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3 authors:


David H Cropley
University of South Australia


Kelsey E Medeiros
University of Nebraska at Omaha


Adam Damadzic
University of Nebraska at Omaha

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David H. Cropley[1], Kelsey E. Medeiros[2], & Adam Damadzic[2]

[1]University of South Australia

[2]University of Nebraska at Omaha

Introduction

The rise of Industry 4.0 – the proliferation of cyber-physical systems, artificial intelligence, big data, and automation – has turned attention, once again, to the interaction between humans and robots[1]. Captivating attention in both academic and public spheres, the debate on how humans and robots interact largely centres around the interplay between human and artificial cognition. The human-robot cognition interaction fuels practical inquiries into the formation of high-performing human-robot teams, leveraging robots to enhance human cognition, and the capacity for robots to overtake human cognition. At the heart of these conversations, however, lies a critical question – what does the Future of Work look like? (see, for example, OECD, 2017). As robots take on more and more tasks previously performed by humans, where does that leave the human worker?

A common argument that forms the basis of the World Economic Forum's characterisation of 21st century *skills* (WEF, 2016, 2020) is that robots, and their underpinning technologies (e.g. artificial intelligence), are ideally suited to routine, algorithmic tasks. Thus, robots can be designed to replace humans as bookkeepers, drivers, administrative assistants, laboratory assistants, telemarketers, paralegals, and even bartenders. This leaves humans with the jobs that robots *cannot* do. These uniquely *human* tasks typically revolve around *soft* skills, for example: leadership and

[1] The term "robot" is used here as a general reference to systems of hardware and/or software that employ artificial intelligence and automation to replicate human actions.

emotional intelligence, persuasion, and negotiation, and, critical to the present discussion, creativity and complex problem solving (WEF, 2020).

In fact, nearly 60 years ago, the psychologist Jerome Bruner anticipated a future in which "thinking machines" (1962b, p. 6) would take on routine problems (i.e. those that are "well-formed" and "amenable to a unique solution"), leaving creativity, and creative problem solving, as the locus of human dignity and worth (1962a, pp. 2-3). Creativity, in other words, is the bastion of human mental sovereignty over robots. This *all-or-nothing* view is now common, and rather appealing. We have nothing to fear from this perspective, provided we focus our attention on developing our unique capacity for creativity. Indeed, creativity is becoming an important focus of school curricula across the world for precisely this reason (e.g. Patston et. al. 2021).

The reality of the Future of Work, however, may be somewhat more complex and nuanced. While psychologists may argue that creativity is a uniquely human ability, we see more and more examples of artificial systems that are claimed to be *creative*. For example, media heralded the win of Google's AlphaGo contestant in its win against the world's top Go player (BBC, 2017). Similarly, the production of *1 the Road,* a novel composed by a trained AI system on a road trip, has been praised as a sign of creativity in artificial intelligence (The Atlantic, 2018). The impact of the Future of Work may therefore not be as clear-cut as some would suggest. Will humans continue to dominate creativity, complex problem solving and related soft skills, or will robots usurp human sovereignty? Or, is there a happy medium in which humans and robots interact productively for a net benefit? To answers these questions, it is first necessary to delve into the nature of human creativity and the potential for artificial systems to replicate this capability.

The subject of creativity is governed by two distinct, overlapping, and perhaps competing, disciplines. On the one hand, *Psychology* has spent over 60 years exploring questions about human creativity and: (a) cognition – especially divergent thinking; (b) attitudes and dispositions – for example, personality traits, feelings and motivations; (c) environmental factors – including organisational and classroom climate and culture, and; (d) the characteristics of products – the properties that make an artefact or idea *creative*. On the other hand, *Computational Creativity* has, more recently, sought to model and replicate creativity in order to: (a) construct an artificial system capable of creativity; (b) uncover algorithmic descriptions of human creativity, and; (c) develop artificial aids to human creativity.

