Received: 17 October 2022 | Revised: 14 November 2023 | Accepted: 17 November 2023
DOI: 10.1111/caim.12580

RESEARCH ARTICLE

WILEY

Creativity and artificial intelligence: A multilevel perspective

Luca Grilli | **Mattia Pedota**

Department of Management, Economics and Industrial Engineering, Politecnico di Milano, Milan, Italy

Correspondence
Mattia Pedota, Politecnico di Milano, Department of Management, Economics and Industrial Engineering, Via Raffaele Lambruschini 4b, 20156, Milan, Italy.
Email: mattia.pedota@polimi.it

Funding information
Italian Ministry of University and Research (MUR)

Artificial intelligence is likely to revolutionize multiple aspects of organizational creativity. Through a multilevel theoretical lens, the present paper reviews the extant body of knowledge on creativity at individual, team and organizational levels, and draws a series of propositions on how the implementation of artificial intelligence may affect each level. Spanning cognitive, behavioural and psychological domains, our propositions aim at directing future research efforts on important creativity-related areas likely to be affected by artificial intelligence, including the trade-off between convergent and divergent thinking, the distribution of skills within groups, and the absorptive capacity of organizations.

KEYWORDS
artificial intelligence, creativity, group, knowledge, team

1 | INTRODUCTION

The purpose of this study is to investigate theoretically the impact of artificial intelligence (AI) on the multilevel declinations of organizational creativity. As AI encompasses a range of technologies including deep learning, natural language processing and image recognition, definitions of AI vary from specific and contextual (Kaplan & Haenlein, 2019) to general and intuitive (Goodfellow et al., 2018; Truong & Papagiannidis, 2022). Among the various definitions available, we adopt the one provided by Rai et al. (2019) for its robustness (Collins et al., 2021): 'the ability of a machine to perform cognitive functions that we associate with human minds, such as perceiving, reasoning, learning, interacting with the environment, problem solving, decision-making, and even demonstrating creativity' (p. iii). As for creativity, we define it as the capability of producing novel and effective ideas (Runco & Jaeger, 2012), which may eventually become inventions or innovations when implemented. The power to generate ideas with such characteristics has traditionally resided only in human minds. However, recent developments in deep learning have endowed even artificially intelligent systems with the capability of writing short stories, composing symphonies, proving mathematical theorems and even drawing works of art indistinguishable from those of famous painters (Dornis, 2020; Köbis & Mossink, 2021; Mazzone & Elgammal, 2019). Not only do these advancements warrant the eradication of the aforementioned assumption of exclusivity but they also require creativity and innovation scholars to rethink the complex nexus of relationships between the material and conceptual antecedents of organizational creativity (Amabile, 2020). While it is widely believed that AI is capable of changing the innovation process, there are many open questions about which process steps and types of innovation will be most affected by AI-based technologies. For instance, Bouschery et al. (2023) propose that 'transformer-based language models' such as GPT-3 have a positive impact on new product development (NPD) dynamics by assisting humans in tasks such as text summarization, customer sentiment analysis and new ideas generation, and in doing so constitute, together with human agency, a sort of 'hybrid intelligence'.

To make sense of this complexity and explore the multiple branchings of AI's implications, we here make an explicit focus on a single but fundamental antecedent of any innovation process, that is, creativity. In particular, we adhere to a multilevel conceptualization of organizational creativity (Woodman et al., 1993), the latter being defined as 'the creation of a valuable, useful new product, service, idea, procedure, or process by individuals working together in a complex social system' (p. 293). According to this framework, organizational creativity is the outcome of a series of nested interactions between individuals, groups and the organization itself. More specifically, the cognitive, psychological and behavioural traits of individuals interact with the structure, size and composition of the groups they constitute, which in turn shape and are shaped by organizational factors like climate, leadership style, financial resources, technological endowment and absorptive capacity. Levels interact bidirectionally, insofar as individuals form groups and organizations, while organizations exercise an array of contextual influences on groups and in turn individuals. Each level has attracted substantial research over the last few decades (Anderson et al., 2014; Mainemelis et al., 2015; McLean, 2005; Tesluk et al., 1997). Despite some minor inconsistencies (e.g. the effect of group heterogeneity on creativity), we already have a coherent picture of creativity-enhancing and creativity-depressing multilevel constructs and interactions.

However, we propose that AI may significantly change this picture. By enabling unprecedented retrieval and elaboration of data, AI reduces bounded rationality, helps decision makers overcome local search routines, supports the exploration of new problems and the generation of solutions, and provides new perspectives to frame extant ones (Bouschery et al., 2023; Haefner et al., 2021; Obschonka & Audretsch, 2020). These multiple enhancements in the quantity and quality of information available are most likely to bolster creativity at all levels, much like other creativity-support tools (Shneiderman, 2002, 2007). However, differently from most other tools, we argue that AI may also change the very way creativity is enacted at all levels, along with the relative importance of enabling factors and conditions.

In the present work, we reflect on the peculiarities of AI in the light of the creativity literature on each level, in an effort to provide theoretically based propositions on how AI may modify the way individuals, groups and organizations carry out their creative endeavours. Our contribution culminates in a research agenda aimed at guiding the exploration of the nascent intersection between AI and organizational creativity.

The remainder of the paper is organized as follows. Adopting a multilevel perspective, Section 2 provides an updated selection of the most relevant contributions on creativity at individual, group and organizational levels. Section 3 briefly reviews extant contributions on the intersection between AI and organizational creativity and draws on Section 2 to build our main arguments on the impact of AI on creativity at individual, group and organizational levels. Section 4 builds an agenda for future research. Some brief concluding remarks round off the paper.

2 | THE MULTILEVEL FOUNDATIONS OF ORGANIZATIONAL CREATIVITY

This section reviews the foundations of creativity at the individual, group and organizational levels. While we have no aspiration to offer an exhaustive review of this vast research field, we aim at giving an account of the most relevant contributions at all levels, as this will be instrumental to evaluating the impact of AI on creativity through a multilevel theoretical lens.

2.1 | The individual level

Organizations are concerts of individuals working in a coordinated way to achieve desired aims. Hence, any rigorous conceptualization of creativity in organizations must consider, to some extent, the individual dimension. Plenty of research has been conducted on the individual traits that facilitate or hinder the generation of creative ideas. While much of the earliest research focused on associations between biographical/personality characteristics and creative eminence (Barron & Harrington, 1981; Chambers, 1964; Singh, 1986), subsequent developments adopted cognitive and psychological perspectives to formulate falsifiable hypotheses, opening prolific research routes.

On the cognitive side, it is now well established that individual creativity rests on a combination of divergent and convergent thinking (Runco & Jaeger, 2012). The former is a multicomponent construct underlying idea generation (Guilford, 1984), whereas the latter denotes the ability to exploit knowledge and expertise to reach a single best answer, a key factor in selecting and retaining the most promising ideas (Cropley, 2006). Since knowledge and expertise are often domain-specific (Amabile, 1983), being creative in one domain does not necessarily imply being creative in any other. Furthermore, there is a trade-off between breadth and depth. On the one hand, spanning multiple domains allows individuals to add heterogeneous knowledge and techniques to their toolbox, increasing their proclivity toward original thinking (Taylor & Greve, 2006). On the other hand, depth in domain-specific knowledge and expertise endows individuals with more clarity and accuracy in the identification of knowledge components and relationships between them (Dane, 2010). A recent study exploiting the natural experiment given by the selective diffusion of mathematical knowledge following the Soviet collapse in 1989 showed that breadth is superior when the pace in the evolution of knowledge is slower, whereas depth and specialization triumph in faster-paced environments (Teodoridis et al., 2019). In both cases, however, the bulk of overall knowledge at one's disposal is generally too large to be managed as it is (Simon, 1991). Thus, knowledge elaboration toward creative solutions happens through heuristics, namely, automatisms and cognitive shortcuts rooted in the experiential and practical context where the individual operates (Lenat, 1982). The relevance of heuristics to the individual creative process is testified by their use as a basis to evaluate creative potential (Vessey & Mumford, 2012). Like knowledge and expertise, heuristics can be improved through training (Scott et al., 2004).

While the cognitive framing explains the individual antecedents and enablers of creative efforts, the psychological one sheds light on the individual drive toward creative accomplishments. Amabile (1983) proposed that intrinsic motivation, namely, a mixture of genuine passion and involvement in a given task, is positively associated with creativity, in contrast to motivation primarily stemming from external influence (e.g. rules, coercive commands and monetary rewards; see Angle, 1989). The proposed positive effect of intrinsic motivation on individual creativity has received considerable empirical support (Eisenberger & Aselage, 2009; Fischer et al., 2019; Zhang & Bartol, 2010). It is worth noting that a peculiar kind of extrinsic motivation, called synergistic, has also been proposed, and to some extent shown, to augment creativity (Amabile, 1993; Fischer et al., 2019). Rather than generating an exogenous drive toward creative accomplishments, synergistic external motivators corroborate the personal drive of the individual, by providing support and confirmation. Examples are public displays of appreciation or symbolic rewards. By consolidating one's sense of self-determination rather than undermining it, synergistic external motivators are particularly beneficial when intrinsic motivation is already high. In addition to motivation, individual perception of meaningfulness of one's own work (Rosso et al., 2010), affect (Amabile et al., 2005; Binnewies & Wörnlein, 2011) and self-efficacy (Bandura, 1997) have been suggested to enhance creativity synergically and dynamically as the individual makes progress toward creative accomplishments or fails constructively (Amabile & Pratt, 2016).

2.2 | The group level

Within organizations, human resources are usually arranged in groups (teams) devoted to specific projects, tasks or functions. Although small groups can be assumed as behaving like individuals, both in cognitive and psychological terms (Amabile, 1988), the factual presence of a multiplicity adds a layer of complexity. The presence of a group as an overarching structure tends to add (or subtract) something to (from) the simplistic aggregation of the creative potential of group members (Woodman et al., 1993).

