The neural and cognitive mechanisms underlying creative thinking

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ABSTRACT

The ability to generate creative ideas and novel solutions is a defining feature of human cognition. However, the cognitive and neural mechanisms that underlie creative cognition are poorly understood. While recent research has highlighted the roles of distinct associative and controlled processes in creative cognition, supported by the default mode and executive control networks, respectively, it remains unclear how exactly creative ideas are produced by the interactions of these processes and networks, or how creative cognition relates to more fundamental processes like executive functions and working memory (WM). The present thesis aims to examine the neurocognitive basis of creative thinking using a combination of behavioral and fMRI experiments. The need for greater computational modeling in neurocognitive creativity research (NCR) is also discussed.

The first study examines how the default mode and executive control networks contribute to creative cognition over time. Results are broadly suggestive of distinct generative and evaluative phases in creative thought. A second study explores relationships between multiple forms of creative thinking and multiple forms of inhibition, finding that divergent thinking is related to cognitive inhibition. In a third study, relationships between creative cognition and control over WM are examined, using measures of executive functions. While no relationships were found between divergent thinking and executive functions, a positive relationship was found between WM updating and convergent thinking and verbal fluency. In a review chapter, the case for greater computational modeling in NCR is made. Previous models of creative cognition, and how these might be improved upon, are discussed, with some examples of the model development process. In a final study, relationships are explored between personality measures and evaluations of the novelty, usefulness, and creativity of ideas. A closing chapter summarizes all findings and discusses avenues for future research.

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DISCLAIMER: *some of the content of this thesis, in particular some of the contents of Chapters 2, 3 and 5, has been published.*

CHAPTER 1: OUTSTANDING QUESTIONS FOR NEUROCOGNITIVE CREATIVITY RESEARCH

1.1 Thesis overview

The ability to think creatively is one of humanity's most defining features, enabling us to make remarkable progress in diverse scientific and artistic domains, as well as to solve simpler problems we encounter every day. While creativity is traditionally considered an elusive target for scientific investigation (Hennessey & Amabile, 2010; Iger, 2019), recent decades have witnessed tremendous growth in neurocognitive creativity research (NCR) – research that aims to uncover the neural and cognitive basis of creative thought. While definitions of creativity vary (e.g., Acar, Burnett, & Cabra, 2017; Simonton, 2018), most NCR defines creative cognition as the production of novel and useful ideas (Diedrich, Benedek, Jauk, & Neubauer, 2015; Runco & Jaeger, 2012; Stein, 1953). Common methods of assessing creativity in a laboratory setting include measures of divergent thinking (the ability to produce multiple creative ideas in response to a single problem), and convergent thinking (the ability to select a single best idea). One of the most common measures of divergent thinking is the Alternative Uses Task (AUT), which requires participants to think of numerous unusual uses for everyday objects (e.g., using a brick to grind up food). A common measure of convergent thinking, meanwhile, is the Remote Associates Test (RAT), in which participants are shown three unrelated words and must generate a response word that relates to all three.

NCR researchers aim to understand creativity as the outcome of more established cognitive processes such as memory and attention (Benedek & Fink, 2019; Wiggins & Bhattacharya, 2014). From this research, a complex picture is emerging in which creative cognition relies on a diverse range of cognitive and psychological factors, including memory (Benedek et al., 2014b; Fugate, Zentall, & Gentry, 2013; Kenett et al., 2018a; Madore, Addis, & Schacter, 2016; Storm, Angello, & Bjork, 2011), attention (Frith et al., 2021b; Zabelina, 2018), personality (Beaty et al., 2018a; Kaufman et al., 2016; Oleynick et al., 2017), executive control (Beaty, Silvia, Nusbaum, Jauk, & Benedek, 2014; Benedek, Jauk, Sommer, Arendasy, & Neubauer, 2014c; Krumm, Arán Filippetti, & Gutierrez, 2018), and reward processing (Beversdorf, 2019; Lin & Vartanian, 2018). Meanwhile, neuroimaging studies have revealed that creative cognition in numerous domains involves cooperation between large-scale brain networks, including the default mode (DMN) and executive control (ECN) networks (Beaty, Benedek, Silvia, & Schacter, 2016a; Beaty, Cortes, Zeitlen, Weinberger, & Green, 2021; Ellamil, Dobson, Beeman, & Christoff, 2012; Mayseless, Eran, & Shamay-Tsoory, 2015).

Despite this progress, however, the field remains far from a precise understanding of how creative cognition arises from neurocognitive processes. It remains unclear what processes underlie the interactions of the DMN and ECN, and how exactly these networks contribute to creative cognition. It has been suggested that the DMN is responsible for the generation of ideas, while the ECN oversees the evaluation of ideas (see Beaty et al., 2016a, 2018b; Kleinmintz, Ivancovsky, & Shamay-Tsoory, 2019; Mayseless et al., 2015), but this is mostly speculative. Meanwhile, it is unknown how exactly executive functions, such as inhibition, switching, and working memory (WM) updating contribute to creative cognition, and whether their contributions vary depending on the nature of the creative task. To fully understand the mechanisms of creative cognition, further research is needed to unpack how these functions (and other cognitive factors) operate and interact differently in different creative contexts.

In addition to more fine-tuned empirical research, NCR would benefit greatly from the wider adoption of computational modeling. While the verbal theories that currently guide NCR are becoming increasingly mechanistic (e.g., Khalil & Moustafa, 2022; Simonton, 2022; Zhang, Sjoerds, & Hommel, 2020) these theories remain more vague and harder to falsify than formal computational models. By contrast, computational modeling can bring considerable clarity and accessibility to theories of creative cognition, and make it easier to develop and compare new hypotheses.

Finally, little research has examined the evaluation of creative ideas, and how this evaluation is affected by factors such as personality and risk-taking. For example, is the novelty of an idea more important to its creativity, or is the usefulness? Evaluation is a key part of the creative process (Basadur, 1995; Goldschmidt, 2016; Kleinmintz et al., 2019; Runco & Smith, 1992), and how people vary in their evaluations of creative ideas is likely to affect how they generate their own ideas.

However, few studies have assessed how individuals evaluate creative ideas or the factors that influence evaluation.

The present thesis aims to address these outstanding questions regarding the mechanisms of creative cognition, in seven chapters. After a more detailed discussion of the current state of NCR and the issues explored by the thesis in the current chapter, Chapter 2 describes a study examining how the DMN and ECN vary in their contributions to creative cognition over time. The study provides tentative evidence for the existence of distinct generative and evaluative phases in creative thought. Chapter 3 then focuses on the relationship between creative cognition and inhibitory control, where both are measured as multi-faceted constructs. The study finds that one particular kind of inhibition – retrieval induced forgetting – may be most related to prominent measures of divergent thinking. Chapter 4 describes a related study examining the roles of switching, inhibition, WM updating and WM capacity in creative cognition, with a focus on automated measures of creative and associative thinking. This study finds little relationship between executive functions and creative cognition, except for a small link between updating and performance in convergent thinking and verbal fluency tasks.

Chapter 5 provides a more detailed discussion of the benefits that computational modeling can bring to verbal theories of creativity, arguing that a new generation of dynamic computational models, that both instantiate a specific cognitive theory of creativity and can model performance on common lab-based tasks, could take NCR much closer to a precise understanding of the mechanisms that produce creative ideas. Chapter 6 presents a final empirical study examining the evaluation of creative ideas, specifically how individuals consider the novelty and usefulness of ideas when assessing their creativity, and whether these considerations vary depending on the context the idea was generated in. The findings of these various empirical studies are then summarized in Chapter 7, which also provides some directions for future research.

1.2 The current state of NCR

NCR's objective is to uncover the neural and cognitive processes that underlie creative thinking (Benedek & Fink, 2019). To this end, researchers have explored how numerous cognitive and psychological factors relate to creative performance. Here, some of these findings are briefly discussed. For example, attention studies suggest that real-world creative achievement may be linked to a form of "leaky" attention (Zabelina, 2018), while creative performance in laboratory settings appears to be associated with selective attention (Vartanian, 2009) or flexible attention (Zabelina, O'Leary, Pornpattananangkul, Nusslock, & Beeman, 2015; Zabelina, Saporta, & Beeman, 2016).

Moreover, research on the connection between creative thinking and intelligence has found a significant overlap between the two in lab-based settings (Frith et al., 2021a; Karwowski et al., 2016; Karwowski, Czerwonka, & Kaufman, 2020), and suggests they may depend on shared neural regions (Benedek, Jung, & Vartanian, 2018; Frith et al., 2021a). Studies have also explored the relationship between creativity and executive functions, finding that aspects of creative performance are related to cognitive functions such as switching (Krumm et al., 2018; Nusbaum & Silvia, 2011; Pan & Yu, 2018; Zabelina & Ganis, 2018), updating (Benedek et al., 2014c; Stolte, García, Van Luit, Oranje, & Kroesbergen, 2020; Zabelina, Friedman, & Andrews-Hanna, 2019), and inhibition (Camarda et al., 2018a; Kaur, Weiss, Zhou, Fischer, & Hildebrandt, 2021; Zabelina et al., 2019).

Regarding the relationship between creative thinking and memory, some studies suggest that creative cognition benefits from strong WM abilities (Benedek et al., 2014c; de Dreu, Nijstad, Baas, Wolsink, & Roskes, 2012; Stolte et al., 2020), while other research presents mixed findings (de Vink, Willemsen, Lazonder, & Kroesbergen, 2021; Krumm et al., 2018), suggesting that the role of WM in creative thinking may depend on the specific task (Krumm et al., 2018). Indeed, studies have employed network science methods to reveal that more creative individuals may possess more flexible and interconnected semantic memory structures (He et al., 2020; Kenett, Anaki, & Faust, 2014; Kenett et al., 2018a; Ovando-Tellez et al., 2022).

Research has also explored less direct connections between creativity and neurocognitive processes, investigating how creativity relates to personality traits like risk-taking (Dewett, 2007; Harada, 2020; Shen, Hommel, Yuan, Chang, & Zhang, 2018) and openness to experience (Batey & Furnham, 2006; Kaufman et al., 2016; Oleynick et al., 2017). Neurodevelopmental conditions, including ADHD (Fugate et al., 2013; Hoogman, Stolte, Baas, & Kroesbergen, 2020) and schizophrenia (Sampedro et al., 2020a, 2020b), have also been examined for their impact on creative thinking.

Furthermore, research has explored how creative performance is related to motivation (Benedek, Bruckdorfer, & Jauk, 2020; Xue et al., 2020) and the functioning of the dopaminergic (Lin & Vartanian, 2018; Zhang et al., 2020) and noradrenergic systems (Beversdorf, 2019; Boot, Baas, van Gaal, Cools, & De Dreu, 2017; Flaherty, 2005). When it comes to the neural correlates of creativity, fMRI studies consistently show that creative thinking involves enhanced cooperation between the DMN, ECN, and salience network (Beaty et al., 2016a; Green, Cohen, Raab, Yedibalian, & Gray, 2015; Mayseless et al., 2015). Additionally, EEG research has indicated that higher creative performance is associated with greater cortical alpha synchronization (Agnoli, Zanon, Mastria, Avenanti, & Corazza, 2020; Camarda et al., 2018b; Fink et al., 2018; Rominger et al., 2019; Stevens & Zabelina, 2020). Meanwhile, research using transcranial brain stimulation has found that increasing alpha power over the prefrontal cortex can enhance the creative quality of ideas (Lustenberger, Boyle, Foulser, Mellin, & Fröhlich, 2015), while stimulation over temporal sites supports the inhibition of non-creative ideas (Luft, Zioga, Thompson, Banissy, & Bhattacharya, 2018).

Guiding this diverse wealth of research are a number of theoretical frameworks. Among the most popular are dual-process accounts, which describe creative cognition as a complex interplay between automatic, spontaneous processes and deliberate, executive control processes (Benedek & Jauk, 2018; Mok, 2014; Sowden, Pringle, & Gabora, 2015; Volle, 2018). These frameworks draw on wider dual-process theories within cognitive science that distinguish between fast, automatic Type 1 processes, and slow, deliberate Type 2 processes (Evans & Stanovich, 2013; Sowden et al., 2015). Alternative accounts describe creativity as involving generative and evaluative processes (Ellamil et al., 2012; Kleinmintz et al., 2019), exploration and exploitation (Baror & Bar, 2016; Hart et al., 2017; Lin & Vartanian, 2018), and focused and defocused attention (Gabora, 2010; Zabelina & Robinson, 2010).

Focusing on dual-process accounts, these are supported by a range of findings. The role of spontaneous processes in creative cognition is supported by evidence that creative performance benefits from defocused periods of idea incubation (Sio & Ormerod, 2009), while studies using free-association (Marron et al., 2018) and verbal fluency paradigms (Beaty et al., 2014) suggest that creative cognition may relate to associative processes that spontaneously propagate through memory (Kenett et al., 2018a; Mednick, 1962; Volle, 2018). Meanwhile, the role of controlled processes in creative thought is supported by links between creative performance and intelligence (Beaty et al., 2014; Benedek et al., 2014c; Frith et al., 2021a) and executive functions (Benedek, Franz, Heene, & Neubauer, 2012; Benedek et al., 2014c; Camarda et al., 2018a). Further support for the dual-process perspective comes from neuroimaging studies, which have shown that creative cognition involves cooperation between the DMN and ECN (Beaty et al., 2016a, 2018b, 2021; Christensen, Benedek, Silvia, & Beaty, 2021; Mayseless et al., 2015). The two networks are typically anti-correlated (Anticevic et al., 2012), but appear to cooperate in creative tasks ranging from musical improvisation (Pinho, de Manzano, Fransson, Eriksson, & Ullén, 2014), visual artistic design (Ellamil et al., 2012), poetry (Liu et al., 2015), and verbal divergent thinking (Beaty, Benedek, Barry Kaufman, & Silvia, 2015; Mayseless et al., 2015).

