figure 1): First, individuals begin by generating ideas (“idea generation”). Second, they develop their initial ideas further based on feedback (“idea development”). Finally, individuals evaluate ideas of others (“idea evaluation”). We draw from psychological and consumer behavior literature to: (1) identify barriers to human creativity that can emerge at each stage, and (2) propose conceptualizations for guiding principles of how AI input at each stage should optimally be designed to overcome these barriers.

Idea Generation

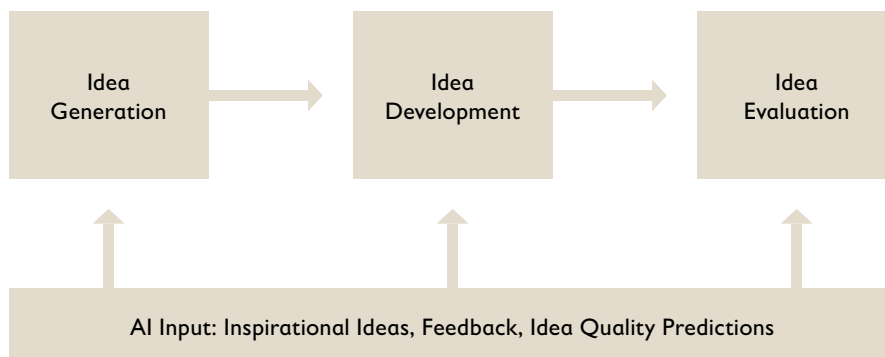
Typically, users of innovation platforms either see the ideas of others before they submit their own, or they see no input at all (if no prior ideas were submitted; Wooten & Ulrich, 2017). Both conditions can inhibit creative performance: Cognitive fixation on ideas of others has been documented on innovation platforms and represents a major constraint to creative performance (Hofstetter et al., 2020). However, the absence of any stimulation can lead to an overreliance on the individual’s own knowledge structures (Moreau & Dahl, 2005). AI tools can help by selecting or producing stimulus ideas that reduce this cognitive fixation.

Conceptualization

Particularly in the early stages of the creativity process, and when the goal is to create a high quantity of ideas, individuals search for ideas in their associative memory to recombine existing knowledge in novel ways (SIAM model; Nijstad & Stroebe, 2006). Therefore, creativity is critically dependent on the accessibility and flexible switching between knowledge structures from different categories (Nijstad et al., 2010).

One way to activate different knowledge structures is the presentation of already

Figure 1: Innovation Process Overview



Source: Own Illustration.



Source: © Adobe Stock.

Management Summary

Current developments in AI technology provide potentially powerful tools to foster idea generation, development, and evaluation on innovation platforms. The value of AI tools consists of automating idea generation, detecting similarities and usefulness, and supplying personalized and conversational input for users. The complexity of innovation contexts and the availability of data sources are limitations that firms seeking to implement AI tools need to consider.

existing ideas prior to idea generation. The effects of this strategy, however, are mixed. On the one hand, the presentation of the ideas of others can be helpful and cognitively stimulating (Paulus et al., 2013), because they activate knowledge structures that were inaccessible before. On the other hand, the presentation of ideas of others can have an adverse effect and lead to a fixation on the ideas already presented (Chrysikou & Weisberg, 2005). The mixed findings on whether others' ideas are stimulating or fixating suggest that it is not trivial which ideas to present for inspiration; for instance, showing words from different semantic categories as stimulating input can increase the diversity of generated ideas (Toubia & Netzer, 2017).

The main benefit of AI-generated stimulus ideas is that they can combine existing elements in novel ways resulting in diverse new ideas, and that they can produce these ideas on a large scale. In comparison to humans, AI is not biased by cognitive fixation on prior ideas—indeed, algorithms and AI are very efficient in exploring novel combinations of existing elements (Boden, 1998; Gobet

& Sala, 2019). Moreover, AI applications can produce many different novel ideas very quickly, such as the image generation model DALL-E 2, which produces multiple images based on user prompts (Ramesh et al., 2021).

Potential AI Applications and Caveats

AI-generated stimulus ideas can be used to inspire human creativity and reduce cognitive fixation on innovation platforms. Thereby, AI can either generate novel ideas, or customize the presentation of user-generated ideas on innovation platforms (e.g., showing highly dissimilar versus very similar ideas). Concretely, firms can develop AI tools that use topic modeling algorithms or language models that can select and generate stimulus ideas based on past suggestions.

One potential downside of AI ideas would be that users tend to fixate even more on AI ideas because they do not feel a social obligation to distance themselves from former ideas. Moreover, the quality and relatedness of the AI ideas would

need to be checked carefully. It is also not clear whether all users would appreciate AI-generated ideas as they might doubt the AI's ability to act creatively (e.g., Haslam, 2006).

Idea Development

Feedback and reward systems are important motivational factors on innovation platforms (Bayus, 2013; Hofstetter et al., 2018b). However, feedback is typically not provided to all users on innovation platforms, because it is time-consuming to produce (Crowdspring, 2020; Lundquist, 2017), and community feedback is attracted only by a small fraction of ideas (Dellarocas & Wood, 2008). This is problematic for users' creative performance because lacking feedback can undermine the effort and motivation to contribute more ideas (Beretta et al., 2018; Piezunka & Dahlander, 2019; Zhu et al., 2019).