Any discussion of the intersection of human and artificial creativity therefore must draw on, and attempt to reconcile, the concepts, tools, and methods of these disciplines. That there has been relatively little integration of these disciplines – see, for example, the comments relative to computational creativity by Lamb, Brown, and Clarke (2018, p.1) – suggests that this is no simple task. It is perhaps no surprise that Psychology, with its focus on human behaviour, cognition and emotions, has a vested interest in refuting claims that *computers can be creative*, while equally, Computational Creativity has a vested interest in demonstrating that these claims are valid.

As the world grapples with the impact of Industry 4.0 on the Future of Work, what is certain is that the question – *can robots be creative* – must be addressed. The answer to this question has important implications for education, the global economy, and ultimately, human dignity and worth. The following provides guidance on solving these problems by first addressing the human-factored centrality of creativity, creative processes, and integrating AI systems.

The Psychological Foundations of Human Creativity

The question of whether or not artificial creativity can replicate, in whole or in part, human creativity, first requires that we define the *scope* of this replication. What is it, exactly, that an artificial system must replicate, with respect to human creativity?

Human creativity encompasses four factors, defined by Rhodes (1961) and Barron (1969) as Process (cognition), Person (attitudes and behaviours), Press (climate and culture) and Product (outcome). In simple terms, our ability to generate creative outputs (Product) is a function of how we think (Process), who we are (Person) and where we work (Press).

Two of these factors address uniquely human *limitations* on creativity. Optimism, enthusiasm, tolerance for uncertainty and openness (facets of the Person) are important *internal* factors for creativity because of their capacity to help or hinder humans in their efforts to think creatively (Process). Thus, while an individual might be highly adept at divergent thinking (Process), if they are closed-minded, intolerant of ambiguity and disinterested (Person), then their overall capacity for creativity – their ability to generate a creative Product – is likely to be low. Time, resources, and support (facets of Press), in similar fashion, are important *external* factors for creativity only because they can support or constrain human efforts to be creative. A motivated, open, and flexible individual (Person) strong in divergent thinking (Process) may still fail to generate creative Products if they are embedded in a workplace (Press) that is hostile to new ideas.

In contrast, an artificial system is neither aided nor restrained by personality and environment – indeed, that is surely one of the *attractions* of artificial creativity – and therefore these facets of human creativity do not need to be replicated. Only Process (*how* creative ideas are generated) and Product (the creative ideas themselves) should therefore be in scope for computational systems seeking to replicate human creativity. The centrality of Process and Product is consistent with the thinking of early *computational* pioneers (e.g. Newell, Shaw & Simon, 1962), but perhaps at odds with more recent computational notions of creativity (e.g. Wiggins, 2006) that seem to focus on replicating the Person: "…*behaviour* [emphasis added] exhibited by natural and artificial systems, which would be deemed creative if exhibited by humans." Artificial systems do not need to mimic the attitudes, behaviours, or actions of the creative human. They must replicate only the cognitive process and the result.

Freed from the uniquely human limitations on creativity (Person and Press), Process and Product define two key constructs that must be understood before human and artificial creativity can be reconciled and perhaps integrated. Product demands that we ask *why* we are creative, while Process requires us to address *how* we are creative.

***Why* are we Creative?**

It is widely agreed, both in the psychological realm (from Bruner, 1962a to Runco & Jaeger, 2012) and in the computational realm (from Newell, Shaw, & Simon, 1962 to Lamb, Brown, & Clarke, 2018), that to be judged creative, a product[2] must be: (a) novel, and; (b) effective. These two criteria represent the final embodiment of the underlying purpose – the driving force – behind creativity. They explain why we bother with creativity in the first place. Moreover, neither novelty nor effectiveness *alone* are sufficient for a creative product. For instance, solving an overcrowded parking problem by “parking on the moon” is novel, but ineffective given its practicality. In contrast, developing additional spaces in an existing parking lot is effective but lacks in novelty.

In a scientific context, these new forms/products (Figure 1) might be new *artefacts*: for example, an electronic device, or a physical material. In an artistic context, they might be new *compositions*: a picture, a melody, or a story. New needs, in a scientific sense, might be *how to reduce carbon emissions*, while in an artistic sense, they might include *how to capture the beauty of a landscape* (see Figure 1).