1.3 Outstanding issues

However, numerous outstanding questions remain for NCR researchers regarding the specific mechanisms that produce creative ideas. Concerning the DMN and ECN, it is unclear exactly how these networks contribute to creative cognition. Given the DMN's involvement in memory and imagination (Andrews-Hanna, Smallwood, & Spreng, 2014; Beaty, Thakral, Madore, Benedek, & Schacter, 2018d) researchers have suggested that the network underlies the spontaneous activation of ideas, accessed through associative processes (Beaty et al., 2020; Beaty & Lloyd-Cox, 2020). The ECN, meanwhile, has been suggested to monitor and guide this spontaneous activity through top-down control, for example to execute particular strategies in a creative task (Benedek & Jauk, 2018; Frith et al., 2021a). Indeed, it is possible that ECN regions can suppress DMN activity to inhibit distracting and poor-quality ideas, allowing access to better ones (Beaty, Christensen, Benedek, Silvia, & Schacter, 2017a; Christensen et al., 2021). This characterization has led researchers to suggest that idea generation is primarily performed by the DMN, while the evaluation and refinement of ideas is mainly performed by the ECN (Beaty et al., 2016a; Ellamil et al., 2012; Jung, Mead, Carrasco, & Flores, 2013; Kleinmintz et al., 2019).

However, this suggestion is mostly speculative. It is unclear whether different stages of creative cognition (e.g., generation and evaluation) can be distinguished, or whether they might involve different proportions of associative and controlled processes, corresponding to different contributions from the DMN and ECN (Kleinmintz et al., 2019). Examining how these networks contribute to creative thinking over the course of a single creative trial (i.e., the generation and output of a single creative idea), could reveal much about the dynamics of the processes performed by these networks, and potentially the existence of distinct generative and evaluative phases in creative cognition.

The notion that the ECN can moderate the activity of the DMN through top-down inhibitory control fits well with the dual-process account of creative cognition. To attain creative ideas, dual-process accounts argue that unoriginal and obvious ideas must be inhibited and suppressed, while particular pathways through memory are strategically selected to increase the novelty of activated concepts (Barr, 2018; Benedek, Beaty, Schacter, & Kenett, 2023; Silvia, Beaty, & Nusbaum, 2013; Volle, 2018). However, as noted, creative ability is not always correlated with inhibitory control (Chrysikou, 2019). Evidence from studies examining jazz improvisation (Limb & Braun, 2008), real-world creative performance (Carson, Peterson, & Higgins, 2003), and in some cases divergent thinking tasks (Dorfman, Martindale, Gassimova, & Vartanian, 2008; Radel, Davranche, Fournier, & Dietrich, 2015), suggest a negative link between creative cognition and inhibition. Indeed, it has been argued that expert-level creative performance might relate to a suspension of cognitive control (Dietrich, 2004), to allow associative processes to operate more freely and flexibly. Moreover, incubation, a key stage of the creative process described by Wallas (1926), and commonly reported by highly creative individuals (Boden, 1990; Kounios & Beeman, 2014) involves a temporary reduction in inhibitory control. This can allow individuals to mind-wander, and overcome self-imposed constraints regarding the nature of a problem, potentially leading to novel insights (Benedek & Jauk, 2018; Ritter & Dijksterhuis, 2014).

However, numerous studies have reported positive relationships between inhibitory control and creative performance, particularly in laboratory-based settings (Benedek et al., 2012, 2014c; Camarda et al., 2018a). Indeed, performance on divergent thinking tasks has been linked to intelligence (of which executive functions such as inhibition are a major predictor; Ardila, 2018;

Arffa, 2007) by several studies (Beaty et al., 2014; Benedek et al., 2014c; Frith et al., 2021a; Karwowski et al., 2016). These somewhat contradictory findings have led researchers to suggest that the importance of inhibitory control for creative cognition likely depends on the specific task context (Benedek & Jauk, 2018; Chrysikou, 2018; Sowden et al., 2015; Volle, 2018). For example, open-ended or loosely-defined tasks might benefit from reduced inhibitory control, while well-defined tasks with time constraints might benefit from greater inhibitory control.

In addition however, it is possible that the relationship between inhibitory control and creativity depends on the nature of the inhibition measure. Inhibition comes in numerous forms (Diamond, 2013; Engelhardt, Nigg, Carr, & Ferreira, 2008), which may have distinct neural bases (Cipolotti et al., 2016), including latent inhibition (Carson et al., 2003; Granger, Moran, Buckley, & Haselgrove, 2016), cognitive inhibition (Engelhardt et al., 2008; Koppel & Storm, 2014), and response inhibition (Benedek et al., 2014c; Friedman et al., 2016). Our understanding of the relationship between creative cognition and inhibitory control would be greatly enhanced by examining both as multifaceted constructs, in a study comparing several measures of creative performance and several measures of inhibitory control.

Questions concerning the role of inhibition in creative cognition highlight the likely importance of WM to creative performance. The need to prevent distracting, unoriginal ideas from activating implies a finite WM store, access to which must be carefully managed to attain optimally creative ideas. Currently, research has found mixed findings on the relationship between WM capacity and creative cognition, with some studies finding support for a connection (Benedek et al., 2014c; de Dreu et al., 2012; Orzechowski, Gruszka, & Michalik, 2022; Stolte et al., 2020), and others suggesting little relationship (de Vink et al., 2021; Gerver, Griffin, Dennis, & Beaty, 2023; Krumm et al., 2018). However, control over access to WM might still be an important factor in creative performance, and may allow individuals to switch flexibly between focusing on the details of a handful of concepts and expanding attention to allow new information to enter awareness. Indeed, researchers have suggested that creative performance involves adjusting attention between narrower and broader states (Dorfman et al., 2008; Gabora, 2010; Zabelina, 2018; Zabelina & Robinson, 2010) and switching between exploratory and exploitative search strategies (Mekern, Sjoerds, & Hommel, 2019b; Nijstad, De Dreu, Rietzschel, & Baas, 2010), and generative and evaluative modes of thought (Ellamil et al., 2012; Kleinmintz et al., 2019). Such processes might be enacted by adjusting input to WM. For example, broad, generative, and exploratory attentional states may involve wider input to WM, where tangential ideas can activate spontaneously. By contrast, narrow, exploitative, and evaluative attentional states might involve limiting WM input to only closely related ideas.

In addition to measures of inhibitory control, control over WM is commonly assessed with measures of executive shifting and updating (Friedman et al., 2016; Miyake et al., 2000). Measures of updating tend to overlap with those designed to assess WM capacity, such as complex span tasks, which involve remembering a growing list of items while performing a simultaneous executive task (Schmiedek, Hildebrandt, Lövdén, Wilhelm, & Lindenberger, 2009; Schmiedek, Lövdén, & Lindenberger, 2014; Smeekens & Kane, 2016; Wilhelm, Hildebrandt, & Oberauer, 2013). Meanwhile, measures of shifting tend to focus on the ability to reassign cognitive resources to distinct tasks (Liu & Yeung, 2020; Miyake et al., 2000; Serrien & O'Regan, 2019). If control over WM is important for creative thinking, to switch between generative and evaluative modes or between conceptual spaces, one might expect those with greater inhibition, shifting, and updating abilities to have greater creative performance, or at least to visit a greater number of conceptual categories in creative tasks (flexibility; see also Zhang et al., 2020). However, while a handful of studies have found a positive relationship between executive functions and creative performance (Benedek et al., 2014c; Krumm et al., 2018; Pan & Yu, 2018; Zabelina & Ganis, 2018), others report mixed findings (de Vink et al., 2021; Gerver et al., 2023; Menashe et al., 2020; Palmiero, Fusi, Crepaldi, Borsa, & Rusconi, 2022), and few studies have examined the relationship between executive functions and the ability to switch between categories of idea in creative tasks.

Theoretically, control over WM could underlie factors such as the speed at which semantic memory is traversed (Beaty & Kenett, 2023; Kenett et al., 2018a; Volle, 2018), the number of conceptual categories visited, or the overall creativity of responses during creative tasks. However, it is currently unknown whether these factors relate to executive functions, whether the same processes underlie switching in both executive and creative contexts, or whether executive functions can also impact the associative processes that are important in creative cognition. A study examining a range of creative and associative tasks, together with measures of executive functions in a broad battery, could go some way toward shedding light on the cognitive mechanisms that produce creative ideas.

Indeed, as a high-level construct, creative cognition is likely impacted by a very large number of psychological and cognitive factors. Developing specific mechanistic hypotheses concerning the interactions of these factors, and how they produce creative ideas, is very difficult with verbal theories alone (Guest & Martin, 2021). This is just one issue with the current state of NCR that can be alleviated through the wider use of computational modeling. For example, if researchers supposed that those higher in the personality trait openness to experience produce more creative ideas by engaging in broader attentional states (Gabora, 2010, 2018), rather than seeking purely correlational support for this hypothesis, it could be embodied in a computational model. Openness might be defined as a set of parameters governing the propensity to use broad conceptual representations. The hypothesis could then be tested by adjusting the parameters reflecting openness and observing whether the changes in simulated creative outcomes are in line with those observed among human participants with varying openness scores.

Beyond making theories more testable, computational modeling can aid the development of more precise and communicable theories (Blohm, Kording, & Schrater, 2020; Borsboom, van der Maas, Dalege, Kievit, & Haig, 2021; Fried, 2020). Since models require theories to be explicitly formalized in terms of equations and algorithms, every aspect of the theory must be precisely defined (Farrell & Lewandowsky, 2015; Maia, Huys, & Frank, 2017). This detail can reveal weak points and false assumptions in theories, highlighting avenues for future research (Blohm et al., 2020). By contrast, purely verbal theories possess a degree of vagueness and ambiguity that makes them harder to falsify and can allow different researchers to have very different interpretations of a theory. Recent years have witnessed a rise in the number of computational models that can simulate performance on common lab-based tasks (e.g., Lopez-Persem et al., 2022; Olteţeanu & Falomir, 2016; Schatz, Jones, & Laird, 2018), but considerably more can be done to better integrate computational modeling with NCR and improve the usefulness of models to empirical researchers.

Finally, amid the wealth of research into the generation of creative ideas, it is also important to consider how individuals evaluate creative ideas. For example, if a creative idea is one that is both novel and useful, it's likely that raters weigh both qualities when assessing its creativity. Which quality is more important to an individual could say much about how they generate their own ideas, and might relate to their curiosity, personality, and approach to risk. However, surprisingly little research has examined how novelty and usefulness contribute to evaluations of creativity, and the factors that can influence these contributions. For example, some evidence suggests that the creativity of an idea depends far more on its novelty than its usefulness (Caroff & Besançon, 2008; Diedrich et al., 2015; Han, Forbes, & Schaefer, 2021; Runco & Charles, 1993), but other research suggests that the impact of novelty and usefulness might depend on the context in which the idea was generated (Acar et al., 2017; Long, 2014; Runco, Illies, & Eisenman, 2005).

Additionally, while research has explored how the evaluation of creativity overall relates to individual differences in expertise (Long, 2014), emotion (Lee, Chang, & Choi, 2017; Mastria, Agnoli, & Corazza, 2019), and uncertainty (Mueller, Melwani, & Goncalo, 2012), little is known about their influence on perceptions of novelty and usefulness. Personality traits such as openness to experience may play a key role here, by affecting individuals' receptiveness to new and unconventional ideas, potentially biasing them towards valuing novelty over usefulness. Currently, however, the extent to which factors like the context of the creative task and the personality of the rater affect the considerations of novelty and usefulness remains unclear. Providing answers to these questions with an empirical study would greatly help to increase our understanding of how creativity is evaluated and defined.

These outstanding questions for NCR are the focus of this thesis.

CHAPTER 2: DECODING GENERATION AND EVALUATION: HOW THE DEFAULT AND EXECUTIVE NETWORKS CONTRIBUTE TO CREATIVE COGNITION OVER TIME

2.1 Introduction

As discussed in Chapter 1, research suggests that creative cognition depends on both associative and controlled processes (Benedek & Jauk, 2018; Chrysikou, 2018; Barr, 2018; Volle, 2018), which may correspond to the brain's default mode (DMN) and executive control (ECN) networks. Indeed, these networks appear to cooperate in many creative tasks (Beaty et al., 2016a, 2021; Ellamil et al., 2012; Mayseless et al., 2015). However, outstanding questions concern how exactly these different networks contribute to creative cognition, and how their contribution varies over time and over different stages of the creative process, such as idea generation and evaluation. Specifically, it remains unclear whether the DMN underlies generation while the ECN underlies evaluation (Beaty et al., 2016a, 2018b; Kleinmintz et al., 2019; Mayseless et al., 2015); whether generation and evaluation occur in cyclic phases (Kleinmintz et al., 2019) or simultaneously (Goldschmidt, 2016); and whether one network is more related to creative performance than the other.

This chapter aims to address these questions by applying multivariate pattern analysis (MVPA) to fMRI data to examine how the DMN and ECN vary in their contributions to creativity over successive phases of creative cognition. MVPA can assess how relevant the activity in a brain region or network is to a particular task, making it an ideal tool for examining the temporal dynamics of creative cognition. Here, machine-learning classifiers were trained to distinguish between two task conditions (the AUT and a similar, non-creative control task) with greater classification accuracy indicating a greater difference in brain activity between tasks, and indirectly, a greater amount of creative activity. MVPA was applied separately to two networks (the DMN and ECN) and three time phases within trials (early, mid, and late), to assess how creative activity fluctuates over time within these networks. Correlations were also computed between classification accuracy and human-rated creativity, to assess the relevance of creative activity in each network and time phase to creative quality specifically. By examining if the DMN and ECN make distinct contributions to creative cognition over time, this study aimed to test theories of creative cognition that posit separate stages of idea generation and evaluation (e.g., Basadur, 1995; Ellamil et al., 2012; Kleinmintz et al., 2019).

2.1.1 The neurocognitive basis of creativity

NCR has found considerable evidence that creative cognition relies partly on associative processes, which operate spontaneously to reinterpret problems and connect distantly-related concepts (Beaty et al., 2014; Kenett et al., 2018a; Volle, 2018), and partly on controlled processes, which can guide thought in strategic directions, and inhibit distracting and unoriginal ideas (Beaty et al., 2017a; Camarda et al., 2018a; Lloyd-Cox, Christensen, Silvia, & Beaty, 2021). While the relative contribution of these processes to creative cognition may depend on the specific task context (Benedek & Jauk, 2018; Chrysikou, 2018; Sowden et al., 2015; Volle, 2018), it remains unclear what precise cognitive operations are enacted by associative and controlled processes, and by what mechanisms they produce creative ideas. Moreover, although generation and evaluation are often described as separate stages of creative cognition (e.g., Basadur, 1995; Ellamil et al., 2012; Finke, Ward, & Smith, 1992; Kleinmintz et al., 2019), it is unknown whether the processes underlying generation and evaluation truly separate out into distinct stages (e.g., Kleinmintz et al., 2019), or instead operate simultaneously (e.g., Goldschmidt, 2016). Indeed, it is unclear whether generation and evaluation map directly to associative and controlled processes, or whether they are higher level operations that each involve some combination of associative and controlled processes.