AI-based feedback tools can help here. Conversational technologies enable automatized user interactions, and AI can personalize this conversation instead of sending a standardized response

(Hildebrand & Bergner, 2020; Puntoni et al., 2021). AI feedback in ideation can therefore provide direct, informational feedback to the ideas submitted by a particular user.

Conceptualization

In creative ideation, individuals tend to follow a path of least resistance (POLR), meaning they begin by developing ideas that they come up with first (i.e., easily accessible ideas) and then stop (Dahl & Moreau, 2002; Moreau & Dahl, 2005). Indeed, the best ideas emerge relatively late in the creativity process, and only if individuals are willing to leave the POLR are they likely to produce truly original outcomes (Lucas & Nordgren, 2015; Nijstad et al., 2010).

But additional motivation is generally needed to venture beyond the POLR. Particularly intrinsic motivation has long been known to influence the likelihood and intensity with which individuals engage in creative cognition (Amabile et al., 1996; Hennessey & Amabile, 2010). Important factors contributing to intrinsic motivation are a sense of competence (Deci & Ryan, 2000) and the related emerging sense of self-efficacy. Creative self-efficacy—described as an individual’s belief that they can produce notable creative results (Tierney & Farmer, 2002)—has been claimed as one of the most important contributors to creative engagement and self-motivated eagerness to make a discovery (Bandura, 1997).

However, lack of information about their own performance can inhibit users from experiencing creative self-efficacy and competence and undermines their willingness to continue with the task after having generated their first few ideas (i.e., they are less likely to leave the POLR). In contrast, being provided with personalized AI feedback that entails concrete suggestions should foster a sense of creative self-efficacy and

motivate the individual to produce more creative ideas.

Potential AI Applications and Caveats

Easily implementable tools to personalize feedback comprise the automatic screening of ideas for length and complexity of the wording (for text-based ideas) and giving feedback on how to simplify the wording. ML models can analyze ideas in terms of these formal quality criteria (Rhyne & Blohm, 2017). Automatized topic analysis (for text data) or similarity analysis (for image data) could also be used to inform users about the degree of novelty of their proposed idea in comparison to ideas already submitted by other users (e.g., “This color combination has already been suggested by 40% of other users”). Such real-time analyses of ideas and

the provision of customized feedback could significantly improve competence perceptions and motivation in investing more effort in the creative task.

However, a backfiring effect of personalized feedback may be that it suggests external control of the ideation process, thus reducing perceived competence and creative self-efficacy. The impression of receiving “controlling” feedback might be more pronounced for personalized feedback, as generic feedback could be more easily attributed to external factors like the platform design. Moreover, if feedback is provided too early in the process or too specialized, users might focus overly on their own initially generated ideas. In turn, they might even produce less diverse ideas and focus on their improvement instead of coming up with novel ideas (Nijstad et al., 2010). Therefore, the AI’s timing and conversational style are likely to be crucial for its beneficial effect.

Main Propositions

- 1 Users of innovation platforms suffer from limitations and cognitive biases along the innovation process.
- 2 AI-generated ideas and the customized presentation of ideas can reduce cognitive fixation if ideas are presented appropriately.
- 3 Conversational AI can provide personalized feedback to increase creative self-efficacy and motivation during idea development if individuals are willing to embrace the feedback.
- 4 Presenting meaningful cues for idea evaluation can help overcome biases against novel ideas if such cues are based on available data.

Idea Evaluation

One of the biggest challenges for companies in digital innovation is selecting one or a few out of many generated ideas (Blohm et al., 2011; Krufft et al., 2019). Screening out ideas is critical because adopting a bad idea—a type I error—is costly for a firm (Chandy et al., 2006; Goldenberg et al., 2001). However, missing blockbuster ideas—a type II error—constitutes a lost opportunity that could eventually prove fatal to the organization (Reinig et al., 2007).

Therefore, accurately evaluating ideas is crucial for innovation managers, who are greatly challenged by the sheer mass of ideas emerging from digital innovation. Consequently, managers often suffer from a cognitive overload and rely on superficial and inaccurate cues (Blohm et al., 2016). Examples are community-based ratings that are often driven by social mechanisms rather than objective idea quality (Chen et al., 2009; Hofstetter et

al., 2018a), information about the person who has produced the idea (Kruft et al., 2019; Magnusson et al., 2016), or superficial cues (e.g., length of the description) of the idea (Beretta, 2019). Even worse, managers may tend to rely on their “gut feeling” about an idea and an inherent bias against novelty. AI tools may help innovation managers make better evaluations by providing objective and informational cues they can rely on, thus reducing cognitive overload and biases against novel ideas.