Structurally, groups can be characterized mainly in terms of size and heterogeneity. Both features have been investigated in relation to creativity. On the one hand, the larger a group is, the more aggregated knowledge it can use as an input for the creative process (Hülsheger et al., 2009; Taylor & Greve, 2006). On the other hand, communication, coordination and conflict typically worsen as group size increases beyond a certain threshold (Becker & Murphy, 1992). This points to a curvilinear (inverted-U) relationship between group size and creative performance (Lee et al., 2015). While size corresponds to the number of group members, heterogeneity can be assessed according to multiple variables, including cognition, personality, culture and demographic profile. Based on the similarity-attraction principle, whereby people are attracted to others who are similar (Tsui & O'Reilly, 1989), some authors argue that heterogeneity tends to depress creativity through its negative impact on affect (Williams & O'Reilly, 1998). Conversely, others advance that heterogeneity enriches the diversity of knowledge at the group's disposal, boosting group creativity in a similar way to how knowledge in different domains stimulates individual creativity (Woodman et al., 1993). Despite the soundness of both theoretical rationales, the objective difficulty in operationalizing such a multifaceted concept and the likelihood of idiosyncrasies has generally led to mixed results (Van Knippenberg & Schippers, 2007). Still, some studies have managed to ascertain interesting effects under restrictive conditions, such as individual self-efficacy positively moderating the relationship between group heterogeneity and individual creativity (Shin et al., 2012).

Besides structure, internal group dynamics matter, including social interactions among group members as well as processes, techniques and heuristics, adopted in the collective creative process. If the group has a leader, the leadership style may affect the group's innovativeness, with transformational and participative leadership being more conducive to idea generation (Mumford et al., 2002). Moreover, the group leader's ties with other individuals and groups within and outside the organization improves the likelihood of success of the group's output (Elkins & Keller, 2003), which may in turn stimulate the creativity of the group (Mainemelis et al., 2015). Independently of the hierarchical structure, a collaborative and respectful climate among group members enhances creative behaviour through its positive effect on intrinsic motivation and relational information processing (Carmeli et al., 2015; Zhu et al., 2018), while a competitive climate relates positively to extrinsic motivation (Zhu et al., 2018). Finally, one should consider techniques and modes of interaction for group-level generation of creative solutions. Verbal brainstorming, the most iconic technique, has been shown to yield disappointing results, which tend to worsen as group size increases (Mullen et al., 1991). This is because it forces group members to manage a trade-off between talking and listening, incurring the risk of forgetting their own ideas or deeming them irrelevant after hearing others (Paulus & Kenworthy, 2019). It is however interesting to note that the effectiveness of brainstorming improves significantly when it happens electronically (DeRosa et al., 2007; Siau, 1995). Besides the technique used, the framing of the interaction is also relevant. For example, group members may ground the collective creative process on a random variation-selective retention principle (Simonton, 1999), whereby ideas are proposed and possibly retained only after evaluation, or through a dialectic process of creative synthesis (Harvey, 2014), implying the reconciliation of diverging ideas as a further route to novelty.

2.3 | The organizational level

The organization as a complex of resources, capabilities, routines and (potentially hierarchically ordered) interactions affects creativity in multiple ways. A substantial share of research in this area focuses on the successful implementation of creative ideas (i.e. innovation), which indeed features important antecedents at the organizational and interorganizational level. However, since our focus is organizational creativity as a microfoundation for innovation (Anderson et al., 2014), rather than innovation itself, we will concentrate specifically on the organizational enablers and inhibitors of creativity, leaving the implementation challenge aside.

A first relevant class of enablers includes the tangible and intangible creativity-relevant resources that the organization incorporates. At the highest level of abstraction, creativity is about knowledge recombination. Thus, the absorptive capacity of a company (Cohen & Levinthal, 1990), defined as its ability to recognize the value of new knowledge, assimilate it, and apply it to commercial ends, fosters creativity in non-trivial ways. The notion of absorptive capacity clarifies that the ability to recognize the value of new knowledge depends on the current stock of knowledge. This has two important implications. First, it entails that organizations with little absorptive capacity may be denied both knowledge and learning, depriving employees of relevant building blocks for creativity. Second, it highlights path-dependent dynamics whereby organizations rooted in domain-specific stocks of knowledge may be unable to recognize the value of knowledge of a different kind, with implications on the learning pathway of their employees and consequently on the type of creativity they will enact. Besides knowledge, more tangible resources like infrastructure, equipment and financial means have been acknowledged to foster creativity, mainly by releasing material constraints and revealing new search and recombination possibilities (Amabile, 1988; Ford, 1996; Woodman et al., 1993).

A second relevant area lies in the management of the organization. By channelling a vision and orchestrating interactions within the organization, leaders exert a clear impact on creativity. The effectiveness of leaders' support is moderated by their ability to evaluate ideas, their communication skills in the focal context, and the perceptions of employees about them. These factors rest on leaders' own technical skills and creative thinking capabilities (Mumford et al., 2002, 2003), their tendency to monitor employees without oppressing them (Amabile et al., 2004; Oldham & Cummings, 1996), and their ability to provide appropriate feedbacks (Zhou, 2008) and goals (Litchfield, 2008). While the role of leaders as facilitators is arguably the most widespread, Mainemelis et al. (2015) recognize that leaders may also act as promoters of their own vision and integrators of heterogeneous contributions.

Lastly, the role of high-level constructs like organizational culture and climate should also be acknowledged. The former denotes the complex of commonly held norms, beliefs, interpretative schemes and axiological structures within the organization, whereas the latter refers to the emerging behavioural patterns and practices (McLean, 2005). Not surprisingly, norms and practices that limit and control the behaviour of employees tend to constrain their creative potential. Organizations based on a strict hierarchy, tight deadlines and a culture for blind obedience are rather unfavourable environments for creativity (Angle, 1989; Kanter, 1983). Perhaps less obvious is the fact that even too loose deadlines and too little pressure may impede creativity, suggesting the need to strike an optimal balance between stimulation and freedom of expression (Amabile, 1988). Based on an extensive literature review, Tesluk et al. (1997) propose that both the standards for creativity and the means to achieve them should be emphasized and made known to employees, through the intraorganizational diffusion of a culture of knowledge sharing, openness and healthy risk-taking. Consistently with other contributions (Amabile, 1983, 1988), they also suggest that organizations should provide employees with both material and socioemotional support with the aim of maximizing their intrinsic motivation toward creativity. By highlighting freedom, autonomy, encouragement and resource availability, a further review by McLean (2005) endorses most of these assertions from a different angle. A last crucial factor related to encouragement and risk-taking is psychological safety: creatively successful employees should be comfortable with failure, as any creative endeavour entails risk and uncertainty (Edmondson, 1999, 2018). This may be partly contingent on organizational climate, especially in small organizations and in the presence of a strong corporate culture (Newman et al., 2017). Norms prioritizing reliability over novelty are likely to discourage creative efforts, as does the practice of penalizing unsuccessful attempts, by acting on employees' receptivity beliefs (Ford, 1996).

3 | THE MULTILEVEL IMPLICATIONS OF AI[1]

Material artefacts, especially technological ones, are a fundamental interface between employees and their actions (Glăveanu, 2020; Tanggaard et al., 2016). Thus, they are key ingredients in the multilevel expressions of organizational creativity. The role of information and communication technologies in facilitating acquisition and dissemination of knowledge is widely acknowledged to foster collective creativity, both in general (Brennan & Dooley, 2005; Dewett, 2003) and through specific devices like virtual teams (Chamakiotis et al., 2013), electronic brainstorming (Siau, 1995) and suggestion system technologies (Fairbank & Williams, 2001). Technological artefacts also support individual creativity by providing alternative visualization mechanisms and facilitating storage and manipulation of information, as testified by the ubiquity of word-processing, computer-aided design and computational software (Shneiderman, 2002, 2007). The role of materiality and technology in the multilevel expressions of creativity has recently seen a surge of interest, with the emergence of the sociocultural perspective on creativity (Glăveanu, 2020) and the conceptualization of domain-driven creativity enhancement (Pedota & Piscitello, 2022).

Concurrently, AI has made substantial progress, enabling an increasing number of applications. Thanks to its ability to extract valuable information from big data (Ng, 2017), AI reduces bounded rationality (Simon, 1991) and helps decision makers overcome local search routines (Gavetti & Levinthal, 2000; Katila & Ahuja, 2002). As a result, AI has been suggested to increase the amount of information available, identify and evaluate more exploratory ideas, enable the recognition of new opportunities, and even create entirely new ones (Bouschery et al., 2023; Haefner et al., 2021). It has also been proposed to support knowledge management, accelerate knowledge creation and enable new ways to investigate existing knowledge (Botega & da Silva, 2020; Pietronudo et al., 2022). By automating routine tasks and freeing human time and energy, as well as unveiling patterns in large amounts of data, AI has been shown to increase organizational creativity and, as a result, organizational performance (Mikalef & Gupta, 2021). AI creativity is increasingly leveraged also in organizational management (Ferràs-Hernández, 2018), where the union of human and AI creativity is expected to generate powerful synergies (Paesano, 2021). Such synergies are particularly relevant, as the potential of AI as a lone creator seems much weaker than its potential as an augmenter of human creativity (Anantrasirichai & Bull, 2021). This is partly because, despite its generative power, AI is incapable of embedding human traits like emotionality in its output, and consumers seem to be sensitive to cultural proximity to humanness (Tubadji et al., 2021). AI is also projected to shape the very heart of entrepreneurial activity in the near future (Obschonka & Audretsch, 2020; Townsend & Hunt, 2019), due to its generative power and far-reaching implications in foundational fields like economics (Acemoglu & Restrepo, 2019), innovation (Aghion et al., 2018), and psychology (Kosinski et al., 2016).