Neuroimaging studies also highlight the roles of distinct associative and controlled processes in creative cognition. Research has found increasing evidence that creative cognition involves cooperation between the DMN and ECN, networks that are strongly implicated in associative and controlled cognition, respectively (Beaty, Kenett, et al., 2018; Chen et al., 2018; Christensen et al., 2021; Ellamil et al., 2012; Mayseless et al., 2015; Yeh et al., 2019; see Beaty, Seli, & Schacter, 2018, for a review). The ECN is formed of lateral prefrontal and anterior inferior parietal regions, and typically activates during focused, goal-oriented cognition, such as WM and switching tasks (Niendam et al., 2012; Seeley et al., 2007). The DMN is formed of cortical midline, medial temporal, and posterior inferior parietal regions, and it is thought to underpin the spontaneous activation of memories, and internally-directed thought about the past and future (Andrews-Hanna et al., 2014; Beaty et al., 2018d).

The two networks are typically anti-correlated, i.e., when one network activates, the other tends to deactivate (cf., Beaty et al., 2021a), and they may compete for resources in many contexts (Anticevic et al., 2012). Interestingly, however, increased connectivity between default mode and executive control regions has been found in a large range of creative tasks, including verbal divergent thinking (Beaty et al., 2015; Green et al., 2015; Mayseless et al., 2015), musical improvisation (Pinho et al., 2014), poetry (Liu et al., 2015), and visual artistic design (Ellamil et al., 2012). Indeed, research has found that participants who give more distant semantic responses exhibit greater connectivity between DMN and ECN regions (Green et al., 2015), while those with more efficient connections across these two networks show greater divergent thinking performance (Beaty et al., 2015). Recently, researchers have even predicted the creative performance of participants based on the strength of connectivity between ECN, DMN, and salience network regions (Beaty et al., 2018b).

Efforts have been made to interpret this pattern of activity in cognitive terms, based on the processes that are typically associated with these regions. Given the DMN's involvement in memory and imagination (Andrews-Hanna et al., 2014; Beaty et al., 2018d) it is possible that the network underlies the spontaneous activation of diverse ideas, accessed through associative processes (Beaty et al., 2020; Beaty & Lloyd-Cox, 2020). The ECN, meanwhile, may act to monitor and guide this spontaneous activity through top-down control, for example to execute particular strategies in a creative task (Benedek & Jauk, 2018; Frith et al., 2021a). Indeed, given that the networks also interact during mind-wandering (Christoff, Gordon, Smallwood, Smith, & Schooler, 2009; Fox & Beaty, 2018), and the construction of future plans (Gerlach, Spreng, Madore, & Schacter, 2014; Spreng, Stevens, Chamberlain, Gilmore, & Schacter, 2010), they may cooperate whenever there is a need for self-generated yet goal-directed thought, as in creative cognition (Beaty et al., 2016a). The networks have also been discussed in the context of generative and evaluative stages in creative cognition, with researchers suggesting that idea generation is primarily performed by the DMN, while the evaluation and refinement of ideas is mainly performed by the ECN (Beaty et al., 2016a; Ellamil et al., 2012; Jung et al., 2013; Kleinmintz et al., 2019).

In terms of more specific cognitive mechanisms by which these regions support creative cognition, little is known. One possibility with reasonable empirical support is that ECN regions can suppress DMN activity to inhibit distracting and poor-quality ideas, allowing access to better ones. Indeed, greater DMN-ECN connectivity has been found when there is a need to overcome fixating, unoriginal ideas, in both verbal (Beaty et al., 2017a) and visual paradigms (Christensen et al., 2021). Evidence of other mechanisms is sparse, but research is beginning to indicate that sub-networks within the ECN and DMN may play different functional roles in creative cognition. For example, different regions within the DMN may support different aspects of memory (i.e., semantic vs episodic), and correspondingly, different aspects of creative cognition (Beaty et al., 2020). Meanwhile, sub-networks of the ECN seem to have different relationships with the DMN (Beaty et al., 2021a; Dixon et al., 2018), and may underly different creative tasks (Peña et al., 2019). Despite this progress, questions remain, particularly concerning how these networks contribute to creative cognition over time. For example, it is unclear whether different stages of creative cognition (e.g., generation and evaluation) involve different proportions of associative and controlled processes, corresponding to different contributions from the DMN and ECN (Kleinmintz et al., 2019; Sowden et al., 2015).

2.1.2 The time course of creative cognition

Our understanding of creative cognition would benefit from a closer examination of how cognitive processes, and the neural regions that underly them, operate and interact over time during creative tasks. Previous research into the temporal dynamics of creative cognition has, for example, revealed the “serial order effect”, whereby ideas increase in creative quality over time (Johns, Morse, & Morse, 2001; Phillips & Torrance, 1977; Runco, 1986; Ward, 1969). While a traditional explanation for this effect (e.g., Mednick, 1962) would attribute it to activation spreading passively from the cue concept to increasingly original concepts, more recent research suggests it may be due to deliberate control processes operating to inhibit previously considered ideas and strategically access more novel ones (Bai, Leseman, Moerbeek, Kroesbergen, & Mulder, 2021; Beaty & Silvia, 2012; Wang, Hao, Ku, Grabner, & Fink, 2017).

Studies using electroencephalogy (EEG) and brain stimulation methods are also helping to advance our understanding of how creative processes operate over time. Considerable evidence suggests that creative cognition relates to cortical alpha synchronization (Benedek, Bergner, Könen, Fink, & Neubauer, 2011; Fink & Benedek, 2014; Stevens & Zabelina, 2020). Indeed, research has found that greater alpha power is related to greater creative performance (Agnoli et al., 2020; Camarda et al., 2018b; Fink et al., 2018; Rominger et al., 2019; Stevens & Zabelina, 2020), while increasing alpha power over frontal cortex through stimulation appears to increase the creative quality of ideas (Lustenberger et al., 2015).

Focusing on the production of a single creative idea, Schwab, Benedek, Papousek, Weis, and Fink (2014) gave participants 10 seconds to generate a creative response in the AUT, while recording EEG. During analysis, the authors divided this generation period into three equal segments, finding a clear pattern of activity over time: alpha power increased at the beginning of generation, decreased during the middle, and increased again at the end. This U-shape pattern of alpha power during idea generation was also reported by Rominger et al. (2019), who found that the pattern was stronger among participants with more original ideas. What the pattern of activity means in terms of cognitive processes is unclear, but the authors of both studies suggest it may indicate associative, memory-related processes operating at the beginning of idea generation (e.g., to retrieve ideas), and controlled, evaluative processes operating at the end (e.g., to suppress common ideas and generate more original ones).

In contrast to EEG studies, very few fMRI studies have explored the time course of creative cognition. One exception is a study by Beaty, Benedek, Kaufman, and Silvia (2015), which examined neural activation during the AUT compared to a control task focused on object characteristics. The authors found that divergent thinking involved a broad network of regions from the DMN, ECN, and salience networks, and that the global efficiency of this network was related to greater creative performance. Importantly however, they also found that the connectivity between these regions varied over time. Extracting a series of 2-second time windows from the 12-second AUT idea generation period, and analyzing these separately, the authors found increased coupling between DMN and salience network regions at the start of creative trials, and between DMN and ECN regions later on. This pattern of connectivity was interpreted to reflect interactions between associative and controlled thought, potentially corresponding to early generative and later evaluative modes of thought.

2.1.3 The present research

Research into the neurocognitive basis of creative cognition has highlighted the complementary roles of associative and controlled processes, which may depend on distinct neural regions (Beaty et al., 2015, 2018c; Benedek & Jauk, 2018; Chrysikou et al., 2020; Zhu et al., 2017). Research also suggests that these processes may interact differently in different creative tasks, and at different time stages of creative performance (Benedek & Fink, 2019; Chrysikou, 2019; Rominger et al., 2019; Volle, 2018). However, it remains unknown how exactly associative and controlled processes, and their underlying neural regions, activate over time during creative cognition. It is also unclear whether these processes contribute differently to the creative quality of ideas, and whether alternating stages of generation and evaluation do in fact exist (Kleinmintz et al., 2019; Sowden et al., 2015). Indeed, examining stages in creative cognition is far from simple, since, if they exist, they are likely to be fluid and without clear distinction, or switched between so rapidly that they are practically indistinguishable (Goldschmidt, 2016). Separating generation and evaluation can be done experimentally, for example by asking participants to first generate an idea and later evaluate it (e.g., Ellamil et al., 2012; cf. Rominger et al., 2018), but this divides the creative process into artificial chunks which could each involve generative and evaluative thought.

An alternative approach is to keep the creative process intact, and to examine how brain networks that have been theoretically linked to associative and controlled processes vary in their contributions to creative cognition over time. Evidence suggests that generative thought may largely depend on the associative activity of the DMN, while evaluative thought may predominantly rely on the controlled activity of the ECN (Beaty et al., 2016a; Ellamil et al., 2012; Jung et al., 2013; Kleinmintz et al., 2019). As such, examining how these networks contribute to creative cognition over successive time phases could provide an indication of the proportion of associative and controlled processes active in each phase, potentially revealing distinct generative and evaluative stages. To date, however, very little research has investigated the temporal dynamics of functional network contributions to creative cognition.

Multivariate pattern analysis (MVPA) is a particularly useful tool for this purpose. MVPA is a machine learning method that takes neural activity as input, and through training, constructs a model that can classify patterns of voxel activation as belonging to different experimental tasks. The ability of the model to correctly classify new trials, that it has not been trained on, is known as classification accuracy. Greater classification accuracy indicates that there is more information available to the classifier during training, and a greater difference in neural activity between conditions. As such, classification accuracy serves as an indirect measure of the amount of activity in a region that is relevant to one condition, but not to others.

In the present study, MVPA was used to assess the quantity of creative processing within the DMN and ECN, over successive time points during creative cognition. Participants completed both the AUT and the object characteristics task (OCT), a control task in which they must recall a characteristic of an object rather than generate a creative use for it. Following a similar procedure to previous studies (e.g., Beaty et al., 2015; Rominger et al., 2019; Schwab et al., 2014), the idea generation periods for both tasks were divided into three equal time windows. For each time window, MVPA classifiers were trained on data from both AUT and OCT trials, and tested to match unseen trials to the correct task. In theory, greater classification accuracy should reflect a greater difference in activity between creative and non-creative trials, and indirectly, a greater amount of activity relevant to creativity (i.e., “creative activity”). Variance in classification accuracy over time in a given network would then indicate varying amounts of creative activity. This process was conducted separately on data from both the DMN and ECN, allowing us to compare the time-course of creative activity in these regions. As a further analysis, correlations were also computed between classification accuracy (in each network and time phase) and behavioral measures of creative quality. The strength of this correlation should indicate how relevant the creative activity in a particular region and time phase is to the actual quality of the idea being generated.

These analyses could do much to inform our understanding of how neurocognitive processes operate over time during creative cognition. The existence of distinct generative and evaluative stages would be supported if the networks show different time patterns of creative activity.

Specifically, if at certain times one network exhibits more creative activity (or stronger correlations with creative quality) than the other network, this would indicate stages in creative cognition, in which some cognitive processes are more dominant than others, and that these stages are long enough to be detected over several seconds. By contrast, equivalent amounts of creative activity (and relevance to creative quality) in both the DMN and ECN across all three time phases would be consistent with several explanations. It could be that distinct stages do not exist, and that associative and controlled processes are equally distributed over time with generation and evaluation occurring simultaneously. Alternatively, it might be that stages do exist, but are shifted between on a smaller timescale than can be detected through fMRI. Finally, it could be that generation and evaluation are equally dependent on both the ECN and DMN, with no difference in their localization.

Our predictions followed from the hypothesis that generative and evaluative stages of thought do exist in creative cognition, and involve different proportions of associative and controlled processing, indicated by different contributions from the DMN and ECN. Specifically, it was predicted that early phases of creative trials would involve more generative thought and a higher proportion of associative processing, reflected in greater creative activity in the DMN. By contrast, it was expected that mid and late phases of creative trials would involve more evaluative thought and a higher proportion of controlled processes, reflected in greater creative activity in the ECN. This would also be consistent with prior work tracking changes in connectivity between brain networks over the course of creative cognition (Beaty et al., 2015). Similarly, it was expected that idea quality would be most strongly correlated with the creative activity of the DMN in early time phases, and with the creative activity of the ECN in later time phases.

2.2 Methods

2.2.1 Participants

Participants (*N* = 186) were recruited from the University of North Carolina at Greensboro (UNCG) and surrounding community (129 females, mean age = 22.74, *SD* = 6.37). Participants gave informed consent prior to data collection, and participated as part of a larger study, completing several additional measures that are not discussed here (for other studies using this dataset, see

Beaty et al., 2018b; Frith et al., 2021a). Sample size was determined by a prior study (Beaty et al., 2018b). Participants were compensated up to $100 for their time, and were all right-handed, with normal or corrected-to-normal vision, and no reported history of neurological disorder, cognitive disability, or medication that affects the central nervous system. Several participants were excluded prior to analysis due to factors including excessive head movement during neuroimaging (mean framewise displacement > .5mm, n = 4; Power, Barnes, Snyder, Schlaggar, & Petersen, 2012), issues with software used during neuroimaging (e.g., E-prime crash), and missing behavioral data. Following exclusions, the final sample was 168 (116 females, mean age = 22.59, *SD* = 6.04). The study was approved by the UNCG Institutional Review Board.

2.2.2 Materials

To assess creativity, the AUT was used. To act as a non-creative control task with a similar memory component, the OCT was used. This task involves recalling characteristics of objects (e.g., “metallic” or “wooden”). The AUT and OCT are highly similar in format, differing only in the nature of the response (most creative idea in the AUT and most prototypical characteristic in the OCT). Stimuli for both tasks were 46 common object names used in prior research (Beaty et al., 2015; Fink et al., 2009).