[2] For the sake of simplicity, we use *Product* to mean any of *idea*, *artefact*, *process*, *system* or *service*. Any tangible or intangible output of a creative process.

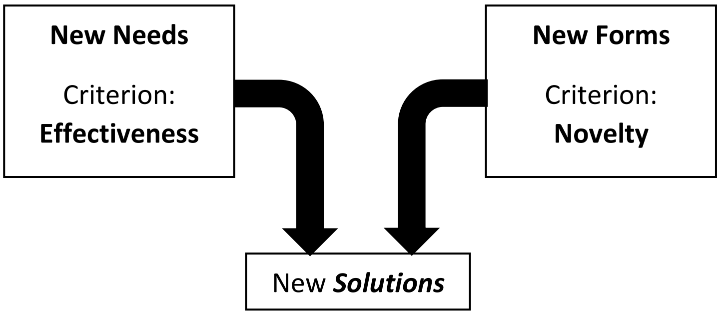

Figure 1: New needs and new forms lead to new solutions

Importantly, creativity is not merely the production of novel forms on their own. Nor is it merely the definition of novel problems (needs). Creativity, ultimately, is the production of new artefacts, ideas, compositions, and systems (judged by the criterion *novelty*) that satisfy an identified need or solve a problem (judged by the criterion *effectiveness*). As such, creativity is the generation of a novel and effective *solution* (Figure 1).

The development of this solution may begin with the desire to create a novel form (that must eventually serve a purpose), or it may begin with a desire to solve a new problem (that can only be tackled with a new solution). However, whether we consider the form or the function, the *origin* of creativity – the reason or purpose, if not the first step – is *the human need*. For instance, the Brassiere invented by Mary Jacob in 1914 (Cropley, 2020) is anchored in the need for a more comfortable and fashionable undergarment to replace the corset, while the Printing Press invented by Johannes Gutenberg in 1450 (Cropley, 2019) is tied to the need share information. Regardless of the pathway followed, there is an underpinning need that is satisfied, and these needs can only be expressed by humans. Lamb, Brown, and Clarke (2018) acknowledge as much in their discussion of the lack of *autonomy* (p.7) in computational systems, or "the [in]ability of the machine to decide for itself what to do."

Why, then, are we creative? To satisfy *human* needs. An algorithm could never determine that Mary Jacob found corsets uncomfortable and unfashionable. An AI could never decide that humans had a desire to share and communicate written information more quickly and easily. Even if a computational system can present a report or provide information that signals an emerging gap or need, *human* cognition is still required to decide if that is a problem, or if a new form is desirable. Asking *why* we are creative shows us that the first stage of creative problem solving (e.g. Guilford, 1959), is *Problem Recognition/Definition*, and is *uniquely* human. As a first step to reconciling, and possibly integrating, human and artificial creativity, we see that the process cannot be entirely separated from human input, or human sovereignty, no matter how sophisticated the artificial means brought to bear. As Guckelsberger et al (2017) acknowledge, the answer to why an artificial system made a creative decision would always, eventually, return to "because my [human] programmer told me to."

In line with this reasoning, *Solution Validation* defined as the final stage in the process of creative problem solving by Guilford (1959), represents how well a product does, in fact, resolve the problem or address the need. It is important to note here the distinction between *verification* and *validation*. The former establishes that a solution meets a specification: the car travels at 60 km/h; the kettle heats water to 100^{o}C. The latter, *validation*, is a matter of establishing that the solution *satisfies the human need*: the Brassiere is, in fact, more comfortable than a corset; the Printing Press does, indeed, allow more rapid and widespread communication of written ideas. Any Process for generating creativity – human or artificial – therefore sits between two uniquely human stages: (a) a front-end of *problem definition*, and, (b) a back-end of *solution validation* (Table 1). The focus of, and potential for, artificial creativity therefore lies between these two *human* stages.

Table 1: The roles of human and artificial creativity

	Problem Definition	**Process**	**Solution Validation**
Human	✓	✓	✓
AI	✗	???	✗

How are we Creative?