Hence, we argue that AI is not an ordinary technological artefact interacting with human creativity through known channels. The unique properties of AI in terms of autonomy and generativity make it a game-changing material agency, not only on its own but also and especially in synergy with humans. While the articles mentioned above, among others, have started to explore the peculiarities of AI in relation to human creativity, we align with Amabile (2020) in advancing the need for theoretical and empirical contributions in this regard. In the following subsections, we build on the multilevel lens delineated in the previous section to advance a series of propositions on how AI may re-shape the individual, group and organizational determinants of creativity.

3.1 | The individual level

The traditional view highlighted in the previous section frames individual creativity as the outcome of a series of biographical, cognitive, psychological and behavioural characteristic of a human being, interacting with path-dependent processes of knowledge and expertise accumulation. Here, the role of technological artefacts is currently limited to their material presence in the sociocultural spectrum of the individual (Glăveanu, 2020), their properties as creativity support tools (Shneiderman, 2002, 2007) and their ability to expand the domain where creative activities take place with new symbols, procedures and heuristics (Pedota & Piscitello, 2022). The advent of AI can overturn this anthropocentric view. We propose that AI could not simply act as a creativity-enhancing tool or a creativity-shaping instantiation of materiality in the spectrum of a human being. AIs can become *the very creators*, alongside individuals. This implies that novel and effective ideas (Runco & Jaeger, 2012) may arise not only from an individual (possibly) aided by technological artefacts but also from a technological artefact (i.e. the AI) (possibly) aided by an individual. This difference does not merely concern the degree of paternity over creative endeavours. From a teleological perspective, creative solutions may well be regarded as the outcome of a symbiotic interaction between an AI and an individual, where the identification of a protagonist is of little interest. Still, we claim that this very mechanism could have substantial implications on the individual determinants of creativity, in both quantitative and qualitative terms.

From a cognitive viewpoint, we argue that AI is likely to change the relative importance of convergent thinking versus divergent thinking. On the one hand, the power of AI to retrieve and elaborate data may reduce the importance of being an expert in the domain where the creative activity takes place. Knowledge and expertise in the focal domain may still be relevant to provide the AI with the right direction of exploration, as well as evaluate and implement the range of creative solutions offered by the AI. However, the AI-driven surge in high-quality information, as well as the speed of obtaining it, is largely a substitute for the previously indispensable human research informed by a lifetime of knowledge accumulation. In this vein, following Carr's (2003, 2004) seminal contributions and subsequent literature on the commoditization of information technology (IT; e.g. Abonamah et al., 2021; Bronkhorst et al., 2019; Neirotti & Paolucci, 2007), AI may increasingly turn convergent thinking into a kind of 'commodity', providing less (strategic) differentiation between users.

While convergent thinking could be increasingly performed by material agency, as the latter becomes more widespread and progressively available to everyone (thanks to AI), the importance of convergent thinking in the creation of new ideas will diminish, thereby making divergent thinking much more relevant for a matter of comparative advantage. In fact, AIs can themselves come up with radical solutions, but such radicalness is often just the outcome of a different thought process. For instance, the AI-powered generation of alternative fashion designs based on a given set of parameters benefits from a combination of computational power and freedom from traditional heuristics. The outcome is novel and different from what human minds typically conceive, the main reason being that the latter suffer from bounded rationality (Simon, 1991) and find themselves tied to heuristics entrenched in consolidated bodies of knowledge and practice (Lenat, 1982). Human heuristics can prove to be a limitation to creativity especially after a technology-driven domain extension, as in the case of glass designers being slow to adapt to the new geometrical configurations enabled by additive manufacturing (Pedota & Piscitello, 2022). Not only does AI constitute a technology-driven domain extension itself but it also provides a heuristics-free elaboration process to exploit domain extensions in general. However, even with unsupervised learning, the creativity enacted by AIs is confined to specific tasks and ensembles of data, whereas human creativity is not. While AIs regularly outperform humans in the originality of solutions produced within a certain perimeter (e.g. the design of a fashion item, or the cleverness of a chess move), they cannot readily and flexibly combine knowledge from multiple, distant (and ex-ante) unrelated domains when the opportunity arises as a purely unpredictable flash of genius. As a matter of fact, serendipity, which is often an important ingredient of many creative discoveries and acts (e.g. Murayama et al., 2015; Tan & Tatsumura, 2015), is usually enacted by the encounter of very distant and 'divergent' domains (Kennedy et al., 2022). Although divergent thinking could be aided by IT (e.g. Campos & Figueiredo, 2002) and AI (see e.g. the recent survey on serendipity in recommender systems by Fu et al., 2023; or the 'AI-augmented double diamond framework' proposed by Bouschery et al., 2023), in its extreme form, it is likely to remain a prerogative of human agency: as Kennedy et al. (2022) put it talking about music listeners, 'perhaps the most divergent suggestions are those created by real people making playlists and not algorithms' (p. 3). Hence, humans should rely even more on their capability of thinking outside the box and combining distant pieces of knowledge, first because AIs cannot do it as proficiently, and second because AIs carry out most of the remaining subtasks in circumscribed creative endeavours (e.g. data gathering and elaboration), freeing human time and energy.

Both AIs and humans are capable of acquiring and elaborating knowledge through both convergent and divergent thinking, but with relevant differences. In the realm of convergence, where the objective is unambiguous and pre-specified, AI and humans may even reach qualitatively similar outcomes, but the former usually do so much more effectively. In the realm of divergence, AI still has a comparative advantage in the sheer generation of multiple solutions (e.g. generative design), but it does so in a circumscribed perimeter; on the contrary, humans can consciously select and recombine knowledge from unlimitedly distant domains, despite not having the computational power to generate countless solutions. Turning back to the art example, it is easy to observe that knowledge of the style of Van Gogh, as well as the convergent thinking to imitate it, become redundant when a well-trained AI can do it almost perfectly. Instead, the divergent thinking to add a final touch to a Van Gogh-based work of art becomes a valuable creative finesse, which is likely to remain a prerogative of human agencies. Even when blending the style of two (or more) different artists to create something entirely new, the AI still acts within a pre-specified perimeter, to which human divergent thinking can add significant value. More specifically, while AIs may produce a work of art reflecting a mixture of Van Gogh and Picasso styles, a human may select the most ingenious style to complement a Van Gogh-based work of art a posteriori among a much wider sample, which includes knowledge coming from domains other than arts, ranging from close areas like interior design and architecture, to distant ones like geology and aerospace (or anything else that can be represented visually). Thus, we put forward:

> **Proposition 1.** In the realm of individual creativity, AI will increase the relevance of divergent thinking relative to convergent thinking in the creative process.

3.2 | The group level

As groups are collections of individuals, the root of the implications of AI on creativity at the group level is the same as the one underlying the individual level. However, the presence of a multiplicity of closely interacting individuals brings forward additional emerging properties. Individuals derive creative solutions through knowledge recombination, guided by cognitive strategies and heuristics for idea generation, selection and retention. A group context can be considered an extension of this framework, where the knowledge to be recombined resides in the minds of different subjects, and the strategies and heuristics for idea generation, selection and retention cross individual boundaries. For instance, while an individual may rely on analogical thinking to develop connections between different knowledge domains (Bonnardel & Marmèche, 2004; Dahl & Moreau, 2002), a group may rely on dynamic collective processes such as random variation-selective retention (Simonton, 1999) or creative synthesis (Harvey, 2014), possibly facilitated by techniques like electronic brainstorming (DeRosa et al., 2007; Siau, 1995). In this respect, rather than a tool facilitating group level interactions as in the case of online platforms, AI may well be regarded as an added group member, with a series of game-changing characteristics.

While there is no definite consensus on whether (and which form of) heterogeneity boosts group creativity (Van Knippenberg & Schippers, 2007; Williams & O'Reilly, 1998; Woodman et al., 1993), we argue that heterogeneity in the dimension of AI expertise will require closer attention in the age of AI. Besides the obvious observation that (at least) a group member with AI expertise is needed to effectively deploy AI for creative tasks, it is difficult to a priori theorize on the optimal distribution of AI expertise within a group (as we outline in the last section). However, we do propose that a certain level of heterogeneity in AI expertise is likely to be beneficial within a group context.[2]

When AI is regularly used as a tool for creative tasks, we suggest that AI expertise is a crucial property that radically changes the way humans approach AIs and collaborate with them in the pursuit of creative tasks. An AI expert is likely to approach the AI with clearer information on its limits and biases, and with a clearer picture of the nature of its creative potential. For example, consider the recently released Open AI chatbot named ChatGPT (based on the GPT model): while a layman may approach it as a digital oracle that (only) occasionally gives incorrect information, or maybe as a free-form source of inputs, an expert is likely to grasp the fact that the underlying generative process is based on mere textual prediction. This gives the expert additional intuitions to contextualize ChatGPT's output. For example, the expert is likely to know that ChatGPT is inherently less reliable in solving complex mathematical problems than in performing textual manipulation. Even in less clear-cut cases, we suggest that experts tend to approach the AI with a critical mindset, by contextualizing the generated insights according to their intuition on the nature and the reliability of the underlying generative process. This is likely to prime the response of the expert along the dimension of acceptance/rejection and/or contextualization of the AI-generated output, steering the creative dialogue in a narrow direction. Conversely, laymen's focus is likely to be entirely on the AI-generated output as it is, prompting its use as a ladder for further (free-form) creative elaborations.