In addition to the AUT and OCT, participants completed three measures of fluid intelligence (Gf) outside the scanner: the letter sets task (Ekstrom, Dermen, & Harman, 1976), which requires selecting a set of letters that does not follow the rule governing other sets (16 items), the number series task (Thurstone, 1938), which requires selecting the next number in a sequence (15 items), and the series completion task from the Culture Fair Intelligence Test (CFIT; Cattell & Cattell, 1961), which requires selecting an image that most appropriately completes a series of images (13 items). These measures were included to assess whether brain activity related to creativity was also related to intelligence, and thus reflective of wider cognitive abilities not limited to creative performance. Participant scores on these three measures were combined using confirmatory factor analysis to produce a single latent factor (see Frith et al., 2021a).

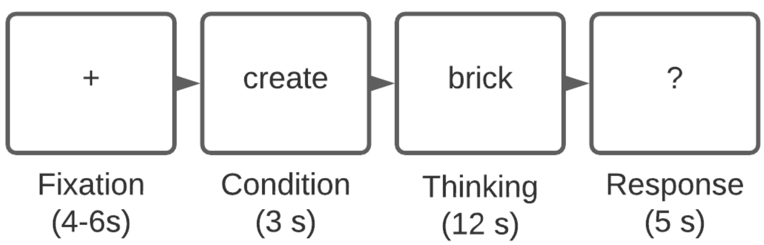
2.2.3 Procedure

Participants completed the AUT and OCT while in the fMRI scanner, in an event-related design. Trials for both tasks were inter-mixed and presented in one block of 46 trials. 23 trials were AUT, and 23 were OCT. All 46 stimuli were presented, with no repeats, in the same order for all participants (i.e., all participants saw “brick” first and “CD” last). However, task condition (AUT or OCT) followed a randomized order across trials, with each participant completing a different sequence of trial types. As such, the task condition for any given stimulus varied across participants (e.g., the stimulus “brick” could occur with equal likelihood as an AUT or OCT trial).

Trials proceeded as follows (see Figure 1). Following a fixation cross jittered between 4 and 6 seconds, participants received an instruction indicating the task condition for the present trial. Specifically, “create” (for the AUT) or “object” (for the OCT) was presented for 3 seconds. A 12-second thinking period then began, with the object name stimulus (e.g., “brick”) presented for the entire duration. Participants were instructed to use the thinking period to either generate the

Figure 1

Trial procedure, from fixation (left) to response (right)



Note. Duration in seconds is presented below each frame.

most creative use they could think of (“create”; creative condition), or the most prototypical physical characteristic they could recall (“object”; non-creative condition). The thinking period could not be ended early; instead, participants were asked to use the full time to generate the most creative/prototypical response they could. This was followed by a 5-second response period, signaled with a green question mark (“?”), during which participants had been instructed to speak their response out loud. Responses were recorded using an MRI-compatible microphone. Participant responses in AUT trials were later rated for creativity by four independent raters, using a 1 (not at all creative) to 5 (very creative) scale (Silvia, Martin, & Nusbaum, 2009). Raters provided a single rating for each trial, which reflected the novelty, originality, and appropriateness of the idea. After the scanning session, participants completed the three fluid intelligence measures as part of a post scan behavioral assessment.

2.2.4 fMRI data acquisition and preprocessing

In-scanner tasks were completed in a single MRI run, and programmed using E-Prime software. Stimuli were viewed through a mirror attached to the head coil. Imaging was performed with a 3T Siemens Magnetom MRI system (Siemens Medical Systems, Erlangen, Germany) equipped with a 16-channel head coil. Functional images were acquired with a T2*-weighted single shot gradient-echo echo-planar imaging (EPI) pulse sequence (repetition time [TR] = 2000ms, echo time = 30 ms, flip angle = 78°, 32 axial slices, 3.5 x 3.5 x 4.0 mm, distance factor 0%, field of view = 192 x 192 mm, interleaved slice ordering) and corrected online for head motion. To allow for anatomic normalization, a high resolution T1 scan was acquired first, and the first two functional volumes were discarded to allow for T1 equilibration effects.

Functional volumes were preprocessed using fMRIPrep 1.4.1rc1 (Esteban et al., 2019). For each subject, a reference volume and its skull-stripped version were generated and co-registered to the T1 reference. Head-motion parameters with respect to the BOLD reference (transformation matrices, and six corresponding rotation and translation parameters) were estimated. BOLD runs were slice-time corrected, before being resampled onto their original, native space by applying a single, composite transform to correct for head-motion and susceptibility distortions. The BOLD time-series were then resampled into standard space (Montreal Neurological Institute [MNI] template brain), and high-pass filtered using a discrete cosine filter with 128s cut-off. Several confounding time-series were then calculated, including framewise displacement (FD), DVARS and its temporal derivative. These were combined with motion estimates to form nine confound time-series per participant. Frames that exceeded a threshold of 0.5 mm FD or 1.5 standardized DVARS were annotated as motion outliers. As is common in studies using MVPA, where differences between individual voxels can hold important information (Coutanche, Thompson-Schill, & Schultz, 2011; Cox & Savoy, 2003; see also Weaverdyck, Lieberman, & Parkinson, 2020), no spatial smoothing was conducted.

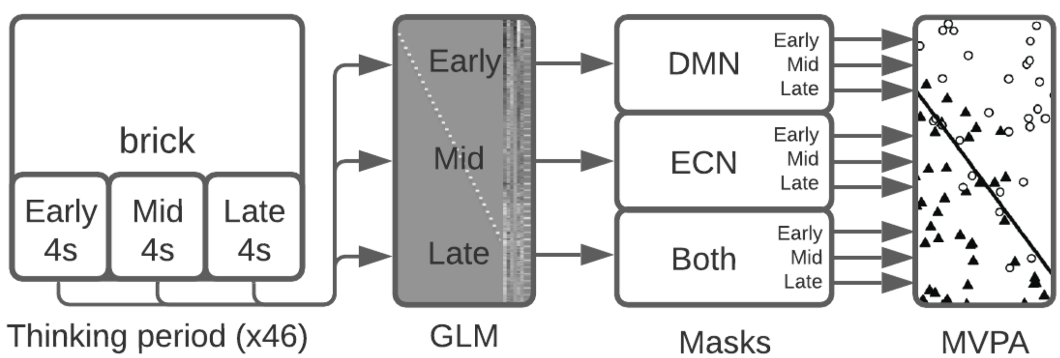
2.2.5 Level 1 analysis

MVPA was conducted on parameter estimates (i.e., model coefficients) extracted from a general linear model (GLM) in line with previous research (e.g., Etzel, Gazzola, & Keysers, 2008; Kim et al., 2015)(see also Haynes, 2015). First level analyses were conducted using SPM12 (http://www.fil.ion.ucl.ac.uk/spm/).

Analysis focused on the 12-second thinking period (see Figure 2). Since there was only one run per participant (i.e., trials did not fall into independent groups), and to increase the number of exemplars for classifier training, trials were not averaged. To compare brain activity during different phases of ideation, thinking periods were split into three parts (early, mid, late), each with a duration of 4 seconds, and formed of two volumes. For each participant, a GLM was fitted with 138 regressors of interest, corresponding to three time periods x 46 trials. These were in addition to nine noise regressors and 46 regressors corresponding to the onsets and durations of verbal response periods, to account for artifacts related to vocalization. The GLM thus produced three sets of 46 parameter estimate images which were used in subsequent analyses.

Figure 2

Analysis process (left to right)



Note. Thinking periods in each of the 46 trials were split into three equal time periods (early, mid, late). For each time period, 46 parameter-estimate images were extracted from the GLM (one for each trial). Three different network masks were then applied to each of these three sets of images, before they were fed into MVPA classifiers.

2.2.6 Networks of interest

Networks of interest were obtained in MNI standard space using the "7 network liberal mask" from Yeo et al. (2011). Masks were extracted for three networks: the DMN, the ECN, and a combined network formed of both the DMN and ECN (Both). The combined mask was included to assess whether providing both networks together as input for classification would result in increased classifier performance, over and above that when only a single network was provided.

2.2.7 Multivariate pattern analysis

Next, MVPA classification of trials as creative (AUT) or non-creative (OCT) was conducted, for all networks of interest. Classifiers were trained on labelled creative and non-creative trials, and then tested to classify unlabeled trials. It was assumed that greater classification accuracy would reflect a greater difference in brain activity between conditions (i.e., more task-relevant information available to the classifier).

MVPA was conducted in MATLAB using a custom script and the CoSMoMVPA package (Oosterhof, Connolly, & Haxby, 2016). Linear Discriminant Analysis (LDA) was used for classification, which was conducted separately for each network (DMN, ECN, Both), and each time phase (early, mid, late), leading to nine separate multivariate classification analyses per participant. Each analysis followed a 23-fold leave-one-out cross-validation procedure, corresponding to the number of trials per condition. The data were organized into 23 folds, where each fold contained two samples: one from a creative trial, and one from a non-creative trial. During each of the 23 iterations, a classifier was trained on 22 folds and tested on the remaining 23rd, with testing and training sets alternating until each fold had been tested. Classification accuracy was then defined as the percentage of the 46 trials that were classified correctly. This produced nine classification accuracies for each participant, one for each network and time phase combination.

To assess whether classifier performance was greater than expected by chance, permutation testing was used, as done previously (Coutanche et al., 2011; Etzel et al., 2008; Golland & Fischl, 2003). This tests the null hypothesis that there is no relationship between the data class labels (AUT or OCT) and the voxel activity patterns, by repeating all nine analyses 1000 times and randomly shuffling the class labels each time. For each relabeled dataset, classification accuracy was calculated, and the average across-participant accuracy was computed. This simulates a null distribution, against which classifier performance on correctly labelled data can be compared. Classifier performance greater than 95% of the random permutations indicates above-chance accuracy (given an alpha of $p < .05$). Since 1000 relabellings were computed, the maximum possible significance level was 0.001.

To examine whether classification accuracy varied significantly over networks and time phases, a two-way ANOVA was conducted, followed by a series post-hoc paired-sample t-tests to compare classification accuracy within and between networks, across the three time phases.

2.2.8 Correlation Analysis

As discussed, classification accuracy in this study reflects the difference in brain activity between creative and non-creative trials. Since greater accuracy implies that creative cognition is more distinguishable from non-creative cognition, it should indicate stronger or more widespread creative cognitive processes (i.e., more "creative activity"). Moreover, it is possible that participants who display more creative activity tend to generate more creative ideas. It is also possible that creative activity in some brain regions and time phases is more related to the creative quality of ideas than in others (e.g., early creative activity might be more related to creative quality than later creative activity). To examine these possibilities, Pearson correlations were computed between participants' classification accuracies (for all networks and time phases) and their rated creativity scores (see Coutanche et al., 2011; Kim et al., 2015).

2.3 Results

2.3.1 Descriptive statistics

Regarding AUT creativity ratings, inter-rater reliability was in the excellent range, with an intraclass correlation coefficient of .92 (.90-.94). Descriptive statistics for the behavioral measures of fluid intelligence (Gf), and rated AUT creativity, together with the nine classification accuracies corresponding to the three network x three time phase combinations, are shown in Table 1.

Table 1

Means and standard deviations for Gf and AUT creativity score, and classifier performance across the three networks and three time phases

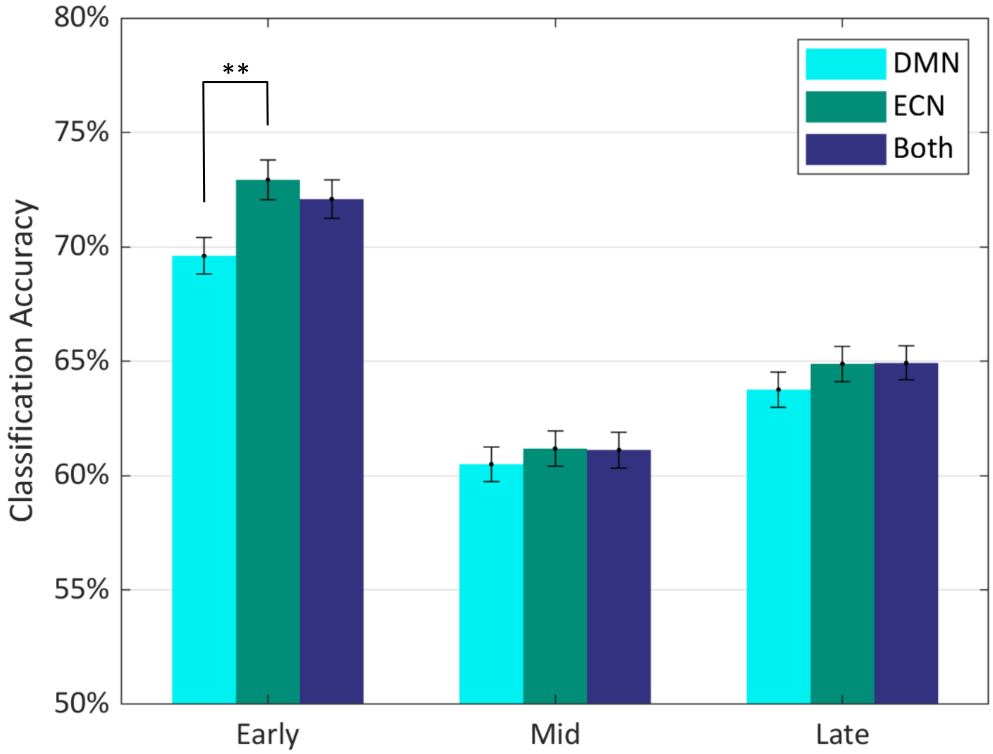
	M	*SD*
Gf	0.00	0.79
AUT creativity	1.85	0.30
Early DMN	0.70	0.10
Early ECN	0.73	0.11
Early Both	0.72	0.11
Mid DMN	0.60	0.10
Mid ECN	0.61	0.10
Mid Both	0.61	0.10
Late DMN	0.64	0.10
Late ECN	0.65	0.10
Late Both	0.65	0.10

Note. Gf = fluid intelligence; AUT = alternate uses task; DMN = default mode network; ECN = executive control network; Both = DMN+ECN.

2.3.2 Classification accuracy and comparisons

Figure 3

Bar chart depicting mean classification accuracy across the three networks and three time phases



Note. A 50% accuracy would be expected by chance, and so is used as a baseline in this chart. DMN = default mode network; ECN = executive control network; Both = DMN+ECN. Only significant differences in accuracy between the DMN and ECN masks are indicated. ** $p < .01$.