With the rationale for creativity established, we turn to the underlying cognitive processes. How, in other words, are creative solutions generated? Guiding this process is the fact that the novel forms may be either: (a) novel variations of what already exists, or, (b) wholly new forms. The former is typically referred to as *incremental* in nature, while the latter is *radical* (Salter & Alexy, 2014).

Guilford (1959) described the two essential, cognitive stages – the *processes* – of creative problem solving. These stages reflect the core issue that Guilford (1950) was seeking to redress: he argued that human intellectual ability had been characterised too narrowly as a matter of speed, accuracy and correctness, or what he described as *convergent thinking*. There was, in his view, more to human mental sovereignty than merely knowing that 2 + 2 = 4, or that the ratio of a circle's circumference to its diameter is 3.14 (pi). This is not to say that this form of cognition is trivial. Much of our lives depends on our ability to know or find, and apply, *the correct answer*. Our ability to solve problems efficiently and economically is anchored to our ability to evaluate options, to select against a list of constraints, and to calculate. All these cognitive activities are instances of convergent thinking, and in a creative, problem-solving process, Guilford (1959) encapsulated these under the single stage of *Idea Evaluation*.

Guilford (1950) argued that human intellectual ability was also a matter of our ability to generate alternatives, to see multiple possibilities, and to link disparate ideas. He defined *divergent thinking* – Idea Generation – as the complement to convergent thinking. In the typical course of problem solving, once a problem has been defined, a range of possible solutions must be generated through divergent thinking, before these are evaluated, and the best solution selected, using convergent thinking (Figure 2).

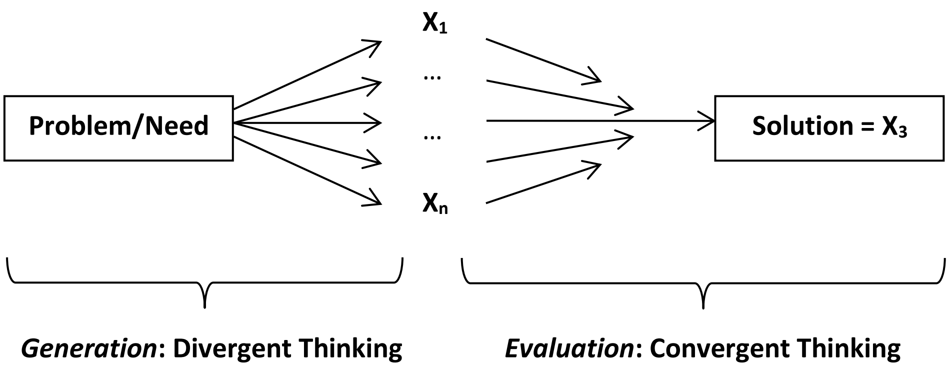

Figure 2: Divergent and Convergent Cognition (Based on Cropley, 2015)

If an artificial means of creativity is to be found – or perhaps, an artificial aid to human creativity – then it must lie in the realm of process. Can artificial systems perform idea generation, and/or idea evaluation?

Process & Artificial Systems

The simplest example of the core divergent process of creativity – idea generation – is *blind*, or random, generation within some *conceptual space* (Boden, 2004). To illustrate this, consider the case of creativity in music. The total number of musical notes on the so-called *equal-tempered scale*, in the range of human hearing (16Hz to 16KHz), is 120. It is possible to imagine an artificial system designed to generate a novel melody (i.e., a form, or solution) based on these available notes, just as a human composer must. A sequence of four notes offers over 200 million variations (i.e., 120^4). A melody of seven notes (think of the first line of *Mary Had a Little Lamb*) is one of more than 350 trillion possibilities! Blind variation of this type is therefore capable of producing wholly new (radical) forms (melodies that have never before been heard) and might therefore be deemed *creative* (see Table 2).