In this regard, we posit that if it is true, as Bouschery et al. (2023) emphasize, that 'such technology should not be trusted and used blindly' (p. 150), approaching the AI-generated output without an expert framing could significantly increase the risk of using false, misleading and/or inappropriate AI-generated content as a baseline brick for the group's creative endeavours. Furthermore, an expert framing is needed not only to contextualize the output ex post but also to optimize its attainment ex ante (e.g. by fine-tuning the AI algorithms). At the same time, approaching the AI-generated output exclusively with an expert framing is likely to make the collective creative dialogue unidimensional, by shifting the group's attention on the technical dimension of the generative process rather than the heuristic potential of the AI-generated output. Thus, we advance that heterogeneity in the group members' AI expertise will enhance the complementarity between AI and human creativity (possibly in a curvilinear manner).

Provided that the AI expertise and convergent thinking in the group are enough to cement the link between the AI and the rest of the members, we claim that divergent thinking, also (perhaps especially) at the group level, is the best complement for AI capabilities. We maintain that this holds at any point in the continuum between a linear and an erratic creative process (though, as argued below, probably to different extents). If group members stick to a linear creative process with clear and distinct idea generation and idea evaluation phases, the AI may be helpful in both. If the creative task consists in drawing a work of art, a well-trained AI may do its own initial draft in the idea generation phase,[3] which then acts as an input for further ideas by other group members, possibly culminating in subsequent AI iterations (perhaps with modified or adjusted parameters). In the idea evaluation phase, the AI may contribute by matching the ideas generated previously with a set of successful works of art, thereby providing an estimate of the probability of success of each idea. At the opposite end of the spectrum lies a creative process where ideas are continuously generated, assessed against each other and synthetized. In the example above, this would amount to a continuous adaptation of AI parameters based on concurrent generation and evaluation of ideas by human peers.

In both cases, provided that human insights can be translated into AI inputs and vice versa with little loss of information, we advance that human divergent thinking may constitute the best complement for the AI also at the group level, with a small caveat. The reasons that we put forward for the increased relative value of divergent thinking for individual creativity have even more relevance for group creativity. First, a group-level creative task typically entails a higher density of convergence-based subtasks relative to data gathering, cleaning and processing, as well as basic knowledge production and categorization. The AI may easily take care of all these mechanical, brute-force subtasks with higher proficiency and efficiency, thus freeing time and energy for all group members. Second, the AI still acts within a circumscribed perimeter both in its convergence-based (evaluation of the probability of success in the example above) and its divergence-based subtasks (the generation of initial drafts in the example above). When the objective is producing creative output, both these subtasks benefit from the ability to cross the boundaries of the perimeter, which requires human divergent thinking. In a group context, the divergent capabilities of members tend to enhance and build on each other, which makes them even more valuable as a complement for AI.

However, it is worth highlighting that, in a group context, AI adds the complications of machine-to-machine and machine-to-human interactions to the traditional layer of human-to-human relationships. To the extent that AI can not only provide inputs for new idea generation but also new ideas themselves, it becomes essential to ensure that the flow of new AI-generated ideas enters smoothly into the creative process of the whole group. While, as argued above, this constitutes a great opportunity, it may also induce a key weakness. Not only will group members have to align their intuition and agree about the ideas worth pursuing, but they will also have to concur on which inputs to feed the AI with, as well as on the interpretation of its output and its prospective integration with other creative inputs. In the presence of a high level of divergent thinking, this is likely to augment the potential for conflict and make creative synthesis more difficult, ultimately slowing down the creative process. We expect this drawback to be more prominent the less structured the creative process is: having a streamlined creative process with clear-cut phases and agreed upon criteria for interacting with the AI and rejecting/advancing ideas may reduce the scope for conflict and facilitate the synthesis of diverging ideas. Relatedly, a positive climate and effective mechanisms for communication are likely to become even more important (Carmeli et al., 2015; Zhu et al., 2018). Thus, we posit:

> **Proposition 2a.** The complementarity between AI and human creativity in a group context will benefit from a certain level of heterogeneity in the AI expertise of the group members.

> **Proposition 2b.** With AI, the relative value of human divergent thinking for group creativity will increase in both linear and erratic creative processes. However, linear creative processes have the added benefit of streamlining the (potentially complex) human-machine interaction and reducing the scope for conflict.

3.3 | The organizational level

Building on Cohen and Levinthal (1990), and using their own terminology (p. 132), we advance the idea that AI can act as an important 'receptor' of the external environment for the organization, enabling the sourcing of a wider variety of inputs. Traditionally, this role should be performed by individuals with a diverse knowledge base. Having a heterogeneous knowledge base is essential for recognizing the value of as much external knowledge as possible. At the same time, for effective absorption, receptors should be able to transmit the acquired knowledge to the rest of the employees quickly and effectively. To this end, there should be optimal communication mechanisms and little cognitive distance between receptors and other employees, which requires homogeneity in the knowledge base. This creates a trade-off between outward- and inward-looking absorptive capacity (Cohen & Levinthal, 1990, p.133): uniqueness in the knowledge base of receptors may facilitate recognition and assimilation of knowledge from outside, but it may also impede internal knowledge transfer (Szulanski, 1996), elaboration and exploitation, with a detrimental impact on realized absorptive capacity (Zahra & George, 2002). In this respect, AI brings the advantage of enabling fluid and bias-free scanning of the external environment. Unlike human receptors, AIs are not constrained by their bounded rationality, prior knowledge and cognitive biases in their scanning efforts. Thus, rather than channelling their vision into predefined epistemological trajectories, they have an inherently larger span of attention. This greatly benefits the potential for outward-looking absorptive capacity. However, AI does not provide insights in forms that humans can readily interpret. AI typically gathers external knowledge in the form of raw data, necessitating AI-specialized personnel to act as translators turning such data into information to be diffused to the rest of the organization.

From a network perspective, we put forward the idea that an ideal structure for information dissemination and knowledge creation within the organization should involve a combination of strong ties built among the AIs (receptors) and AI-specialized personnel (translators), and weak ties between this core and the rest of employees. Network structure plays an important role in relation to absorptive capacity (Todorova & Durisin, 2007). Both strong and weak ties have been shown to be potentially beneficial to knowledge processes, depending on the kind of process and the level of knowledge complexity (Hansen, 1999). In particular, while strong ties are beneficial for processing complex knowledge, weak ties are useful as bridges between different parts of the organizational network, enabling the flow of novel information (Granovetter, 1973). While some characteristics of strong ties, notably empathy and emotional support, do not apply to the interaction between humans and AIs, most of them do. Having a common language, a shared context and a high frequency of interaction (i.e. strong ties) with AIs enable AI-specialized personnel to maximize the effectiveness of the AIs as receptors (through ad hoc programming), concurrently maximizing the effectiveness of the AI-specialized employees as translators. At the same time, having a multitude of weak ties between the AI-specialized personnel and the rest of the employees maximizes the likelihood of diffusion of the knowledge absorbed by AIs in the organization.

Furthermore, thanks to its raw computational power, AI can gather a much higher volume of information than human receptors, dramatically extending the creative potential of the organization. While the value of inputs from customers, suppliers and other key stakeholders is certainly well-acknowledged in the literature (e.g. von Hippel, 2006), AI may change the ability of the organization to create and exploit algorithms and neural networks to propose new unforeseen combinations and creative solutions intercepting consumers' preferences more effectively (Kittur et al., 2019). In this respect, also in combination with other advanced digital and automation technologies (e.g. 3D printing), AI can greatly enlarge customization possibilities and provide consumers with unique items tailored to their needs. The ability to nurture deep learning processes with data and obtain constant algorithmic improvements throughout time will not only streamline existing production processes and facilitate the search for quicker solutions to extant problems (Sherry & Thompson, 2021) but it will also augment the potential for consumers' profilization (see the recent campaign by Ferrero with 'Unique Nutella'). In other words, AI increases the potential for the absorptive capacity of both solution knowledge and need knowledge (Schweisfurth & Raasch, 2018). At the same time, however, the AI receptors are likely to require strong ties with AI-specialized personnel to make the most out of such expanded possibilities. Data gathered from customers, suppliers and other stakeholders need to be contextualized according to expected trends and business priorities (e.g. cost reduction, differentiation and/or dynamic efficiency). Strong ties with AI-specialized personnel enable the framing of such data as additional inputs for the synergistic human-AI creative process, rather than generic ingredients for operational efficiency or mass customization. Concurrently, weak ties between the 'AI core' and the other employees enable a quick flow of up-to-date information (e.g. on consumer trends), stimulating creativity in the whole organization.

Proposition 3a. AI can function as a powerful and peculiar 'receptor' of the organization, with a high potential for outward-looking absorptive capacity. Alongside AI receptors, AI-specialized employees acting as 'translators' are needed to preserve inward-looking absorptive capacity.

Proposition 3b. Firms' creativity benefits from having strong ties between AIs (receptors) and AI-specialized personnel (translators) and weak ties between this 'AI core' and the rest of the employees.

4 | AGENDA FOR FUTURE RESEARCH

The five propositions advanced in this piece are far from definite. Quite the opposite, they are primarily meant to stimulate and steer future theoretical and empirical inquiries in directions that could have important implications from both scholarly and managerial perspectives. One of such directions, which is transversal to all three levels of analysis, is the role of AI expertise. At all levels, AI expertise performs the crucial function of mediating between the creativity of employees and the creativity of AIs. At the individual level, AI expertise enables a more effective interaction between the employee and the AI, both in terms of pre-programming and ex post interpretation of AI-generated output. At the group level, a distribution dilemma emerges: while AI expertise is certainly needed for effective AI deployment, how many AI experts are needed to optimize the pursuit of creative endeavours is a big question mark. Similarly, at the organizational level, AI expertise is needed to perform the 'translator' function, but it is not clear how many translators are too many, and what is the level of AI expertise needed by the other employees for them to be receptive to the (translated) AI-generated insights.