Figure 3 depicts classification accuracies for each network and time phase. In all nine network and time phase combinations, classification accuracy was significantly above chance level, as determined by permutation analysis (*p*s = .001). Specifically, all accuracies were greater than all 1000 randomly relabeled permutations. Classification accuracy reached the highest point in the ECN during the early time phase, suggesting that brain activity in this region and at this time shows the greatest difference between creative (AUT) and non-creative (OCT) trials. Across time phases, classification accuracy was highest in all networks in early phases, dropped to its lowest point in mid phases, and increased moderately in late phases of trials.

A two-way ANOVA was conducted to test the significance of differences in accuracy across networks and time phases. Significant main effects were found for network (F [1,168] = 7.06, p = .008, η_p^2 = 0.01) and time phase (F [2,168] = 90.54, p < .001, η_p^2 = 0.15). The interaction between network and time phase was non-significant (p = .201). To further investigate the differences in classification accuracies within networks (between time phases) and between networks (for each time phase), post-hoc paired-sample t-tests were conducted. For all t-tests, Cohen's d_{av} is reported as a measure of effect size (Lakens, 2013). Results can be seen in Table 2. Considering differences in classification accuracy between the DMN and ECN, a significant difference was found only

Table 2

Results of t-tests contrasting classification accuracy between networks in each time phase, and between time phases in each network

(A) Across networks (DMN vs ECN)

DMN vs ECN	*t*	*p*	Cohen's D*av*
Early	-2.80	.005	0.31
Mid	-0.64	.524	0.07
Late	-1.04	.299	0.11

(B) Across time (within DMN)

DMN	*t*	*p*	Cohen's D*av*
Early vs Mid	8.22	.000	0.90
Early vs Late	5.27	.000	0.57
Mid vs Late	-3.03	.003	0.33

(C) Across time (within ECN)

ECN	*t*	*p*	Cohen's D*av*
Early vs Mid	10.15	.000	1.11
Early vs Late	6.93	.000	0.76
Mid vs Late	-3.42	.001	0.37

Note. DMN = default mode network; ECN = executive control network.

during the early time phase (see Figure 3), with accuracy in the ECN (M = 0.73, SD = 0.11) significantly greater than in the DMN (M = 0.70, SD = 0.10; t [167] = 2.80, p = .005, d_{av} = 0.31).

Considering differences in classification accuracy between the three time phases (for each network separately), within the DMN, classification accuracies in all time phases were significantly different from one another (ps < .005). Likewise, within the ECN, classification accuracies in all time phases were significantly different from one another (ps < .001).

I also conducted t-tests to examine whether classification accuracy using the combined mask was greater than using the individual network masks. During early phases, classification accuracy in the combined (Both) network (M = 0.72, SD = 0.11) was significantly greater than in the DMN (M = 0.70, SD = 0.10; t [167] = 2.15, p = .032, d_{av} = 0.23), but did not differ significantly from accuracy in the ECN (p = .485). No other significant differences were found (ps > .05), suggesting that classification accuracy was not markedly improved simply by providing more information to the classifier in the form of both networks together.

2.3.3 Correlations

To assess how the creative brain activity within each network and time phase related to behavioral measures, Pearson correlations were computed between AUT creativity, fluid intelligence (Gf), and the six classification accuracies corresponding to the individual networks (i.e., DMN and ECN), and three time phases. Table 3 displays the results of these correlations. Fluid intelligence was not found to correlate with classification accuracy in any of the six network and time phase combinations. By contrast, AUT creativity correlated significantly with classification accuracy in all networks and time phases. The strongest correlation was found between AUT creativity and classification accuracy in the DMN in early phases of trials (r = .25, p = .001).

Table 3

Pearson correlations between behavioral measures and classification accuracy, across all time phases and networks

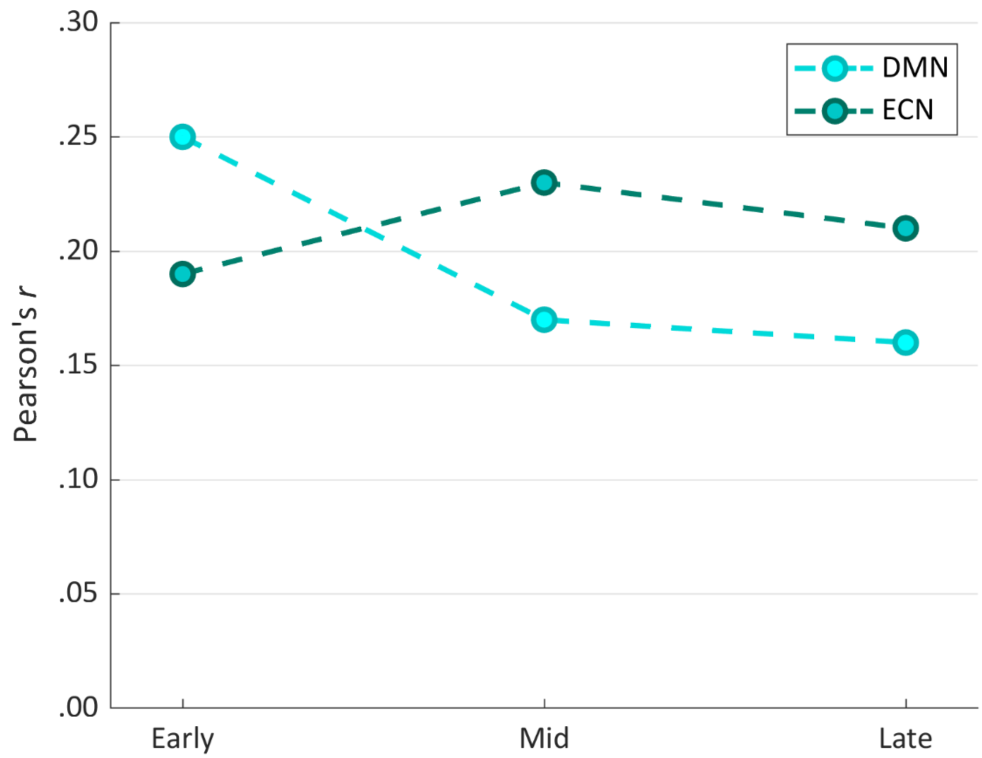
	Gf	AUT creativity
AUT creativity	0.24**	-
Early DMN	0.01	0.25**
Early ECN	0.00	0.19*
Mid DMN	0.07	0.17*
Mid ECN	0.06	0.23**
Late DMN	-0.06	0.16*
Late ECN	-0.07	0.21**

Note. Gf= fluid intelligence; AUT = alternative uses task; DMN = default mode network; ECN = executive control network. * $p < .05$, ** $p < .01$.

Looking at correlations between AUT creativity and classification accuracy over time reveals a clear difference between the DMN and ECN. While the correlation between AUT creativity and classification accuracy in the DMN was highest during early phases of trials, dropping off in mid and late phases, the same correlation in the ECN was lowest in early phases, highest at mid phases, and dropped again in late phases of trials. Figure 4 displays a graphical comparison of the strengths of correlations between AUT creativity and classifier performance in the ECN and DMN, in each time phase.

Figure 4

Strength of correlation between AUT creativity and classification accuracy in the DMN and ECN, across all time phases



Note. DMN = default mode network; ECN = executive control network.

These results suggest that the activity with the greatest relevance to creative quality occurs in the DMN during early phases of trials. Indeed, while classification accuracies alone indicate that the ECN holds the greatest amount of creative activity during early phases (see Figure 3), correlations with quality suggest that this activity may be less relevant to idea quality than the creative activity of the DMN in early phases. Instead, creative activity in the ECN appears to be most relevant to idea quality during mid phases of trials. Taken together, these findings suggest a distinction between brain activity that differs between creative and non-creative trials, and brain activity that both differs between trials and is related to the actual creative quality of the generated idea.

Steiger's Z tests for differences between dependent, overlapping correlations were conducted for each time phase separately (Steiger, 1980). No significant differences were found between the DMN and ECN, in terms of correlations between classification accuracy and creative quality, for early phases (z = 1.36, p = .177), mid phases (z = -1.07, p = .288), or late phases (z = -0.86, p = .391). While differences between correlations are non-significant in each time phase individually, results may suggest a modest difference between networks in terms of the time-pattern of how their activity relates to creative quality.

2.4 Discussion

The present study examined how two brain networks, the DMN and ECN, contribute to creative cognition over time during the production of a single creative idea. The study aimed to inform several outstanding questions regarding the roles of these networks, and the cognitive processes they support, in creative cognition. One key aim was to examine whether creative cognition involves distinct stages of generation and evaluation, supported by different proportions of DMN and ECN activity. Dividing trials into three successive time phases, MVPA was used to classify trials as creative or non-creative. Classification accuracy was used to indicate the amount of creative activity in each network and time phase. Correlations were also computed between classification accuracy and rated creative performance, to assess how relevant the creative activity in each network and time phase was to the quality of generated ideas.

Our hypotheses assumed that generative and evaluative stages involve different combinations of associative and controlled processes, and so different proportions of DMN and ECN activity. Specifically, it was expected that early phases of creative trials would involve greater creative activity in the DMN, reflecting generation, while later phases would involve greater creative activity in the ECN, reflecting evaluation. Similarly, it was expected that creative quality would be more strongly correlated with DMN creative activity in early time phases, and with ECN creative activity in later time phases. The findings suggest a distinction between neural activity that is relevant to creative cognition overall (in the sense of differing between creative and non-creative trials), and activity that is both relevant to creative cognition and also relevant to creative quality specifically. Overall, these findings provide tentative evidence for distinct stages in creative cognition, potentially corresponding to generation and evaluation.

2.4.1 Neurocognitive mechanisms of creative cognition

These findings offer new insight into the dynamics of neurocognitive processes during creative cognition. As discussed, research suggests that the DMN, which typically activates during tasks involving spontaneous cognition and memory retrieval (Andrews-Hanna et al., 2014; Buckner, Andrews-Hanna, & Schacter, 2008; Fox & Beaty, 2018), contributes to creativity through spontaneous recall and association-making processes (Bashwiner, Wertz, Flores, & Jung, 2016; Beaty & Lloyd-Cox, 2020; Marron et al., 2018; Shi et al., 2018). Research also indicates that the ECN, which typically activates in executive tasks including WM and inhibitory control paradigms (Niendam et al., 2012; Seeley et al., 2007; Shen et al., 2020), may aid creative cognition by guiding thought in strategic directions and inhibiting unoriginal ideas (Beaty et al., 2017a; Benedek & Jauk, 2018; Christensen et al., 2021). Linking these findings to the notion that creativity involves distinct and cyclic phases of generation and evaluation (Basadur, 1995; Finke et al., 1992), researchers have suggested that associative DMN-based processes may underlie the generation of ideas, while controlled ECN-based processes oversee the evaluation of ideas (Beaty et al., 2016a; Jung et al., 2013; Kleinmintz et al., 2019; Mayseless et al., 2015). Indeed, while it is likely that generative and evaluative stages each involve both DMN and ECN activity, for example with the ECN aiding generation by inhibiting unoriginal concepts (Beaty et al., 2017a), it seems likely that generation relies mostly on the DMN, while evaluation relies mostly on the ECN (Beaty et al., 2016a; Benedek & Jauk, 2018; Mayseless et al., 2015).

However, these ideas are largely speculative. Even if idea generation and evaluation are distinctly localized on the DMN and ECN, respectively, it is far from clear that generative and evaluative thought occur in cycles (Kleinmintz et al., 2019), as opposed to simultaneously (Goldschmidt, 2016). Very few studies have examined the temporal dynamics of neural network activity during creative cognition. Indeed, previous fMRI studies have examined generative and evaluative stages (e.g., Ellamil et al., 2012), but only by asking participants to first generate ideas and later evaluate them. By contrast, the present research followed a small number of recent fMRI and EEG studies (Beaty et al., 2015; Rominger et al., 2019; Schwab et al., 2014), to keep the creative process intact during task performance, only separating it into distinct phases during analysis. The study offers some of the first, tentative neuroimaging findings of distinct generative and evaluative stages in creative cognition.

2.4.2 The time-course of brain network contributions to creative cognition

Overall, very similar time patterns of classification accuracy in the DMN and ECN were found: accuracy was highest in early phases, decreased to the lowest point in mid phases, and rose again in late phases of trials. This suggests closely-matched proportions of creative activity in both networks, consistent with strong coupling between the networks during creative cognition (see Beaty et al., 2016a). In isolation, this finding might suggest that generative and evaluative phases either do not exist, do not last long enough to be detectable over 4-second time periods, or do not depend on different proportions of DMN and ECN activity. Moreover, a significant difference in classification accuracy between networks was found only during early phases, in which accuracy was significantly higher in the ECN than the DMN. This was contrary to expectations, suggesting that early stages of creative cognition involve a greater contribution from controlled processes than associative processes. This finding could still be consistent with an initial generative stage, but one that is not primarily dependent on the DMN, and requires ECN-based processes to initiate creative search, monitor for unoriginal ideas, and drive association-making in the most fruitful directions (Kenett et al., 2018b; Madore, Thakral, Beaty, Addis, & Schacter, 2017).

However, correlations between classification accuracy and rated creative quality paint a more nuanced picture of the contributions of these networks to creative cognition over time. Markedly different time-patterns of correlations between the two networks were found. Accuracy within the DMN was most correlated with creative quality in early phases of trials, becoming less correlated in mid and late phases. By contrast, accuracy within the ECN was least correlated with creative quality in early phases, becoming most correlated in mid phases, before dropping slightly in late phases. While differences between each pair of correlations were found to be non-significant, the varying patterns of correlations over time could indicate that early periods of creative cognition are characterized by more quality-relevant creative activity in the DMN, while middle and late periods are characterized by more quality-relevant creative activity in the ECN – a pattern consistent with a generation-evaluation cycle in creative cognition (e.g., Finke et al., 1992; Kleinmintz et al., 2019).