Critical, however, is the question of effectiveness. As stated earlier, creativity is not merely the production of novel forms. As Runco and Jaeger (2012) noted, “originality can be found in the word salad of a psychotic and can be produced by monkeys on word processors” (p. 92). The forms resulting from blind generation must, in the end, satisfy a need, judged by humans for their effectiveness, if they are to qualify as *creative*. In the case of music, that need might be as straightforward as eliciting a favourable reaction in the listener. Because not all combinations of notes are equally pleasing to listeners (if they were, there would be no difference between the music of Mozart, and the music of an infant banging on a toy xylophone) it is clear that this strategy for the generation of artificial musical creativity is risky, and likely to consume enormous computational resources, with no guarantee of an effective outcome. Bruner (1962a, p.6) recognised this, noting that creativity is “…not a taking of known elements and running them together by algorithm into a welter of permutations.” Indeed, he went on to say that “One could design a calculator to do that, but it would be with some embarrassment, for this is stupid even for a calculator”. Blind idea generation, on its own, therefore is not enough.

Even though blind generation appears to offer the possibility of high, radical novelty (i.e. wholly new melodies), the likelihood of effectiveness is very low. If creativity requires both novelty *and* effectiveness, then this method is more likely than not to produce very low creativity (see Table 2). In addition, the cost of attempting to satisfy the need – seeking out the *one-in-a-billion* melody that humans might deem effective – is very high.

Artificial musical creativity has, of course, progressed beyond the "stupidity" and computational inefficiency of blind generation. What is needed is an algorithm, or an *evaluative* approach, that is able to raise the likelihood of finding an *effective* melody – i.e. one that is pleasing to the listener. What is needed, therefore, is a means to raise the likelihood of successful *solution validation*. Bruner (1962a, p.7) again anticipated this, suggesting the need for "…a heuristic that guides one to fruitful combinations". Simonton (2011), echoing Campbell (1960), spoke of Blind Variation and Selective Retention (BVSR). In the simplest form, BVSR would be represented by an only slightly less stupid algorithm, designed to compute a subset of variations of notes according to some heuristic or rule, thus reducing the conceptual space. Nevertheless, this approach retains most of the same limitations of blind generation, even if it is computationally more efficient. At best, by raising the likelihood of finding an effective melody, the result of BVSR might be *low* (as opposed to *very low*) creativity.

With artificial systems designed for blind generation or BVSR *effectively* limited to low levels of creativity and high computational cost, computational creativity must turn to other means if it is to replicate, or replace, human creativity in a practical way. Can modern AI approaches such as machine learning generate novel and effective (i.e. creative) outcomes?

Unlike blind generation or BVSR of the kind described above, Artificial Intelligence (AI) and more specifically, Machine Learning (ML), offers a means to achieve a more direct pathway to Bruner's *fruitful* combinations. Take a simple case of *supervised*, classical learning[3]. An AI is *trained* on the music of Mozart. The system learns that certain combinations of notes are "correct", and is trained to generate new forms, in effect, *in the style of* Mozart. This algorithm, called *Narrow Training* here, avoids the billions of *ineffective* combinations of notes inherent in the algorithms

[3] It is not our intent here to discuss, in detail, the mechanisms or methods of Machine Learning. We are drawing on well-established broad properties of different classes of Machine Learning to illustrate their potential application in artificial creativity.

described previously by incorporating an evaluative component. The result is more likely to be effective, precisely because it emulates music that has been defined, *a priori*, as effective. The conceptual space, in other words, is substantially reimagined. However, the stronger the training – the more the AI learns from the music of Mozart and the more it evaluates and restricts its own output – the lower the novelty. The *autonomy* (Lamb, Brown, & Clarke, 2018) of the artificial system is highly constrained. In fact, as the training becomes more focused on Mozart, what is lost first is radical novelty. The stronger the training is focused on Mozart, the more the creativity becomes incremental in nature – variations on a theme by Mozart – and if too strong, it is possible to imagine an AI unable to generate anything more than the reproduction of *Eine Kleine Nachtmusik*. The artificial system has become merely a system for plagiarising Mozart (see Table 2)!