In general (i.e. without reference to a specific level of analysis), AI expertise plays a key role in the training phase of the AI. This phase is crucial, as it may induce persisting biases (Sturm et al., 2021). Incorrectly training an AI has long-lasting consequences on the type of problems the AI will focus on, as well as the range of solutions it will identify.[4] This, in turn, has implications on what individuals making use of it will regard as creative and employ as an input for their own generative processes. Giving a solid foundation to AI creativity requires AI expertise, as well as knowledge of what the AI is meant for in a given organizational setting. Thus, appropriate AI training should be embedded in a feedback loop whereby organizational objectives set the stage for AI training (top-down), and AI-driven outcomes spur a continuous reevaluation of AI training (bottom-up), aimed at spotting potential biases and adjusting algorithms accordingly. Research is needed on the role and predominance of top-down directives versus bottom-up feedbacks in this bidirectional process, as well as on the dynamics of interaction between the individual, the group and the organizational levels in affecting AI training.

At the individual level, AI expertise is needed to provide appropriate inputs, reprogram and adjust subsets of software as needed, understand and react to malfunctioning, and interpret output accordingly. This is far from implying that (all) individuals will have to become experts in machine learning to exploit AI creativity. In many cases, AI-based software can be treated as an outsourceable commodity, which can be designed even for completely untrained people. Still, we claim that a basic level of understanding of the way AI functions and its language, along with the convergent thinking to use it effectively, may become, if not a requirement, a significant benefit in the pursuit of creative endeavours. Even with the most basic, non-customizable software, knowing how the AI reasons may give the human operator an edge in the iterative optimization of the software's parameters, as well as the correct interpretation (and thereby exploitation) of its output (of course, this becomes more relevant as the complexity and customizability of the software increases). Thus, a complete lack of AI expertise may impair the ability to benefit from the AI, either directly (e.g. small software adjustments) or indirectly (e.g. acquaintance with AI reasoning). However, too much AI expertise may constrain the perspective of the individual approaching the AI within a narrow technical framing, impeding the recognition of potentially valuable creative hints and insights. Thus, the optimal degree of AI expertise to maximize the complementarity between human and AI creativity at the individual level should be the object of future research efforts.

At the group level, in principle, every additional piece of knowledge brought on board by group members is beneficial to group creativity (Hülsheger et al., 2009; Taylor & Greve, 2006). As for groups featuring AI, for the same reasons holding at the individual level, a minimum level of AI expertise is beneficial.[5] However, the group level opens interesting questions as to the distribution of such expertise among members. There is in fact a key difference between AI expertise and other pieces of knowledge with respect to their ability to foster collective creativity. The value of knowledge and expertise in a group context generally lies in added recombinatory potential: the more knowledge members possess, and the more diverse it is, the higher the number of ways in which it can be combined, following group-level interactions. Instead, outside of specific domains (e.g. computer science), AI expertise does not have recombinatory value. It serves mostly as an interface between the AI and the rest of the group members. Thus, its value is derivative. Moreover, whether recombinable knowledge resides in few or many group members makes a difference only insofar as intra-group mechanisms for communicating and sharing insights may work more (or less) effectively than individual mechanisms of recombination. Instead, the optimal level of concentration or dispersion of AI expertise within a group relates to the trade-off between bridging the gap with AI creativity (through AI expertise) and complementing it (through heterogeneity in knowledge and expertise). As for the former, what matters is the ability to translate human creative inputs into parameters and specifications interpretable by the AI and vice versa. To this end, as in the case of expressive languages, the benefits of increasing the number of 'translators' within the group are likely to incur diminishing marginal returns, to the point that one individual is often enough. Thus, we suggest that one (or very few) strong expert(s) in machine learning per group could be sufficient to act as a joining link between the AI and the rest of the group. However, a basic level of AI expertise may be beneficial on the part of every group member, for two interrelated reasons. First, reaching a minimum threshold of expertise facilitates comprehension and communication among group members, especially with the AI expert(s). A certain area of commonality in the knowledge base is essential to ensure smooth knowledge transfer (Szulanski, 1996). Second, being well-versed in the same knowledge domain may reduce cognitive distance and promote positive affect, also due to the similarity-attraction principle (Tsui & O'Reilly, 1989; Williams & O'Reilly, 1998). Hence, while having one or few 'translator' has the benefit of efficiency (i.e. maximizing knowledge heterogeneity with only a minimal loss in the quality of the translation), a more equal distribution of AI expertise may enhance the cognitive and emotional drivers of creative endeavours (e.g. knowledge transfer, cognitive distance and positive effect). While we have previously argued that the extremes are probably suboptimal (i.e. a certain degree of heterogeneity in AI expertise is likely to be beneficial), dedicated empirical inquiries are needed to understand more precisely how much heterogeneity is needed and how AI expertise should be distributed within groups.

At the organizational level, we have argued that the AI may act as a powerful receptor of the organization, with the advantage of largely bypassing the problems of cognitive distance and bounded rationality. However, it has the disadvantage of providing insights that are not always readily interpretable and easily transferrable. We have suggested that this requires ad hoc AI experts (translators) that make the AI-generated insights accessible to all the employees, and we have proposed a combination of strong and weak ties to strike a balance between AI-human synergies and knowledge diffusion. However, research is needed on the exact role and distribution of such AI experts within the organization. First, future research should determine how far the involvement between (AI) receptors and (human) translators should go. While a weak human involvement would imply a perspective with less human biases, a stronger involvement may make the process potentially more effective (at the cost of an increased risk of bias). Second, future research should investigate how many translators are needed and how centralized the translating function should be. Various AI solutions could be deployed to monitor different aspects of the external environment: should each AI solution have a dedicated AI expert acting as a translator, or should there be a unique core of translators (linked by strong ties) aimed at finding business value in all AI-generated insights and diffusing them within the organization? Is there any need for intermediating roles? Should the technical interpretation of the AI-generated insights be decoupled from the identification of business value in them? Is a basic level of AI expertise from all employees a necessary condition for effective diffusion of AI-generated insights or, provided that translators are effective, is it (partially or completely) superfluous (if not counterproductive, given its backlash on heterogeneity)? What types of leadership styles are most instrumental in making the aforementioned different arrangements of AI-driven absorptive capacity effective? These are only some of the questions that future theoretical and empirical works could address.

Future research should also empirically deepen and test our (admittedly general) propositions on the increased value of divergent thinking in both individual and group contexts (Propositions 1 and 2b). As AIs free human time and energy from routinary tasks and perform convergent thinking-based subtasks comparatively more effectively, we have proposed that human divergent thinking goes up in relevance. However, the contingencies that limit or enhance this effect (e.g. the role of different industrial domains and organizational contexts) still need to be unveiled, as well as the repercussions that a different weight in the creative process of the two components of thinking may exert on the meaningfulness of one's own work and on individuals' motivations to be creative. Furthermore, while AIs excel at convergent thinking-based tasks, they are increasingly capable of performing divergent thinking-based tasks as well, as testified by the ongoing progress in generative AI. Thus, we also encourage further research on the relationship between human and artificial divergent thinking. Unlike humans, who are characterized by different thinking styles and face opportunity costs in specializing in different knowledge domains, AIs can be programmed to perform any task at a relatively low cost. Thus, even if they have a comparative advantage in convergent thinking, they can easily be deployed also to augment humans in their divergent thinking-based tasks. However, research is needed on the dynamics of this augmentation. If employees were instructed to make a free use of AI for subtasks requiring divergent thinking, both augmentation due to operative complementarities and deterioration due to humans piggybacking on AIs seem, in principle, equally possible scenarios. The difference between one scenario and the other may lie in a variety of factors, including leadership styles, group dynamics and the nature of the creative process. Regarding the latter, for instance, establishing routines that require a compulsory elaboration of the output of generative AIs may disincentivize AI-induced laziness. At the group level, this may also imply collective creative processes where, iteratively, a single member takes the role of providing the generative AI with inputs, other members elaborate on them, and others take a critical perspective. Lab and field experiments are likely to provide important insights on how to optimize individual and collective creative processes for the interaction with generative AI.

5 | CONCLUDING REMARKS

Empirical and conceptual papers on the managerial, strategic and organizational implications of AI are flourishing at an increasing pace. Among these dimensions, we believe that organizational creativity deserves special consideration. By putting forward a fundamentally different type of reasoning and providing an abundance of new possibilities, AI is likely to alter the way humans approach creativity in organizations, both individually and collectively. However, the scholarly community has yet to unpack the resulting effects, and the research agenda we provide here is meant to complement the others that have been recently proposed on the topic of AI and innovation (e.g. Bouschery et al., 2023; Mariani et al., 2023). In particular, with the present paper, we provide a set of propositions on the impact of AI on creativity at individual, group and organizational levels. Informed by extant multilevel research on organizational creativity, we have analysed the characteristics of AI in relation to the cognitive, psychological and behavioural drivers of creativity, as well as key creativity-related organizational constructs like absorptive capacity. While the resulting propositions are not meant to be exhaustive, they constitute a useful initial roadmap to channel future research efforts. Clearly, all of them require extensive empirical testing, with a mixture of quantitative and qualitative research methodologies. With the present work, we hope to have given them motivations and directions of inquiry.

ACKNOWLEDGEMENTS

The authors would like to thank the editor, two anonymous reviewers, participants to the XXXIV AiIG Scientific Meeting held at Politecnico di Milano for their valuable comments and insights. This research is part of the HumanTech Project, funded by the Italian Ministry of University and Research (MUR) for the period 2023–2027 under the 'Departments of Excellence' programme (L. 232/2016).