Overall, the findings suggest a distinction between neural activity that is relevant to creative cognition in general, and neural activity that is relevant to creative quality specifically. In particular, while classification accuracy alone indicates a greater amount of creative activity in the ECN than the DMN during early phases, correlations suggest that it is actually the creative activity of the DMN that is most relevant to creative quality during this time. One possible explanation for this discrepancy could be that classification accuracy can also result from activity that is relevant to non-creative (OCT) trials. Specifically, rather than creative trials being distinguishable from non-creative trials due to more prevalent creative activity, greater classification accuracy could also result from creative trials simply not containing activity unique to non-creative trials, such as particular kinds of memory recall processes. However, the fact that classification accuracy did not significantly correlate with fluid intelligence, in any network or time phase, does provide some indication that accuracy reflects creative activity, and not more general cognitive processing. A more likely possibility is that activity related to creative cognition is not always related to the actual creative quality of the produced idea. For example, the initial creative activity of the ECN may include processes that help to initiate creative cognition, or inhibit obvious and uncreative ideas, rather than directly shaping original ideas. The early creative activity of the DMN, by contrast, might be more directly responsible for the specific idea that is generated, as would be consistent with the DMN's role in spontaneous memory and simulation processes (Andrews-Hanna et al., 2014; Beaty et al., 2018d; Beaty & Lloyd-Cox, 2020).

While the greater correlation between creative quality and classification accuracy in the DMN during early phases of trials is suggestive of an initial generative period, in mid and late phases the pattern of correlations flips, with the activity of the ECN becoming most relevant to creative quality. This may be consistent with a later evaluative stage in creative cognition, in which controlled processes based in the ECN assess and refine ideas (Beaty et al., 2016a; Jung et al., 2013; Kleinmintz et al., 2019). With the initial generation of ideas now being completed, DMN processes might become less important to creative quality, while the ECN operates to select a single best idea and shape it into a final state (Sowden et al., 2015; Zhou et al., 2018). The fact that both networks remain at least somewhat relevant to creative quality in all time phases is consistent with the notion that generative and evaluative stages each involve some combination of associative and controlled processes, and indeed some combination of DMN and ECN activity (Beaty et al., 2016a; Benedek & Jauk, 2018; Mayseless et al., 2015).

Taking a wider view, classification accuracy in both networks followed a U-shaped pattern over time. This was strikingly similar to the pattern of alpha activity found by recent EEG studies examining the temporal dynamics of creative cognition (Rominger et al., 2019; Schwab et al., 2014). As noted, stronger alpha activity is often correlated with greater creative performance (Agnoli et al., 2020; Fink et al., 2018). Interpreting classification accuracy as indicating the quantity of creative activity, the present results mirror these previous studies by suggesting an initial peak in creative activity at the beginning of trials, followed by a slump during the middle of trials and a final rise at the end of trials prior to verbalization. Also in line with prior research, a small correlation between fluid intelligence and creative performance was found (r = .24), as expected from previous findings regarding the relationship between intelligence and creativity (Benedek et al., 2014c, 2018; Nusbaum & Silvia, 2011).

2.4.3 Limitations and directions for future research

To my knowledge, the present study is the first to use MVPA methods to assess the contributions of functional brain networks to creative cognition over successive time phases of a creative task. MVPA can indicate the quantity of task-relevant activity in a given region, enabling comparison of this activity across regions and time phases. These findings highlight the considerable promise MVPA holds as a methodological tool for examining the dynamics of neurocognitive processes during creative cognition. Future studies could expand on the present research in several important ways.

First, the sample of participants was 70% female. Given differences in functional brain activity between males and females, both during resting-state (e.g., Dhamala, Jamison, Sabuncu, & Kuceyeski, 2020; Filippi et al., 2013) and creative cognition (Abraham, Thybusch, Pieritz, &

Hermann, 2014), future studies should seek to confirm the present findings in a more evenly distributed sample of participants.

Second, the present study took a broad view, focusing on the roles of the entire ECN and DMN in creative cognition. However, these networks are comprised of numerous sub-regions. Recent research indicates that different regions of the DMN and ECN underlie different aspects of creative cognition (Beaty et al., 2020, 2021a; Peña et al., 2019). As such, future studies might examine a larger number of more restricted brain regions, to gain a richer understanding of how these regions contribute to creative cognition at different stages of the creative process.

Third, the present research focused on only one creative task: the AUT. However, creative cognition is a broad and high-level construct, and can be studied in musical and visual as well as verbal domains. DMN-ECN coupling has been found in a large variety of creative tasks (see Beaty et al., 2016a), and so future research could explore whether the time-pattern of creative activity (and quality-relevant creative activity) found in this study is unique to the AUT or also present in creative tasks in different domains.

Moreover, the poor temporal resolution of fMRI is an additional, and somewhat inevitable, limitation of this research. Without more fine-grained temporal resolution, our understanding of more detailed aspects of the neurocognitive processing underlying creative cognition will remain highly speculative. Future research could explore more time-sensitive neuroimaging methods, for example combining MRI and EEG techniques (e.g., Mele et al., 2019). An additional point relating to the temporal aspect of this study concerns the decision to divide the thinking period into three equal stages. While this followed previous research (Rominger et al., 2019; Schwab et al., 2014), subsequent studies might define the time stages in a more evidence-based way, for example by considering estimates of the precise point at which an idea is first generated. Indeed, the present study found modest but non-significant differences between the correlations of each network's classification accuracy with creative quality. More precisely defined time phases with higher temporal resolution might help future studies to better contrast the relevance of activity in different networks to creative quality, leading to a clearer understanding of the nuances of creative cognition.

Lastly, the fact that greater classification accuracy can also reflect activity unique to a control task underlines that it cannot, by itself, be used to measure creative activity. Instead, relationships between classification accuracy and behavioral measures should also be examined. However, MVPA need not be restricted to distinguishing creative and non-creative trials. For example, future research could divide creative trials into groups based on the rated quality of the ideas (e.g., poor vs good). Rather than classifying trials as creative or non-creative, MVPA classifiers could instead be trained to match neural activity to its correct creativity rating (cf. Stevens & Zabelina, 2020). Poorer creative ideas would in effect constitute a more appropriate control task, with classification accuracy now reflecting differences in activity relevant to better creative performance, rather than to creative performance in general.

2.4.4 Conclusion

Creative cognition is increasingly understood as a product of ordinary cognitive processes including memory, attention, and cognitive control (Benedek & Fink, 2019; Chrysikou, 2019; Volle, 2018; Zabelina, 2018). While NCR remains far from possessing a complete, process-level understanding of creativity, further progress toward this goal would benefit greatly from an increased focus on how neural activity changes over time during creative cognition. However, a clearer understanding of the mechanisms of creative cognition cannot rely on neuroimaging studies alone. In addition to more fine-grained examinations of the time dynamics of creative cognition, NCR requires a greater focus on how the cognitive processes that produce creative ideas vary across tasks and individuals. For example, the role of inhibitory control in creative thought likely depends on the specific creative task being examined, and the kind of inhibition in question (Benedek & Jauk, 2018; Chrysikou, 2018; Diamond, 2013). This particular example will be explored in greater detail in the following chapter.

CHAPTER 3: CREATIVITY AND INHIBITION: UNRAVELING A PARADOXICAL RELATIONSHIP

3.1 Introduction

One of the most prominent theoretical accounts of creative cognition is the dual-process account, which argues that creative ideas are produced by the interactions of associative, spontaneous processes and deliberate, controlled processes (Barr, 2018; Benedek & Jauk, 2018; Sowden et al., 2015; Volle, 2018). As discussed in Chapter 2, this account is supported by recent neuroimaging evidence that the DMN and ECN, networks which are usually anti-correlated and which support spontaneous memory-related processes and deliberate control processes, respectively, are co-activated and functionally connected during a range of creative tasks (Beaty et al., 2015; Ellamil et al., 2012; Green et al., 2015; Liu et al., 2015; Mayseless et al., 2015; Pinho et al., 2014).

At the cognitive level, the role of spontaneous processes in creative thought is evidenced by the importance of non-task-focused incubation (Koppel & Storm, 2014; Smith & Blankenship, 1991), mind-wandering (Baird et al., 2012; Fox & Beaty, 2018) and insight (Kounios & Beeman, 2014; Tik et al., 2018) to creative thought, as well as research linking creative ability to performance on verbal fluency and free association tasks (Kenett et al., 2014, 2018a; Marron et al., 2018). The role of controlled processes in creative cognition, however, is less clear, with some evidence highlighting a positive relationship between creativity and inhibition (Beaty et al., 2014; Benedek et al., 2012, 2014c; Camarda et al., 2018a), and some evidence finding a negative relationship or no relationship (Carson et al., 2003; Dorfman et al., 2008; Radel et al., 2015).

This diversity of findings has led many to suggest that the optimal degree of inhibitory control for creative performance depends on the specific creative task in question (Barr, 2018; Chrysikou, 2019; Volle, 2018), and that those who perform best overall might possess flexible inhibitory control (Zabelina et al., 2016; Zabelina & Robinson, 2010). However, a thorough analysis of which creative contexts benefit from which degree of inhibitory control has not yet been conducted. Creative tasks used by NCR range from simple verbal tasks like the AUT and RAT, to more complex poetry and story-writing tasks (e.g., Green et al., 2015; Liu et al., 2015) and tasks in other domains such as musical improvisation and drawing (Limb & Braun, 2008; Rominger et al., 2018).

Meanwhile, evidence suggests that in-lab creative performance has a different relationship with inhibitory control than lifetime creative achievement (e.g., Zabelina & Ganis, 2018). How performance on different kinds of creative task and measures of creative lifetime achievement relate to inhibitory control should be examined in a single study.

Furthermore, little research has examined differences between kinds of inhibitory control. For example, most NCR studies examining inhibitory control tend to use measures of response inhibition (the suppression of prepotent responses), whereas performance on divergent thinking tasks (e.g., the RAT or AUT) is likely to require cognitive inhibition (the suppression of distracting ideas; Cipolotti et al., 2016; Diamond, 2013; Engelhardt et al., 2008). The present chapter examines the relationship between inhibitory control and creative cognition using multiple measures of both constructs.

3.1.1 The role of disinhibition in creativity

Evidence from a variety of sources suggests that creative cognition, in at least some contexts, benefits from reduced inhibitory control. For example, it is commonly reported by creative experts that their best ideas emerge during an extended period of non-task-focused rumination (i.e., an incubation period; Ritter & Dijksterhuis, 2014), during which unconscious processing can operate freely and unhindered by inhibitory control, potentially leading to creative insights ("Aha!" moments; Tik et al., 2018; Kounios & Beeman, 2014). Moreover, creative performance has often been associated with mind-wandering (Baird et al., 2012; Christoff, Irving, Fox, Spreng, & Andrews-Hanna, 2016; Fox & Beaty, 2018), a mental state characterized by spontaneous, task-unrelated thoughts and imagination.

A period of mind-wandering when working on a problem might help to reduce fixation, where unhelpful or limiting assumptions about the problem can hamper efforts to find a solution (Camarda et al., 2018b; Chrysikou & Weisberg, 2005). Indeed, it has been found that inserting a period of rest into the middle of a creative task can reduce fixation effects, leading to more creative ideas (Koppel & Storm, 2014; Smith & Blankenship, 1991;see also Sio & Ormerod, 2009). In addition, working on an unrelated task for a short period of time has also been found to have beneficial effects for creative performance (Gilhooly, Georgiou, & Devery, 2013; Lu, Akinola, & Mason, 2017), possibly due to a "refreshing" of WM. Indeed, the lack of task-focused attention and inhibitory control during periods of incubation and mind-wandering might help new ideas to enter WM, many of which might be tangential or irrelevant to a problem, but some of which might lead to enlightening insights through unexpected connections (Benedek & Jauk, 2018). Indeed, studies have linked creative ability to performance on free-association (Marron et al., 2018) and verbal fluency paradigms (Beaty et al., 2014), suggesting that creative cognition relates to associative processes that spontaneously propagate through memory (Volle, 2018), and which may operate best without the constraints of task-related inhibitory control.

Further support for the role of uninhibited and free-flowing associative processes in creative cognition comes from connections between sleep and creativity. For example, REM sleep has been found to improve association-making activity, more than quiet rest or non-REM sleep, through reorganisational activity uninhibited by the hippocampus (Cai, Mednick, Harrison, Kanady, & Mednick, 2009). It has also been suggested that iterative cycles of REM and non-REM sleep can enable the formation of novel associations and the extraction of abstract rules, restructuring knowledge in a way that enhances creative cognition (Lewis, Knoblich, & Poe, 2018). Moreover, the role of the DMN in creative performance also highlights the importance of associative processes to creativity. As noted, the network is strongly associated with spontaneous thought and mind-wandering (Andrews-Hanna, Reidler, Huang, & Buckner, 2010; Andrews-Hanna et al., 2014; Buckner et al., 2008). In addition to its co-activation with and connectivity to the ECN during creative thought (Beaty et al., 2016a), the gray matter volume of the DMN has been linked to performance on divergent thinking tasks (Kühn et al., 2014).

Research has also probed more direct links between disinhibition and creativity. For example, it has been found that exhausting inhibitory control through a prolonged response inhibition task improves subsequent creative performance in terms of the number of ideas being generated (i.e., fluency score; Radel et al., 2015). Research has also found that those who perform better on the AUT tend to perform worse on measures of response inhibition (Dorfman et al., 2008). Finally, greater real-world creative achievement has been associated with increased distractibility

(Zabelina et al., 2016), and reduced latent inhibition (the ability to ignore stimuli previously experienced as irrelevant; Carson et al., 2003).

3.1.2 The role of inhibition in creative cognition

Despite the apparent importance of periods of reduced inhibitory control to creative cognition, research has also found that creative performance in certain contexts is linked to greater inhibitory control abilities. For example, intelligence, a construct that is strongly linked to executive functions including inhibitory control (Ardila, 2018; Arffa, 2007), is often linked to performance in laboratory-based divergent thinking tasks such as the AUT (Beaty et al., 2014; Benedek et al., 2014c; Frith et al., 2021a; Karwowski et al., 2016; Lee & Therriault, 2013). Moreover, a study by Benedek et al. (2012) found that greater performance on a measure of cognitive inhibition was linked to greater performance on a range of creative tasks, in particular promoting the number and diversity of generated ideas. Further research has linked creative performance (in terms of the creative quality of ideas) to response inhibition (Benedek et al., 2014c; Edl, Benedek, Papousek, Weiss, & Fink, 2014). Researchers have also found that reducing inhibitory control during creative performance via a simultaneous response-inhibition task can decrease the number of generated ideas as well as their novelty (Camarda et al., 2018a).