Is there an approach to artificial creativity in this *idea generation/idea evaluation* paradigm that maximises the opportunity for radical novelty, while at the same time maximising the likelihood of effectiveness? The use of Machine Learning coupled with *Broad Training* has some potential. Training an AI on, for example, a set of classical composers raises the potential incremental novelty (i.e. variations on an amalgam of Mozart, Beethoven, Schubert and Haydn), and may even offer the potential for radical novelty (a new style that is a blend of Mozart, Beethoven and others). The likelihood of effectiveness is raised from that of the gamble of blind generation or BVSR, though not as high as the certainty that comes with narrow training or plagiarism. The overall creativity, therefore, is potentially higher than any of the other options so far considered, though still not guaranteed. A summary of these varying possibilities is presented in Table 2.

Table 2: Opportunities for Artificial Cognition in Creativity

Algorithm	**Need**	**Potential Novelty (N)**	**Potential Effectiveness (E)**	**Potential Creativity (N x E)[a]**	**Cost of satisfying Need**
Blind Generation	Write me a 7-note melody	Very High Radical	Very Low	Very Low	Very High
BVSR	Write me a 7-note melody	High Radical	Low	Low	Very High
Broad Training	Write me a classical symphony	High Incremental/ Low Radical	Moderate	Moderate	Very High
Narrow Training	Write me a symphony in the style of Mozart	Moderate Incremental	High	Low	High
Plagiarism	"OK Google – play *Eine Kleine Nachtmusik"*	None	Very High	None	Very Low

There is an important caveat here. We cannot reasonably hold an artificial system to a higher standard than a human. Even human composers have bad days. This is why the *probability* or *potential* of an effective solution has to be considered, as well as the computational cost. Each approach, from blind generation to ML, can, *in theory*, meet the requirement of generating novel, and effective, outcomes (e.g. in music). Whether or not it does so remains a question for the human-centric solution validation. However, if an artificial system can only ever do as well as a human, and no better, in idea generation, and lacks autonomy, then is it a candidate to replace humans in this stage of creative problem solving? Furthermore, if an AI can only reach a modest level of creativity at a prohibitive energy cost (see Strubell, Ganesh, & McCallum, 2019), is the possibility of artificial creativity sustainable?

Case Studies in Artificial Creativity

To explore the concepts outlined, we present two case studies of artificial systems that are claimed to be, or have the apparent potential to be, creative. The first is an autonomous laboratory assistant, and the second is a story-writing AI.

The Catalysing Computer

In mid-2020, researchers at the University of Liverpool in the UK (Burger et al, 2020) announced the creation of an intelligent, mobile, robot scientist, capable of undertaking chemical experiments independently of humans[4]. The robot in question works in a normal laboratory, using typical *human* instruments. The Liverpool robot is able to work for up to 21.6 hours each day, stopping only to recharge its batteries. In Burger et al's study, the robot performed 688 experiments in 8 days, and found new photocatalyst mixtures. The researchers estimated that the same experiments would have taken a human several months to perform. The robot scientist used a *batched Bayesian search algorithm* (see, for example, Shahriari, 2015) to explore a 10-dimensional search space, with more than 98 million points. This technique, broadly speaking, is a form of supervised machine learning. As such, the University of Liverpool's robot scientist is undoubtably an exemplar of a robot taking over the work of a human. However, is that work routine and algorithmic – with the robot simply doing it faster and more accurately than a human – or is the work creative?

Using the criteria listed in Table 2, it seems clear that this is an example of *narrow training*. The system was programmed, very explicitly, to identify photocatalyst mixtures with particular properties. Indeed, the robot scientist did uncover photocatalyst mixtures "that were six times more active than initial formulations" (Burger et al, 2020, p. 237) indicating not only a clear capacity for some degree of incremental novelty, but for *effective* incremental novelty. However, it was trained, so to speak, for this one very specific purpose. In the same way that we would not expect the music AI trained on Mozart to suddenly compose a piece in the style of Stravinsky, the robot scientist could not autonomously decide to pursue different experiments. It could only ever (without human intervention, in the form of reprogramming) search for photocatalysts. Indeed, unless the laboratory was restocked by a compliant human, the robot scientist could not find anything at all. The robot

[4] See: https://www.eurekalert.org/pub_releases/2020-07/uol-lrb070620.php

scientist lacks autonomy, with the authors noting (p. 241) that "this autonomous system does not at present generate and test scientific hypotheses by itself".