DATA AVAILABILITY STATEMENT

Data availability is not applicable to this article as no new data were created or analysed in this study.

ORCID

Luca Grilli https://orcid.org/0000-0003-4550-9276

Mattia Pedota https://orcid.org/0000-0002-3749-5313

ENDNOTES

[1] While the literature review in the introductory part of this section is mostly narrative, we also conducted a brief systematic Scopus search to ensure a good coverage of important articles on the intersection between AI and creativity in the field of management. We proceeded from a keyword query including 'creativity' and 'artificial intelligence', yielding a starting sample of 2161 articles. We then restricted the search to Journal articles in the field of Business, Management and Accounting (149 articles). Among these, we focused on articles published in Journals in the first quartile according to the SCImago Journal Rank and we selected the most relevant to our review, adding a total of eight articles (net of overlaps with articles already included).

[2] By AI expertise we mean all those *technical* skills 'that are directly associated with the knowledge of AI technology or the ability to use AI-related software' (Alekseeva et al., 2021, p. 1). For the sake of simplicity (and as a potential caveat), we do not distinguish between different AI skills (e.g. knowledge of specific programming languages or data mining techniques) for different AI technologies (e.g. transformer-based language models or image recognition algorithms), leaving a more fine-grained categorization and its potential relevance in this domain in the background.

[3] The portrait called Edmond de Bellamy, sold for hundreds of thousands of dollars, is a fitting example of AI capabilities in this respect. For an interesting viewpoint on how AI will (not) change art, see Zylinska (2023).

[4] Bouschery et al. (2023) express the same form of concern referring to the use of training data for language models based on text taken from the Internet. An emblematic example of the risks and dangers associated with the training phase is Microsoft's Twitter chatbot Tray. Fed with malicious and tendentious conversations, it was dismissed after less than 24 h, because it was offensive to users (The Guardian, 2016). Another prominent example is Google's Smart Reply System, based on recurrent neural networks, which aimed at delivering short answers to emails. In the initial training stage, the chatbot responded 'I love you' too often due to poor training. In the own words of a Google researcher (Google AI Blog, 2015): '[…] Another bizarre feature of our early prototype was its propensity to respond with "I love you" to seemingly anything. As adorable as this sounds, it wasn't really what we were hoping for. Some analysis revealed that the system was doing exactly what we'd trained it to do, generate likely responses—and it turns out that responses like "Thanks", "Sounds good", and "I love you" are super common—so the system would lean on them as a safe bet if it was unsure.'

[5] To the extent that 'prompt engineering' will become increasingly important in the design of product innovation (Bouschery et al., 2023), having a basic, but not necessarily superficial, understanding of how AI technologies 'work' can improve 'prompt engineering' itself and help the entire NPD process.

REFERENCES

Abonamah, A. A., Tariq, M. U., & Shilbayeh, S. (2021). On the commoditization of artificial intelligence. *Frontiers in Psychology*, *12*, 696346. https://doi.org/10.3389/fpsyg.2021.696346

Acemoglu, D., & Restrepo, P. (2019). Automation and new tasks: How technology displaces and reinstates labor. *Journal of Economic Perspectives*, *33*(2), 3–30. https://doi.org/10.1257/jep.33.2.3

Aghion, P., Jones, B. F., & Jones, C. I. (2018). Artificial intelligence and economic growth. In *The economics of artificial intelligence: An agenda* (pp. 237–282). University of Chicago Press.

Alekseeva, L., Azar, J., Gine, M., Samila, S., & Taska, B. (2021). The demand for AI skills in the labor market. *Labour Economics*, *71*(8), 102002. https://doi.org/10.1016/j.labeco.2021.102002

Amabile, T. M. (1983). The social psychology of creativity: A componential conceptualization. *Journal of Personality and Social Psychology*, *45*(2), 357–376. https://doi.org/10.1037/0022-3514.45.2.357

Amabile, T. M. (1988). A model of creativity and innovation in organizations. *Research in Organizational Behavior*, *10*(1), 123–167.

Amabile, T. M. (1993). Motivational synergy: Toward new conceptualizations of intrinsic and extrinsic motivation in the workplace. *Human Resource Management Review*, *3*(3), 185–201. https://doi.org/10.1016/1053-4822(93)90012-S

Amabile, T. M. (2020). Creativity, artificial intelligence, and a world of surprises. *Academy of Management Discoveries*, *6*(3), 351–354.

Amabile, T. M., Barsade, S. G., Mueller, J. S., & Staw, B. M. (2005). Affect and creativity at work. *Administrative Science Quarterly*, *50*(3), 367–403. https://doi.org/10.2189/asqu.2005.50.3.367

Amabile, T. M., & Pratt, M. G. (2016). The dynamic componential model of creativity and innovation in organizations: Making progress, making meaning. *Research in Organizational Behavior*, *36*, 157–183. https://doi.org/10.1016/j.riob.2016.10.001

Amabile, T. M., Schatzel, E. A., Moneta, G. B., & Kramer, S. J. (2004). Leader behaviors and the work environment for creativity: Perceived leader support. *The Leadership Quarterly*, *15*(1), 5–32. https://doi.org/10.1016/j.leaqua.2003.12.003

Anantrasirichai, N., & Bull, D. (2021). Artificial intelligence in the creative industries: A review. *Artificial Intelligence Review*, *55*, 589–656.

Anderson, N., Potočnik, K., & Zhou, J. (2014). Innovation and creativity in organizations: A state-of-the-science review, prospective commentary, and guiding framework. *Journal of Management*, *40*(5), 1297–1333. https://doi.org/10.1177/0149206314527128

Angle, H. L. (1989). Psychology and organizational innovation. In A. H. Van de Ven, H. L. Angle, & M. S. Poole (Eds.), *Research on the Management of Innovation: The Minnesota studies* (pp. 135–170). Harper & Row.

Bandura, A. (1997). *Self-efficacy: The exercise of control*. Freeman Lawrence.

Barron, F., & Harrington, D. M. (1981). Creativity, intelligence, and personality. *Annual Review of Psychology*, *32*(1), 439–476. https://doi.org/10.1146/annurev.ps.32.020181.002255

Becker, G. S., & Murphy, K. M. (1992). The division of labor, coordination costs, and knowledge. *The Quarterly Journal of Economics*, *107*(4), 1137–1160. https://doi.org/10.2307/2118383

Binnewies, C., & Wörnlein, S. C. (2011). What makes a creative day? A diary study on the interplay between affect, job stressors, and job control. *Journal of Organizational Behavior*, *32*(4), 589–607. https://doi.org/10.1002/job.731

Bonnardel, N., & Marmèche, E. (2004). Evocation processes by novice and expert designers: Towards stimulating analogical thinking. *Creativity and Innovation Management*, *13*(3), 176–186. https://doi.org/10.1111/j.0963-1690.2004.00307.x

Botega, L. F. D. C., & da Silva, J. C. (2020). An artificial intelligence approach to support knowledge management on the selection of creativity and innovation techniques. *Journal of Knowledge Management*, *24*(5), 1107–1130. https://doi.org/10.1108/JKM-10-2019-0559

Bouschery, S. G., Blazevic, V., & Piller, F. T. (2023). Augmenting human innovation teams with artificial intelligence: Exploring transformer-based language models. *Journal of Product Innovation Management*, *40*(2), 139–153. https://doi.org/10.1111/jpim.12656

Brennan, A., & Dooley, L. (2005). Networked creativity: A structured management framework for stimulating innovation. *Technovation*, *25*(12), 1388–1399. https://doi.org/10.1016/j.technovation.2004.08.001

Bronkhorst, J., Schaveling, J., & Janssen, M. (2019). Commoditization and IT product innovation strategies from an IT firm perspective. *Information Systems Management*, *36*(2), 126–140. https://doi.org/10.1080/10580530.2019.1587575

Campos, J., & Figueiredo, A. D. D. (2002). Programming for serendipity. In *Proceedings of the 2002 AAAI fall symposium on chance discovery-the discovery and Management of Chance Events AAAI technical report FS-02-01*.

Carmeli, A., Dutton, J. E., & Hardin, A. E. (2015). Respect as an engine for new ideas: Linking respectful engagement, relational information processing and creativity among employees and teams. *Human Relations*, *68*(6), 1021–1047. https://doi.org/10.1177/0018726714550256

Carr, N. G. (2003). IT doesn't matter. *Harvard Business Review*, *81*(5), 41–49.

Carr, N. G. (2004). *Does IT matter?* Harvard Business School Publishing.

Chamakiotis, P., Dekoninck, E. A., & Panteli, N. (2013). Factors influencing creativity in virtual design teams: An interplay between technology, teams and individuals. *Creativity and Innovation Management*, *22*(3), 265–279. https://doi.org/10.1111/caim.12039

Chambers, J. A. (1964). Relating personality and biographical factors to scientific creativity. *Psychological Monographs: General and Applied*, *78*(7), 1–20. https://doi.org/10.1037/h0093862

Cohen, W. M., & Levinthal, D. A. (1990). Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly*, *35*(1), 128–152. https://doi.org/10.2307/2393553

Collins, C., Dennehy, D., Conboy, K., & Mikalef, P. (2021). Artificial intelligence in information systems research: A systematic literature review and research agenda. *International Journal of Information Management*, *60*, 102383. https://doi.org/10.1016/j.ijinfomgt.2021.102383

Corrado, G. (2015). Computer, respond to this email. *Google AI Blog*. 3/11/2015

Cropley, A. (2006). In praise of convergent thinking. *Creativity Research Journal*, *18*(3), 391–404. https://doi.org/10.1207/s15326934crj1803_13

Dahl, D. W., & Moreau, P. (2002). The influence and value of analogical thinking during new product ideation. *Journal of Marketing Research*, *39*(1), 47–60. https://doi.org/10.1509/jmkr.39.1.47.18930

Dane, E. (2010). Reconsidering the trade-off between expertise and flexibility: A cognitive entrenchment perspective. *Academy of Management Review*, *35*(4), 579–603.