Conceptualization

Evaluating ideas on innovation platforms is an evaluation problem under uncertainty (e.g., Tversky & Kahneman, 1974). Very novel ideas increase the uncertainty because they are by definition less familiar and therefore seen as less feasible, uncertain, and riskier (Boudreau et al., 2016; Girotra et al., 2010). This bias against new and preference for familiar ideas is termed *novelty aversion*, and it can result in the rejection of very novel ideas (Crisuolo et al., 2017; Eidelman et al., 2009).

Distraction–conflict theory (Baron, 1986) holds that people tend to narrow their attention to a few central cues when they suffer from cognitive overload (as is the case for the complex and highly uncertain evaluation of many novel ideas). In the absence of informational cues, individuals are likely to narrow their evaluation of an idea to their “gut feeling” (Baumeister et al., 2008) and are consequently more likely to reject highly novel ideas that they feel uncertain about (Mueller et al., 2014). Therefore, the main goal of AI tools in idea evaluation is to reduce cognitive overload and novelty aversion.

Potential AI applications and caveats

Potentially successful cues to reduce novelty aversion are providing clear

Lessons Learned

- 1 Managers are well-advised to embrace the potential of AI to reduce user biases and rethink one-size-fits-all designs of innovation platforms and challenges.
- 2 However, AI tools need to be carefully tailored to each innovation platform, its users, and in some cases the innovation problem.
- 3 Additionally, a realistic estimation of the quality and availability of data to first calibrate the AI tool is necessary.
- 4 Importantly, both user overdependence on and aversion against AI input can diminish the effectiveness of this human–AI approach to facilitate innovation.

and personalized rating instructions, pre-screening and displaying of similar ideas, and objective measures for the novelty and usefulness of an idea. Conversational AI could give rating tips that may be personalized if the AI detects that the rater systematically discounts ideas (using similarity detection and compa-

The main goal of AI tools in idea evaluation is to reduce cognitive overload and novelty aversion.

ring rating scores). The response would be a hint such as: “This idea is novel, do you think it can be feasible?” Moreover, pre-screening ideas may help facilitate comparisons of ideas by presenting similar ideas alongside each other, which may facilitate ratings and reduce cognitive overload (Banken et al., 2019; Klein & Garcia, 2015). Such an approach could also help to not contrast ‘extreme’ ideas with highly familiar ones, in which case users might be particularly adverse to novelty. Finally, AI tools may automatically

provide objective novelty and usefulness scores. Novelty scores could be developed by similarity detection; proxies for usefulness could be developed if information about successful solutions for similar innovation challenges is available (e.g., ideas rewarded in prior contests, rated favorably by users, or successfully implemented in the market). Showing AI pre-ratings would certainly reduce uncertainty and cognitive overload of raters, thus mitigating the risk of relying on inaccurate cues or failing to novelty bias (e.g., Riedl et al., 2013).

However, optimizing the presentation of ideas and their AI evaluations is a challenging task. For instance, showing many highly similar ideas next to each other may intensify rather than reduce novelty aversion. Moreover, individuals may differ in their adoption of AI cues and evaluations. For instance, experts might rather trust their own experience and intuition and could be less willing to rely on evaluation aids and AI input (Logg et al., 2019). Moreover, the calibration of the AI cues is critical: Novel ideas should not be promoted only because they are novel; instead, they should be balanced with cues that point to the idea’s usefulness. A final important caveat regarding this approach would be to make sure that the

AI tools can be trained on meaningful data to determine adequate usefulness ratings.

Conclusion, Limitations, and Outlook

Digital platforms have become key elements to foster external and internal innovation. This research discusses the use of AI tools to reduce systematic biases

in human creativity on such platforms, including cognitive fixation, PLOR, and novelty aversion. The stepwise integration of AI tools in idea generation, development, and evaluation can result in a novel human-machine approach in which humans and machines interact to achieve a joint creative performance.

However, developing meaningful AI models in the innovation context remains

challenging (Haefner et al., 2021). Firstly, the need for data is particularly important in these contexts, as challenges and generated ideas are often highly specific for the individual firm and innovation challenge (e.g., the generation of usefulness ratings would largely depend on a previous innovation challenge). Moreover, many problems require a deeper understanding and societal, organizational, and economic context, which is hard to grasp for

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AI tools. Secondly, managing the tradeoff between novelty and usefulness/feasibility is a task that requires a careful a-priori definition of the innovation challenge. Merely relying on pre-trained AI models will in most cases prove insufficient, requiring AI tools to be customized to each individual innovation challenge. Thirdly, even if a useful AI tool can be developed, novel human biases can diminish their usability: Both overdependence (e.g.,

a blind reliance on tools) and aversion against algorithmic input may decrease the effectiveness of tools on the user side (e.g., Carmon et al., 2019; Logg et al., 2019).

Overall, AI has a powerful potential to improve open innovation processes, but it has to be tailored to platforms and the users interacting with it. Following a generic innovation process, we offer a novel perspective that helps organizations to

systematically mitigate the behavioral biases that are central impediments to using these platforms and to effective ideation in general. Managers and policy makers can implement and test our suggestions and combine human with AI creativity to build more effective socio-technical systems—a theme that will gain in importance as AI and machine learning become increasingly integrated into decision-making processes. ■

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