Summarising the abilities of the robot scientist against the criteria in Table 2 suggests that it possesses a limited capacity to *support* incremental creativity. It cannot autonomously decide what need is to be satisfied, and it cannot decide if its output actually satisfies that need. Those decisions – *problem definition* and *solution validation* – remain a matter for the humans who program and control the robot scientist. It can, however, explore a large, specific conceptual space much more quickly than a human scientist, evaluating candidate solutions, and presenting those to its human colleagues in a form of highly efficient *technology push* (Martin, 1994; Cropley & Cropley, 2015). In this sense, perhaps artificial intelligence should be thought of as a support in the creative process even, as one team member noted, "free[ing] up time for the human researchers to think creatively"[4].

The Android Author

In 2016, the Kimagure Artificial Intelligence Writer Project, based in Japan, produced a story[5], which was submitted as an entry for the Nikkei Hoshi Shinichi Literary Award[6]. The story – *The Day a Computer Wrote a Novel* – was hailed for the fact that it made it through the first of four rounds of evaluation by the competition's (human) judges. It was eliminated in the second round.

The process that delivered this apparently creative output was, however, not as straightforward as an AI *writing a novel*. A story was first written by the team responsible for the project. This was then *structuralized* – broken into its components parts (words). In another example of classical, supervised learning, the researcher team then fed these data into their AI, along with a

[5] https://www.smithsonianmag.com/smart-news/ai-written-novella-almost-won-literary-prize-180958577/
[6] The Nikkei Hoshi Shinichi Literary Award is open to both human and non-human (i.e. AI) authors.

set of instructions/rules for how to reassemble the words into a coherent story. Perhaps not surprisingly, the result was a something resembling a story.

Assuming that the algorithm was some form of machine learning, and not merely pseudo-random recombination of the original words, then this example is at best an instance of *narrow training*, possibly bordering on a form of automated self-plagiarism. It is unclear if the original story served as an exemplar of a good story from which the AI could learn, or merely a library of possible words, comprising a finite conceptual space. Regardless, we can apply the criteria of Table 2 to assess the potential creativity of this story-writing AI.

With a single exemplar used to train this AI, and a highly constraining set of rules for reassembling the story, the potential novelty of this example remains frustratingly incremental. Unlike the robot scientist, the incremental novelty here is not simply an output that is “two times faster” or “three times more efficient”, but incremental in the sense of “what happens if the main character finds a new object in chapter 2, instead of losing something they had?” The novelty is reflected in improvements to, or changes in, a baseline output.

The story-writing AI did produce an output representing at least some degree of effectiveness. Unlike the robot scientist, for which effectiveness is more explicitly definable, the output of the story-writing AI is judged with a greater degree of subjectivity. However, this does not mean that effectiveness is undefinable for an “artistic” output - only that it may be subject to greater variability. However, as the Consensual Assessment Technique (see Amabile, 1982, 1996) has shown, it is perfectly possible for knowledgeable experts to reach agreement, even for outputs of an artistic nature. Therefore, while you may like *The Day a Computer Wrote a Novel*, the expert judges, in the end, did not.

Therefore, with only moderate incremental novelty, and even with high effectiveness, the story-writing AI is, like the robot scientist, limited to *supporting incremental creativity*. The need, in this case defined not only by the original (human-authored) story, but also by the rules for writing the AI-authored story, remains firmly the job of humans. Solution validation, similarly, remains a task for humans.

AI and Humans in Partnership

The majority of work conducted in organizations is done in teams – especially creative teams (Reiter-Palmon et al., 2012). In addition, the to the subject of how AI can be creative, it is paramount to consider the partnership of AI and human integration in solving creative problems. Creative teams typically benefit from varied perspective, multiple domains of expertise, and increased knowledge. Integrating AI into this formula may serve to free-up some cognitive stress placed on human (i.e., acquiring resources in terms of information). Although AI lacks in conceptual thinking, developing strategies that facilitate AI and humans working together, boasting the benefits of AI (i.e., rapid information acquisition) may allow for *more* creative efforts by addressing areas that typical human-centered teams struggle with. In simple terms, AI can serve as a method to implement checks and balances to circumvent weak spots within teams.