DeRosa, D. M., Smith, C. L., & Hantula, D. A. (2007). The medium matters: Mining the long-promised merit of group interaction in creative idea generation tasks in a meta-analysis of the electronic group brainstorming literature. *Computers in Human Behavior*, *23*(3), 1549–1581. https://doi.org/10.1016/j.chb.2005.07.003

Dewett, T. (2003). Understanding the relationship between information technology and creativity in organizations. *Creativity Research Journal*, *15*(2–3), 167–182. https://doi.org/10.1207/S15326934CRJ152&3_08

Dornis, T. W. (2020). Artificial creativity: Emergent works and the void in current copyright doctrine. *Yale Journal of Law & Technology*, *XXII*, 1.

Edmondson, A. (1999). Psychological safety and learning behavior in work teams. *Administrative Science Quarterly*, *44*(2), 350–383. https://doi.org/10.2307/2666999

Edmondson, A. C. (2018). *The fearless organization: Creating psychological safety in the workplace for learning, innovation, and growth*. John Wiley & Sons.

Eisenberger, R., & Aselage, J. (2009). Incremental effects of reward on experienced performance pressure: Positive outcomes for intrinsic interest and creativity. *Journal of Organizational Behavior: the International Journal of Industrial, Occupational and Organizational Psychology and Behavior*, *30*(1), 95–117. https://doi.org/10.1002/job.543

Elkins, T., & Keller, R. T. (2003). Leadership in research and development organizations: A literature review and conceptual framework. *The Leadership Quarterly*, *14*(4–5), 587–606. https://doi.org/10.1016/S1048-9843(03)00053-5

Fairbank, J. F., & Williams, S. D. (2001). Motivating creativity and enhancing innovation through employee suggestion system technology. *Creativity and Innovation Management*, *10*(2), 68–74. https://doi.org/10.1111/1467-8691.00204

Ferràs-Hernández, X. (2018). The future of management in a world of electronic brains. *Journal of Management Inquiry*, *27*(2), 260–263. https://doi.org/10.1177/1056492617724973

Fischer, C., Malycha, C. P., & Schafmann, E. (2019). The influence of intrinsic motivation and synergistic extrinsic motivators on creativity and innovation. *Frontiers in Psychology*, *10*, 137. https://doi.org/10.3389/fpsyg.2019.00137

Ford, C. M. (1996). A theory of individual creative action in multiple social domains. *Academy of Management Review*, *21*(4), 1112–1142. https://doi.org/10.2307/259166

Fu, Z., Niu, X., & Maher, M. L. (2023). Deep learning models for serendipity recommendations: A survey and new perspectives. *ACM Computing Surveys*, *56*(1), 19. (august 2023), 26 pages

Gavetti, G., & Levinthal, D. (2000). Looking forward and looking backward: Cognitive and experiential search. *Administrative Science Quarterly*, *45*(1), 113–137. https://doi.org/10.2307/2666981

Glăveanu, V. P. (2020). A sociocultural theory of creativity: Bridging the social, the material, and the psychological. *Review of General Psychology*, *24*(4), 335–354. https://doi.org/10.1177/1089268020961763

Goodfellow, I., Bengio, Y., & Courville, A. (2018). *Deep learning book*. MIT Press.

Granovetter, M. S. (1973). The strength of weak ties. *American Journal of Sociology*, *78*(6), 1360–1380. https://doi.org/10.1086/225469

Guilford, J. P. (1984). Varieties of divergent production. *The Journal of Creative Behavior*, *18*(1), 1–10. https://doi.org/10.1002/j.2162-6057.1984.tb00984.x

Haefner, N., Wincent, J., Parida, V., & Gassmann, O. (2021). Artificial intelligence and innovation management: A review, framework, and research agenda✰. *Technological Forecasting and Social Change*, *162*, 120392. https://doi.org/10.1016/j.techfore.2020.120392

Hansen, M. T. (1999). The search-transfer problem: The role of weak ties in sharing knowledge across organization subunits. *Administrative Science Quarterly*, *44*(1), 82–111. https://doi.org/10.2307/2667032

Harvey, S. (2014). Creative synthesis: Exploring the process of extraordinary group creativity. *Academy of Management Review*, *39*(3), 324–343. https://doi.org/10.5465/amr.2012.0224

Hülsheger, U. R., Anderson, N., & Salgado, J. F. (2009). Team-level predictors of innovation at work: A comprehensive meta-analysis spanning three decades of research. *Journal of Applied Psychology*, *94*(5), 1128–1145. https://doi.org/10.1037/a0015978

Hunt, E. (2016). Tay, Microsoft's AI chatbot, gets a crash course in racism from Twitter. *The Guardian*. 24/03/2016

Kanter, R. M. (1983). *The change masters: Innovation for productivity in the American corporation*. Simon and Schuster.

Kaplan, A., & Haenlein, M. (2019). Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. *Business Horizons*, *62*(1), 15–25. https://doi.org/10.1016/j.bushor.2018.08.004

Katila, R., & Ahuja, G. (2002). Something old, something new: A longitudinal study of search behavior and new product introduction. *Academy of Management Journal*, *45*(6), 1183–1194. https://doi.org/10.2307/3069433

Kennedy, I. G., Whitehead, D., & Ferdinand-James, D. (2022). Serendipity: A way of stimulating researchers' creativity. *Journal of Creativity*, *32*(1), 100014. https://doi.org/10.1016/j.yjoc.2021.100014

Kittur, A., Yu, L., Hope, T., Chan, J., Lifshitz-Assaf, H., Gilon, K., Ng, F., Kraut, R. E., & Shahaf, D. (2019). Scaling up analogical innovation with crowds and AI. *Proceedings of the National Academy of Sciences*, *116*(6), 1870–1877. https://doi.org/10.1073/pnas.1807185116

Köbis, N., & Mossink, L. D. (2021). Artificial intelligence versus Maya Angelou: Experimental evidence that people cannot differentiate AI-generated from human-written poetry. *Computers in Human Behavior*, *114*, 106553. https://doi.org/10.1016/j.chb.2020.106553

Kosinski, M., Wang, Y., Lakkaraju, H., & Leskovec, J. (2016). Mining big data to extract patterns and predict real-life outcomes. *Psychological Methods*, *21*(4), 493–506. https://doi.org/10.1037/met0000105

Lee, Y. N., Walsh, J. P., & Wang, J. (2015). Creativity in scientific teams: Unpacking novelty and impact. *Research Policy*, *44*(3), 684–697. https://doi.org/10.1016/j.respol.2014.10.007

Lenat, D. B. (1982). The nature of heuristics. *Artificial Intelligence*, *19*(2), 189–249. https://doi.org/10.1016/0004-3702(82)90036-4

Litchfield, R. C. (2008). Brainstorming reconsidered: A goal-based view. *Academy of Management Review*, *33*(3), 649–668. https://doi.org/10.5465/amr.2008.32465708

Mainemelis, C., Kark, R., & Epitropaki, O. (2015). Creative leadership: A multi-context conceptualization. *Academy of Management Annals*, *9*(1), 393–482. https://doi.org/10.5465/19416520.2015.1024502

Mariani, M. M., Machado, I., Magrelli, V., & Dwivedi, Y. K. (2023). Artificial intelligence in innovation research: A systematic review, conceptual framework, and future research directions. *Technovation*, *122*(4), 102623. https://doi.org/10.1016/j.technovation.2022.102623

Mazzone, M., & Elgammal, A. (2019). Art, creativity, and the potential of artificial intelligence. *Art*, *8*(1), 26. https://doi.org/10.3390/arts8010026

McLean, L. D. (2005). Organizational culture's influence on creativity and innovation: A review of the literature and implications for human resource development. *Advances in Developing Human Resources*, *7*(2), 226–246. https://doi.org/10.1177/1523422305274528

Mikalef, P., & Gupta, M. (2021). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. *Information & Management*, *58*(3), 103434. https://doi.org/10.1016/j.im.2021.103434

Mullen, B., Johnson, C., & Salas, E. (1991). Productivity loss in brainstorming groups: A meta-analytic integration. *Basic and Applied Social Psychology*, *12*(1), 3–23. https://doi.org/10.1207/s15324834basp1201_1

Mumford, M. D., Connelly, S., & Gaddis, B. (2003). How creative leaders think: Experimental findings and cases. *The Leadership Quarterly*, *14*(4–5), 411–432. https://doi.org/10.1016/S1048-9843(03)00045-6

Mumford, M. D., Scott, G. M., Gaddis, B., & Strange, J. M. (2002). Leading creative people: Orchestrating expertise and relationships. *The Leadership Quarterly*, *13*(6), 705–750. https://doi.org/10.1016/S1048-9843(02)00158-3

Murayama, K., Nirei, M., & Shimizu, H. (2015). Management of science, serendipity, and research performance: Evidence from a survey of scientists in Japan and the US. *Research Policy*, *44*(4), 862–873. https://doi.org/10.1016/j.respol.2015.01.018

Neirotti, P., & Paolucci, E. (2007). Assessing the strategic value of information technology: An analysis on the insurance sector. *Information & Management*, *44*(6), 568–582. https://doi.org/10.1016/j.im.2007.05.005

Newman, A., Donohue, R., & Eva, N. (2017). Psychological safety: A systematic review of the literature. *Human Resource Management Review*, *27*(3), 521–535. https://doi.org/10.1016/j.hrmr.2017.01.001

Ng, A. (2017). Artificial intelligence is the new electricity. In *Presentation at the Stanford MSx Future Forum*.