Moreover, one of the most reliable findings in divergent thinking studies is the serial order effect, in which ideas for the same problem get more creative over time (Bai et al., 2021; Wang et al., 2017). This phenomenon has been attributed to deliberate inhibitory control acting to suppress unoriginal and obvious ideas, gradually allowing access to more novel ideas (Beaty et al., 2014; Beaty & Silvia, 2012). Indeed, studies using “think aloud” paradigms to examine divergent thinking task performance indicate that participants use a variety of strategies to attain creative ideas, many of which are executively demanding and may rely on inhibitory control (Gilhooly, Fioratou, Anthony, & Wynn, 2007). Evidence from studies using the RAT also suggest that initial responses relate to only one of the three objects shown, and may need to be inhibited to allow access to correct solutions (Smith, Huber, & Vul, 2013).

In addition to these cognitive studies, neuroimaging studies also support the role of inhibition in lab-based assessments of creativity. For example, studies have found that the connectivity between the DMN and ECN during creative cognition is enhanced when there is a greater need for inhibition (Beaty et al., 2017a; Christensen et al., 2021), suggesting that the interactions of these networks across creative tasks may be due, at least in part, to the need for ECN-based processes to inhibit and constrain the spontaneous, generative processes of the DMN. These findings have led researchers to suggest that inhibitory control is needed during creative cognition to suppress distracting and unoriginal thoughts (Beaty et al., 2017a; Camarda et al., 2018a; Volle, 2018), and direct activation towards more novel ideas. For more detailed overviews of the costs and benefits of inhibitory control for creative cognition, see recent reviews (Chrysikou, 2018; Benedek & Jauk, 2018; Volle, 2018).

3.1.3 Towards a clearer understanding of the relationship between creative cognition and inhibitory control

The diversity of findings regarding the relationship between creativity and inhibitory control has led researchers to suggest that optimal creative performance might require flexible inhibitory control (Zabelina, 2018; Zabelina et al., 2016). The most creative individuals might be those that can readily shift between disinhibition, to acquire a broader attentional state and allow diverse ideas to activate, and inhibition, to narrow attention to only the most task-relevant ideas (Bristol & Viskontas, 2006; Dorfman et al., 2008; Gabora, 2018). Indeed, some research has linked real-world creative achievement to leakier attention (a reduced ability to shut out distracting information; Zabelina et al., 2015, 2016), while other research has linked in-lab divergent thinking performance to the ability to flexibly engage inhibitory control when needed in global-local switching paradigms (Zabelina et al., 2016; Zabelina & Ganis, 2018). Researchers have also suggested that creative cognition involves shifting between flexible, explorative modes of thought and persistent, exploitative modes (Mekern et al., 2019b; Nijstad et al., 2010; Zhang et al., 2020).

Another likely explanation for the conflicting findings regarding inhibitory control and creativity is that the relationship depends on the nature of the creative task (Amer et al., 2016; Benedek & Jauk, 2018; Chrysikou, 2018; Sowden et al., 2015; Volle, 2018). For example, some creative endeavors, such as musical improvisation, might involve expert-level motor skills operating in the absence of inhibitory control (Bashwiner et al., 2016; Limb & Braun, 2008). Open-ended or loosely-defined tasks, where it is difficult to say exactly which information is task-related (and likewise, which information should be inhibited), might also benefit from reduced inhibitory control, while well-defined problems, even those that require creative solutions, may benefit from enhanced inhibitory control (Benedek & Jauk, 2018; Chrysikou, 2018). An additional factor is the time individuals have to complete a problem. For example, real-world creative problems might last several days or weeks, and thus are far more likely to benefit from periods of reduced inhibitory control than laboratory-based tasks in which participants only have minutes to generate their ideas (Chrysikou, 2018). Periods of incubation and mind-wandering might lead to creative insights (Christoff et al., 2016; Fox & Beaty, 2018), but such a lack of task-focus is likely to impair creative performance in the very short term (Hao, Wu, Runco, & Pina, 2015a; Smeekens & Kane, 2016).

A further explanation for the diverse findings regarding creative cognition and inhibitory control, and one seldom explored within NCR, is that the relationship depends on the specific measure of inhibition that is used. Inhibition comes in a variety of forms, including response inhibition (the suppression of prepotent responses), cognitive inhibition (the suppression of distracting concepts), and latent inhibition (the suppression of task-irrelevant information) (Cipolotti et al., 2016; Diamond, 2013; Friedman & Miyake, 2004; Gartner & Strobel, 2021). Indeed, evidence suggests that these different forms of inhibition depend on distinct neural regions and networks (Cipolotti et al., 2016; Rodríguez-Nieto et al., 2022).

The majority of studies examining the relationship between creative cognition and inhibitory control use measures of response inhibition (e.g., Benedek et al., 2014c; Camarda et al., 2018a; Edl, Benedek, Papousek, Weiss, & Fink, 2014), or the ability to suppress distracting visual information (Radel et al., 2015), as opposed to measures of cognitive inhibition, such as the "garden path" task (Engelhardt et al., 2008), or the Hayling 2 (Cipolotti et al., 2016). However, from the standpoint of laboratory-based divergent thinking tasks, where the inhibition concerned acts to suppress distracting or unoriginal semantic information from entering WM, cognitive inhibition would seem to be more relevant than response inhibition.

One measure of cognitive inhibition is retrieval-induced forgetting (RIF). RIF is the suppression of associated, but distracting information, during recall of target information, which can cause forgetting of the distracting information (Wimber, Alink, Charest, Kriegeskorte, & Anderson, 2015). Research has shown that those who exhibit greater RIF effects are better able to overcome fixation in the RAT (Koppel & Storm, 2014; Storm & Angello, 2010), but little research has examined relationships between RIF and divergent thinking. One exception is a study by Lin and Lien (2013), who found mixed-results regarding the relationship between RIF and both divergent and convergent thinking across two studies. In short, further research is needed to examine how RIF relates to a range of real-world and lab-based measures of creativity.

Meanwhile, a handful of studies have linked reduced latent inhibition to greater real-world creative achievement (Carson et al., 2003), and lab-based creative performance (Lorca Garrido, López-Martínez, & de Vicente-Yagüe Jara, 2021). These results have led researchers to suggest that creative individuals may have difficulties shutting out information that isn't directly related to the current task (Carson et al., 2003; Zabelina et al., 2015), which can be detrimental in situations where time is a limiting factor, but can also lead to creative insights through unexpected associations with non-task-related information. Relative to response inhibition, however, few empirical studies have examined relationships between latent inhibition and creative cognition.

3.1.4 The present study

Examining the relationship between creative cognition and inhibitory control using multiple measures of both constructs could shed considerable light on the question of which forms of inhibitory control are relevant to which forms of creative cognition. For example, creative problems or activities in everyday life may not require as much inhibitory control as those encountered in the lab, and may be more likely to benefit from periods of mind-wandering that, while not time-efficient, could lead to unexpected associations between remote ideas. As such, it is possible that reduced inhibitory control, in particular as measured by latent inhibition, is related to greater real-world creative performance (Carson et al., 2003). Meanwhile, greater inhibitory control, as measured by response inhibition and cognitive inhibition, may relate to greater in-lab creative performance. Indeed, our understanding of the role of inhibitory control in creative cognition would also benefit from examining whether cognitive inhibition or response inhibition is more relevant to measures of divergent and convergent thinking.

The present study examines the relationship between creative cognition and inhibitory control, measuring both as multi-faceted constructs. To this end, both verbal and visual measures of divergent thinking (the AUT and a figural completion drawing task, respectively) were included, together with a common measure of convergent thinking (the RAT). Several self-report measures of real-world creative achievement were also included. Concerning inhibitory control, the study includes two measures of response inhibition (the Stroop task and the Emotional Stroop), a measure of cognitive inhibition (RIF), a measure of latent inhibition, and a self-report measure of self-monitoring.

I also include several measures that may influence how inhibitory control relates to creative cognition. Specifically, the personality trait openness to experience provides a measure of how open individuals are to new ideas (Kaufman et al., 2016; Oleynick et al., 2017), and has been found to relate to reduced latent inhibition (Peterson, Smith, & Carson, 2002). Openness to experience is also a reliable predictor of creative performance both in the laboratory and the real world (Beaty et al., 2016b, 2018a; Oleynick et al., 2017). The trait is commonly studied in terms of its twin aspects of openness and intellect, and research has found that while the former predicts creative achievement in the arts, the latter predicts creative achievement in the sciences (Kaufman et al., 2016). Given this characterization, it is possible that those higher in the sub-trait openness attain creative ideas through (or despite) reduced inhibitory control (Carson et al., 2003; Peterson et al., 2002), while those higher in intellect attain creative ideas through greater inhibitory control.

Likewise, risk-taking may have an influence on the relationship between inhibitory control and creative cognition. Risk-taking is not reliably found to relate to creative ability (e.g., Erbas & Bas, 2015; Shen et al., 2018; Tyagi, Hanoch, Hall, Runco, & Denham, 2017), and tends to be negatively related to inhibitory control (Dohmen, Falk, Huffman, & Sunde, 2018). However, it is possible that those who are more willing to take risks attain creative ideas through reduced inhibitory control, which might lead to greater novelty-seeking, while those lower in risk-taking follow more analytical paths to creative ideas, and show a greater relationship between creative performance and inhibitory control. Finally, a measure of intelligence, a reliable correlate of both lab-based divergent thinking (Frith et al., 2021a) and inhibitory control (Ardila, 2018) is included. This is primarily to examine whether any relationships found between inhibitory control and creative cognition are still present when accounting for intelligence.

While this study is partly exploratory, the following predictions can be made. It is predicted that response inhibition and cognitive inhibition will be related to lab-based measures of divergent and convergent thinking, but not to real-world creative achievement. It is also expected that cognitive inhibition will be more related to behavioral measures of creativity than response inhibition, given the need to suppress distracting ideas rather than prepotent responses in creative thinking tasks. By contrast, it is expected that latent inhibition will be related to real-world creative achievement, but not to behavioral measures of creative cognition. No specific predictions are made regarding self-reported self-monitoring.

Concerning measures of creative cognition, it is expected that convergent thinking as measured by the RAT will be less related to inhibitory control than measures of divergent thinking. This is because despite the common characterization of convergent thinking as involving considerable deliberate, controlled processes (e.g., Cropley, 2006; Runco, 2014), the RAT itself is largely an associative task (Cortes, Weinberger, Daker, & Green, 2019; Kounios & Beeman, 2014; Marko, Michalko, & Riečanský, 2018).

3.2 Methods

3.2.1 Participants

Participants (*N* = 151; 77 females; mean age = 33.3 years, *SD* = 11.9) were recruited from Prolific. Participation was contingent on a Prolific approval rating of 90% or above and a minimum of 50 previously completed studies. Fluency in English was also required. Informed consent was given prior to data collection. Ethical approval for the study was given by the Local Ethics Committee of the Department of Psychology at Goldsmiths, University of London.

3.2.2 Materials

All tasks were coded in Psychopy and PsychoJS (Peirce et al., 2019). Screen color for all tasks was gray.

Creative thinking

Our measures of creativity included tasks designed to tap verbal and visual divergent thinking and verbal convergent thinking, as well as two self-report measures of creative achievement.

Alternative Uses Task

To assess verbal divergent thinking, the AUT was used. Participants were given an object word and asked to generate as many creative uses for the object as they could in 3 minutes. This was repeated for two object words ("box" and "rope"), presented in a random order. Participants first saw a fixation cross for 1s, followed by the object word and a white input box, for 3 minutes. A countdown timer was displayed on the bottom right of the screen as participants generated and typed ideas. The following instructions also remained in small white font at the top of the screen: “Type as many creative uses as you can think of for this object. Press ENTER after each idea”.

Ideas were later rated for creativity by four independent raters, on a 1 (not at all creative) to 5 (very creative) scale (Silvia et al., 2009). Raters were instructed to consider the originality, novelty, and usefulness of each idea and to combine these aspects into a single creativity rating. The number of (valid) responses generated in each trial (fluency score) was also recorded. Invalid responses were those that could not be interpreted as a use (e.g., nonsense, “I don’t know”, etc.).

Figural drawing task

To assess visual divergent thinking, a figural completion drawing task was used. In each trial, participants were presented with a starting image of a simple line-drawn shape, and were asked to use the shape to produce the most creative drawing they could think of, using the mouse. Participants were told “your drawings don’t have to be pretty: they should simply show how creative and interesting your ideas are”. Trials began with a fixation cross for 2s, followed by the starting image. Participants then had 30s to complete their drawing, and were instructed to use all the time available to work on their drawing. After the 30s, participants were asked to type a short label describing their drawing. Participants first completed a single practice trial, followed by 10 real trials. The 11 starting images for these trials were selected from a larger set of 20 used in a previous study (Lloyd-Cox et al., 2021), which were in turn selected from prior studies on visual creative thinking (Jankowska & Karwowski, 2015; Lubart, Besançon, & Barbot, 2011; Torrance, 1966; Wallach & Kogan, 1965). Drawings were subsequently rated for both creativity and drawing skill by four independent raters (the same raters as used for the AUT assessment). The skill measure was not used in the analysis but was included to encourage raters to consider creativity separately to drawing ability. When rating creativity, raters were instructed to ignore artistic talent, and to consider how original the ideas in the drawing were compared to other drawings, and how creatively the starting image was used in the drawing.

Remote Associates Test

As a measure of verbal convergent thinking, the compound RAT (Bowden & Jung-Beeman, 2003) was used. In this task participants are shown three unrelated cue words and must think of a fourth word that relates to all three cues (e.g., the cues “safety”, “cushion”, “point” are not closely related to each other but all closely relate to the solution “pin”). In each trial, the three cues were presented in a single line in the middle of the screen, in a random order left to right. Participants had 30s to think of and type the answer, before seeing the next trial. Trials ended early after participants pressed the “enter” key. Participants first completed two practice trials (in which the correct answer was shown as feedback after each trial), before completing 10 real trials. The 12 RAT problems in these trials were drawn from Bowden and Jung-Beeman (2003). Performance was the number of correctly solved problems.