Despite the attraction of integrating AI into teams, there are, of course, potential drawbacks. High-performing teams balance on a high level of psychological safety and trust (Braun et al., 2013; Lee et al., 2010; Langfred, 2004). Thus, one should consider how incorporating AI into teams impacts the composition and configurations of the teams. Although AI can aid creative teams by having the ability to collect, store, and process information at high speeds (Elkins & Derrick, 2013), these benefits are fruitless if that same information is not shared due to a lack of trust in using AI. Notably, humans have an initial distrust from their beginning interaction with AI (Sheridan & Hennessy, 1984). That said, more interaction with AI systems and their popularity in mainstream press appearances may increase the confidence a human places on the benefits and likelihood of using the AI system (Ashton, 1990). In evidence of this, Elkins and Derrick (2013) demonstrated that the trust within an interaction between humans and AI was temporally variant and could be explained by a linear change in time.

Taken together, the avenue on integrating a partnership of AI and Humans may be better positioned from the focus of *Humans* and AI. Specifically, attention to how AI will influence teamwork and strategies that facilitate this experience will be vital for organizational performance.

Conclusions

The question *can robots be creative* grows in significance the deeper we move into the era of Industry 4.0. If only humans can generate novel and effective ideas, then the Future of Work holds no fears for us, provided we educate ourselves to be effective creative problem solvers. If, on the other hand, robots displace humans even in this key ability, then we face significant challenges. Indeed, we face the prospect of being confined to the jobs that *even the robots refuse to do*[7]!

In this chapter we have hypothesised that with regard to the defining activity of creativity – the ability to generate novel and effective outputs – artificial systems are limited to, at best, moderate levels of incremental creativity. In other words, artificial systems have the potential to generate new, and effective, variations of existing ideas, solutions, systems, and artefacts. Furthermore, even with improvements and changes to the technology of AI, this capacity is likely *not* to transition, eventually, into an autonomous ability for radical creativity, but simply into higher levels of incremental creativity, at a lower cost. While computing power will increase, and algorithms will continue to improve, the limiting factor on artificial creativity (aside from a possible data and energy constraints) is not *how* (the process): it is the rationale (why). No matter how good AI

[7] This could be either in the sense that robots, literally, pick and choose what they do, or figuratively, in the sense that the owners of expensive, intelligent robots would not waste this resource on menial, dangerous or dirty tasks that risk damaging their robot.

technology becomes, the reason why we are creative – problem definition and solution validation – remains the job of humans.

Nevertheless, the debate will no doubt continue. It is driven, however, not by questions of technology, but by deeply ingrained myths and misconceptions about creativity that continue to dog this field of research (e.g. Patston et al, 2018). The discipline of psychology has been consistent in its definition of creativity – always anchored to the production of novel and effective outcomes – however, the computational field has exhibited a much greater flexibility. Newell, Shaw and Simon (1962) were closely aligned with what psychology now refers to as the *standard definition* (Runco & Jaeger, 2012), however, as Wiggins (2006, p. 210) demonstrates, computational definitions also frequently choose to focus on "…behaviour which would be deemed creative if exhibited by humans." Embedded in the Wiggins definition is an important, yet false, premise. The human behaviour referred to seems to be the *act of creating* – in other words, the assumption is that "humans bring things into being (they create), and computers can be programmed to bring things into being (to create), therefore, computers are *creative*." This ignores the standard definition of creativity, as it ignores the rationale for creativity.

Taking this into account, we are left with one final consideration. What value is derived from the ability that artificial systems do possess to support the core processes of creativity: idea generation and idea evaluation? As the cases of the C*atalyzing Computer* and the *Android Author* illustrate, artificial systems first and foremost radically speed up tasks that are necessary, but not sufficient elements in the process of creative problem solving. They relieve humans of slow, repetitive, algorithmic tasks – whether trying out hundreds of possible chemical formulae, or exploring the potential of different story lines – creating more time and more opportunity for humans to identify unresolved needs and match these to genuinely new and effective solutions.

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