Obschonka, M., & Audretsch, D. B. (2020). Artificial intelligence and big data in entrepreneurship: A new era has begun. *Small Business Economics*, *55*(3), 529–539. https://doi.org/10.1007/s11187-019-00202-4

Oldham, G. R., & Cummings, A. (1996). Employee creativity: Personal and contextual factors at work. *Academy of Management Journal*, *39*(3), 607–634. https://doi.org/10.2307/256657

Paesano, A. (2021). Artificial intelligence and creative activities inside organizational behavior. *International Journal of Organizational Analysis*, *31*(5), 1694–1723.

Paulus, P., & Kenworthy, J. (2019). Effective brainstorming. In P. Paulus & B. A. Nijstad (Eds.), *Handbook of group creativity: Innovation through collaboration* (pp. 287–306). Oxford University Press.

Pedota, M., & Piscitello, L. (2022). A new perspective on technology-driven creativity enhancement in the fourth industrial revolution. *Creativity and Innovation Management*, *31*(1), 109–122. https://doi.org/10.1111/caim.12468

Pietronudo, M. C., Croidieu, G., & Schiavone, F. (2022). A solution looking for problems? A systematic literature review of the rationalizing influence of artificial intelligence on decision-making in innovation management. *Technological Forecasting and Social Change*, *182*, 121828. https://doi.org/10.1016/j.techfore.2022.121828

Rai, A., Constantinides, P., & Sarker, S. (2019). Next generation digital platforms: Toward human-AI hybrids. *MIS Quarterly*, *43*(1), iii–ix.

Rosso, B. D., Dekas, K. H., & Wrzesniewski, A. (2010). On the meaning of work: A theoretical integration and review. *Research in Organizational Behavior*, *30*, 91–127. https://doi.org/10.1016/j.riob.2010.09.001

Runco, M. A., & Jaeger, G. J. (2012). The standard definition of creativity. *Creativity Research Journal*, *24*(1), 92–96. https://doi.org/10.1080/10400419.2012.650092

Schweisfurth, T. G., & Raasch, C. (2018). Absorptive capacity for need knowledge: Antecedents and effects for employee innovativeness. *Research Policy*, *47*(4), 687–699. https://doi.org/10.1016/j.respol.2018.01.017

Scott, G., Leritz, L. E., & Mumford, M. D. (2004). The effectiveness of creativity training: A quantitative review. *Creativity Research Journal*, *16*(4), 361–388. https://doi.org/10.1080/10400410409534549

Sherry, Y., & Thompson, N. C. (2021). How fast do algorithms improve? [point of view]. *Proceedings of the IEEE*, *109*(11), 1768–1777.

Shin, S. J., Kim, T. Y., Lee, J. Y., & Bian, L. (2012). Cognitive team diversity and individual team member creativity: A cross-level interaction. *Academy of Management Journal*, *55*(1), 197–212. https://doi.org/10.5465/amj.2010.0270

Shneiderman, B. (2002). Creativity support tools. *Communications of the ACM*, *45*(10), 116–120. https://doi.org/10.1145/570907.570945

Shneiderman, B. (2007). Creativity support tools: Accelerating discovery and innovation. *Communications of the ACM*, *50*(12), 20–32. https://doi.org/10.1145/1323688.1323689

Siau, K. L. (1995). Group creativity and technology. *The Journal of Creative Behavior*, *29*(3), 201–216. https://doi.org/10.1002/j.2162-6057.1995.tb00749.x

Simon, H. A. (1991). Bounded rationality and organizational learning. *Organization Science*, *2*(1), 125–134. https://doi.org/10.1287/orsc.2.1.125

Simonton, D. K. (1999). *Origins of genius: Darwinian perspectives on creativity*. Oxford University Press.

Singh, B. (1986). Role of personality versus biographical factors in creativity. *Psychological Studies*, *31*, 90–92.

Sturm, T., Gerlach, J. P., Pumplun, L., Mesbah, N., Peters, F., Tauchert, C., Nan, N., & Buxmann, P. (2021). Coordinating human and machine learning for effective organizational learning. *MIS Quarterly*, *45*(3), 1581–1602. https://doi.org/10.25300/MISQ/2021/16543

Szulanski, G. (1996). Exploring internal stickiness: Impediments to the transfer of best practice within the firm. *Strategic Management Journal*, *17*(S2), 27–43. https://doi.org/10.1002/smj.4250171105

Tan, S. Y., & Tatsumura, Y. (2015). Alexander Fleming (1881–1955): Discoverer of penicillin. *Singapore Medical Journal*, *56*(7), 366–367. https://doi.org/10.11622/smedj.2015105

Tanggaard, L., Laursen, D. N., & Szulevicz, T. (2016). The grip on the handball – A qualitative analysis of the influence of materiality on creativity in sport. *Qualitative Research in Sport, Exercise and Health*, *8*(1), 79–94. https://doi.org/10.1080/2159676X.2015.1012546

Taylor, A., & Greve, H. R. (2006). Superman or the fantastic four? Knowledge combination and experience in innovative teams. *Academy of Management Journal*, *49*(4), 723–740. https://doi.org/10.5465/amj.2006.22083029

Teodoridis, F., Bikard, M., & Vakili, K. (2019). Creativity at the knowledge frontier: The impact of specialization in fast-and slow-paced domains. *Administrative Science Quarterly*, *64*(4), 894–927. https://doi.org/10.1177/0001839218793384

Tesluk, P. E., Farr, J. L., & Klein, S. R. (1997). Influences of organizational culture and climate on individual creativity. *The Journal of Creative Behavior*, *31*(1), 27–41. https://doi.org/10.1002/j.2162-6057.1997.tb00779.x

Todorova, G., & Durisin, B. (2007). Absorptive capacity: Valuing a reconceptualization. *Academy of Management Review*, *32*(3), 774–786. https://doi.org/10.5465/amr.2007.25275513

Townsend, D. M., & Hunt, R. A. (2019). Entrepreneurial action, creativity, & judgment in the age of artificial intelligence. *Journal of Business Venturing Insights*, *11*, e00126. https://doi.org/10.1016/j.jbvi.2019.e00126

Truong, Y., & Papagiannidis, S. (2022). Artificial intelligence as an enabler for innovation: A review and future research agenda. *Technological Forecasting and Social Change*, *183*, 121852. https://doi.org/10.1016/j.techfore.2022.121852

Tsui, A. S., & O'reilly, C. A. III (1989). Beyond simple demographic effects: The importance of relational demography in superior-subordinate dyads. *Academy of Management Journal*, *32*(2), 402–423. https://doi.org/10.2307/256368

Tubadji, A., Huang, H., & Webber, D. J. (2021). Cultural proximity bias in AI-acceptability: The importance of being human. *Technological Forecasting and Social Change*, *173*, 121100. https://doi.org/10.1016/j.techfore.2021.121100

Van Knippenberg, D., & Schippers, M. C. (2007). Work group diversity. *Annual Review of Psychology*, *58*, 515–541. https://doi.org/10.1146/annurev.psych.58.110405.085546

Vessey, W. B., & Mumford, M. D. (2012). Heuristics as a basis for assessing creative potential: Measures, methods, and contingencies. *Creativity Research Journal*, *24*(1), 41–54. https://doi.org/10.1080/10400419.2012.652928

Von Hippel, E. (2006). *Democratizing innovation*. MIT Press.

Williams, K., & O'Reilly, C. (1998). Demography and diversity in organizations: A review of forty years of research. In R. I. Sutton & B. M. Staw (Eds.), *Research in organizational behavior* (pp. 77–140). JAI Press.

Woodman, R. W., Sawyer, J. E., & Griffin, R. W. (1993). Toward a theory of organizational creativity. *Academy of Management Review*, *18*(2), 293–321. https://doi.org/10.2307/258761

Zahra, S. A., & George, G. (2002). Absorptive capacity: A review, reconceptualization, and extension. *Academy of Management Review*, *27*(2), 185–203. https://doi.org/10.2307/4134351

Zhang, X., & Bartol, K. M. (2010). Linking empowering leadership and employee creativity: The influence of psychological empowerment, intrinsic motivation, and creative process engagement. *Academy of Management Journal*, *53*(1), 107–128. https://doi.org/10.5465/amj.2010.48037118

Zhou, J. (2008). Promoting creativity through feedback. In J. Zhou & C. E. Shalley (Eds.), *Handbook of organizational creativity* (pp. 125–145). Erlbaum.

Zhu, Y. Q., Gardner, D. G., & Chen, H. G. (2018). Relationships between work team climate, individual motivation, and creativity. *Journal of Management*, *44*(5), 2094–2115. https://doi.org/10.1177/0149206316638161

Zylinska, J. (2023). Art in the age of artificial intelligence. *Science*, *381*(6654), 139–140. https://doi.org/10.1126/science.adh0575

AUTHOR BIOGRAPHIES

Luca Grilli is Full Professor of Business and Industrial Economics at Politecnico di Milano (Italy). His main research interests revolve around the economics of innovative entrepreneurship and the economics of network and digital industries. On these subjects, he has participated in numerous scientific projects (promoted by private and public institutions), published articles in several international scientific journals and acted as an editor for journal special issues and a book.

Mattia Pedota is an Assistant Professor of Economics and Management at Politecnico di Milano (Italy). His main research interests and scientific publications span the dynamics of technological change, the management of technology and innovation, and the microfoundations of innovation. His recent studies revolve around the impact of artificial intelligence on innovation dynamics within organizations.

How to cite this article: Grilli, L., & Pedota, M. (2024). Creativity and artificial intelligence: A multilevel perspective. *Creativity and Innovation Management*, 1–14. https://doi.org/10.1111/caim.12580