Self-report creative achievement

I also collected two self-report measures of creative ability: the Creative Achievement Questionnaire (CAQ; Carson, Peterson, & Higgins, 2005), and the Inventory of Creative Activities (ICAA-Act; Diedrich et al., 2018). In the CAQ, participants mark the levels of achievement they have reached in 10 separate domains including “music”, “creative writing”, and “scientific discovery”. In each domain, participants are shown eight items ranging from no achievement (e.g., “I have no training or recognized talent in this area”) to achievement at the national level (e.g., “My work has been critiqued in national publications”). Participants tick all the levels of achievement they have reached. Items in each domain are weighted from 0 to 7, and weighted scores are summed across items to produce a domain specific score. For the present purposes, scores were then summed across domains to produce a total creative achievement score. In the ICAA-Act, participants are shown six items in each of eight domains (e.g., ‘Literature’, ‘Music’, ‘Cooking’). Each item is an activity (e.g., “wrote a short story”), and participants mark how often they have completed the activity in the past 10 years on a five point scale ranging from 0 (never) to 4 (more than 10 times). Averaging across the six items produces a domain-specific score. The present study summed across domains to produce a domain-general creative activity score.

Inhibitory control

Our measures of inhibitory control included two measures of response inhibition (the suppression of prepotent responses), a measure of cognitive inhibition (the suppression of distracting thoughts), a measure of latent inhibition (the non-deliberate suppression of a non-task-relevant cue), and a self-report measure of self-monitoring.

Stroop

To assess response inhibition, the Stroop task was used, a classic measure of response inhibition (Friedman et al., 2016; Zabelina et al., 2019). The task was based on methods used in prior studies (Friedman et al., 2016; Parris, 2014). In each trial, participants were shown a color word (“red” or “green”) in one of two font colors (red or green). Participants were told to ignore the text itself and to instead indicate whether the font was red (‘X’ key; left index finger) or green (‘M’ key; right index finger). The prepotent response is to read the text, and so to perform well, participants must suppress this response. Participants were asked to respond as quickly as possible. In congruent trials, the color of the font matched the text displayed (e.g., the word “green” displayed in green font). In incongruent trials, the color of the font was different to the text displayed.

There were 140 trials in total (70 congruent and 70 incongruent) presented in a random order. Trials proceeded as follows: a 0.5s white fixation cross was followed by presentation of the colored text, which remained on screen until the participant responded, or until 5s had elapsed. Trials in which participants pressed the wrong key or did not respond were classed as incorrect; in these cases the word “incorrect” was shown for 1s. The added time cost of incorrect trials thus served to discourage random responding. Throughout the task, two reminders of the keys (“X = green”, “M = red”) were presented in smaller, white font at the bottom of the screen. Prior to the main task, participants completed 20 practice trials in which feedback was always given (the word "correct" or "incorrect" as appropriate). Incongruent trials, which involve more conflict, tend to have larger reaction times. As such, the dependent variable for the task was calculated as the mean reaction time for correct, incongruent trials minus the mean reaction time for correct, congruent trials. A larger value indicates a greater Stroop effect and weaker response inhibition.

Emotional Stroop

As an additional, alternative measure of response inhibition, the face-color emotional Stroop task was used. This was based on a previous study by Rey et al. (2014), but adapted to more closely mirror the classic Stroop described above in terms of number of trials, trial time, and response keys. In the task, participants were shown a face expressing either fear or joy. On top of the face, the word "JOY" or "FEAR" appeared. Participants were told to ignore the text displayed and pay attention to the emotion in the face, pressing the 'X' key (left index finger) if the face was fearful, and the 'M' key (right index finger) if the face was joyful. As in the classic Stroop task, participants must suppress the prepotent tendency to read the text. Face stimuli were images of nine males and nine females, each showing one joyful expression and one fearful expression (36 images in total). Images were taken from the NimStim Face Stimulus Set (Tottenham et al., 2009), and edited following Rey et al. (2014). Specifically, images were cropped to show only the face, and converted to grayscale using MATLAB. Face images were then presented in the center of the screen, with the word presented in red font over the face. Word position was varied randomly in each trial, occupying one of five positions but never covering the eyes.

Participants completed 144 real trials (each image was presented four times, twice with incongruent text, and twice with incongruent text), and 14 practice trials. As in the classic Stroop task, a white 0.5s fixation cross was followed by presentation of the image and word for up to 5s or until the participant responded. A 1s feedback message was displayed for incorrect trials, while for practice trials, feedback was given for both incorrect and correct trials. The dependent variable was calculated as the mean reaction time of correct, incongruent trials minus the mean reaction time of correct, congruent trials.

Retrieval-induced forgetting

To assess cognitive inhibition, a measure of retrieval induced forgetting (RIF) was used. This task was based on a study Koppel and Storm (2014), but with half the number of cues to reduce task time (24 instead of 48). The RIF task involves three consecutive phases: a study phase, a practice phase, and a test phase. In the study phase, participants were shown 24 category-item pairs (e.g., “Furniture : Chair”). Participants were told to study the pairs well since they would be tested on whether they could remember them. There were eight categories in total and each category contained three items. For a complete list of category-item pairs, see the leftmost column in appendix C of Anderson, Bjork and Bjork (1994). Pairs were grouped into three sets of eight pairs (each set contained one pair from each category). Sets were presented in a random order, and pairs were presented in a random order within sets. Each pair was shown for 4 seconds, with a 0.5s inter-trial interval (ITI).

In the practice phase, participants were told they would practice thinking of some other items that fit these categories. In each trial, they were given a category (e.g., “Drinks”), and a 2-letter stem for an item (e.g., “Wh”). They then had 10s to think of a word that completes the stem (e.g., “whisky”) and type it. Participants were randomly assigned to one of four conditions, which each contained a different set of practice trials. Each set contained four of the eight categories (the practiced categories), each with three category – stem pairs (12 pairs in total). Each set was repeated three times, for a total of 36 practice trials.

In the final, test phase, participants were asked to recall the original 24 category-item pairs. For each pair, they were shown the category and the first letter of the item (e.g., “Furniture : C”). They were given 10 seconds to type the original word and press ‘enter’ when finished. Pairs were presented as in the study phase, in three groups of eight pairs. Groups were again presented in a random order and pairs were presented in a random order within sets. Due to retrieval induced forgetting, items from practiced categories should be more difficult to recall than items from non-practised categories. As such, each participant’s RIF score was calculated as the number of correctly remembered words from non-practiced categories minus the number of correctly remembered words from practiced categories, with a higher score reflecting a greater RIF effect.

Latent inhibition

To assess latent inhibition, a task based on Granger et al. (2016) was used. The task consists of an initial exposure phase, where a given cue is unrelated to task performance, and a subsequent test phase, in which the same cue is related to task performance. In the exposure phase, participants were told to watch a sequence of letters, and count how many times the letter M appeared. The sequence contained "filler" letters (D, M, T, V), in addition to a pre-exposure stimulus letter (S or H; counter-balanced across participants). Filler letters appeared 15 times each, while the stimulus letter appeared 20 times. Letters (in white font) were presented for 1s each, with a 0.5s blank interval. After the exposure phase, participants were asked to indicate how many times the letter M appeared.

In the test phase, participants were instructed to watch another sequence of letters and try to predict when the letter X would appear. Specifically, they were told "if you think you know when the letter 'X' will appear then you can press the space bar early in the sequence, before the letter 'X' appears on screen. Alternatively, if you are unable to do this please press the spacebar as soon as you see the letter 'X'. There may be more than one rule that predicts the 'X'". Participants were also told to try to be as accurate as possible but not to worry about making the occasional error. Stimuli in the test phase were the same filler letters again (D, M, T, V), together with both S and H, and the target letter X. The test phase comprised 178 trials. Letters were presented for 1s each, with a 0.5s ITI. Filler letters were presented 32 times each, while X was presented 30 times and both S and H were presented 10 times each. Importantly, X appeared 10 times after a random filler letter, 10 times after S, and 10 times after H. As such, S and H always predicted the X. Depending on the counter-balance condition of the participant, either S or H would serve as the pre-exposed (PE) stimulus (i.e., present in the exposure phase), while the other letter would serve as the non-pre-exposed (NPE) stimulus.

If latent inhibition is present, participants should take longer to react to the PE stimulus than the NPE stimulus. Calculation of the dependent variable was as follows (see also Granger et al., 2016): reaction times (RTs) were recorded from the onset of the PE or NPE stimulus until the offset of the target (X). RTs for responses (spacebar presses), could thus range from 0-1500ms for predicting the X, and 1500-2500ms for responding to the X. A latent inhibition score was calculated as the median of the PE RT minus the median of the NPE RT, with higher scores reflecting greater latent inhibition.

Self-monitoring scale

In addition to these behavioral measures of inhibitory control, the self-monitoring scale (SMS; Snyder, 1974; Soibel, Fong, Mullin, Jenkins, & Mar, 2012) was included. The scale contains 25 items (e.g., “I may deceive people by being friendly when I really dislike them”), roughly half of which are reverse-scored. Participants indicate whether each statement is true (1) or false (0). Scores across items are summed to produce a final SMS score.

Additional measures

In addition to measures of creative ability and inhibitory control, measures of personality (including the propensity to take risks) and intelligence were also recorded, since these may be relevant to the relationship between creative thinking and inhibition.

Openness/Intellect

To assess openness to experience, the Openness/Intellect subscale of the Big Five Aspect Scale (BFAS; DeYoung, Quilty, & Peterson, 2007) was employed. This subscale comprises 20 items, with 10 items evaluating openness and 10 intellect. Each item consists of a statement (e.g., "I can handle a lot of information"), and participants express their agreement with these statements on a 1 (strongly disagree) to 5 (strongly agree) rating scale. Scores for openness and intellect were analyzed separately.

Risk-taking

To evaluate risk-taking propensity, the Domain Specific Risk-taking Scale (DSRS; Blais & Weber, 2006) was employed. The scale is composed of 30 items, with six items dedicated to each of five domains of risk-taking: ethical, financial, health/safety, recreational, and social. Items describe activities or behaviors (e.g., "Betting a day’s income at a high-stake poker game"), and participants indicate their likelihood of engaging in each activity, on a scale ranging from 1 (extremely unlikely) to 7 (extremely likely). The participants' scores across all five domains were aggregated to form a single risk-taking score.

Fluid intelligence

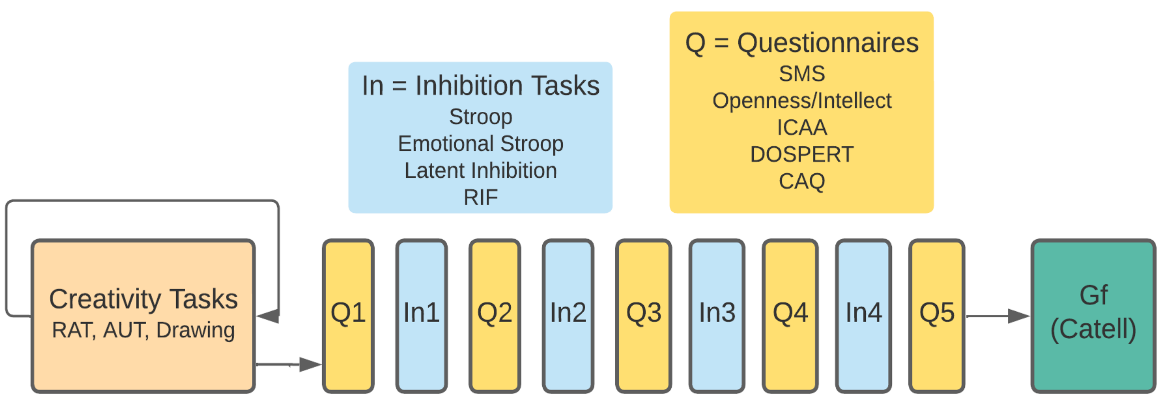
Finally, to assess fluid intelligence, the Cattell pattern completion task (a segment of the Culture Fair Intelligence Test; Cattell & Cattell, 1961) was used. Participants were given 3 minutes to solve 13 problems, presented in order of increasing difficulty. In each problem participants select an image that most logically continues a series of images. Performance is the number of correctly solved problems.

3.2.3 Procedure

The procedure was as follows (see Figure 5). Participants completed the three creative tasks first, in one of three counter-balanced orders. They then completed the four inhibitory control tasks in one of four counter-balanced orders. Importantly, to reduce fatigue, inhibitory control tasks were interleaved with the five questionnaires in the study (SMS, Openness to experience, ICAA, DOSPERT, and the CAQ), which always appeared in a fixed order. Finally, participants completed the Cattell pattern completion task.

Figure 5

Experimental procedure (left to right)



Note. Participants first completed creative tasks in one of three counterbalanced orders, before completing inhibition tasks in one of four counterbalanced orders. Inhibition tasks were interleaved with questionnaires, which appeared in a fixed order. The Cattell task was completed last.

3.3 Results

3.3.1 Data processing and exclusions

Additional processing was carried out for the Stroop and Emotional Stroop tasks, prior to calculation of each participant's mean reaction times for congruent and incongruent trials in these tasks (see also Friedman et al., 2016). First, incorrect trials were excluded (3.21% of all trials for Stroop; 4.86% of all trials for Emotional Stroop). Participants' mean accuracy was 96.88% in the Stroop task (*SD* = 2.83%) and 95.27% in the Emotional Stroop task (*SD* = 3.91%). Second, trials with RTs below 0.2s or further than 3 SDs from the mean for each participant and each condition (congruent or incongruent) were removed (2.03% of all trials for Stroop; 1.92% of trials for Emotional Stroop). Following these exclusions, task scores for each participant were calculated as discussed (mean incongruent RT minus mean congruent RT).

Data across all variables of interest was then processed for outliers. At the participant level, for each variable separately, values greater than 3.5 SDs above or below the mean were identified, and replaced with the value 3.5 SDs from the mean (i.e., the data was winsorized). This process affected one participant in the latent inhibition task, three in the Stroop task, one in the emotional Stroop task, and two in the CAQ.

Responses to the AUT and drawing task were rated for creativity by four independent raters (the same raters for both tasks; Silvia et al., 2009). Inter-rater reliability was in the good range for the drawing task, with an intraclass correlation coefficient (ICC) of .89 (.85–.91), in the good range for the "Rope" cue of the AUT, with an ICC of .80 (.75 – .85) and in the excellent range for the "Box" cue of the AUT, with an ICC of .94 (.92 – .95).

3.3.2 Analyses

Analyses explored the relationships between different measures of creative thinking and different measures of inhibitory control. To this end, correlations were first computed between the main variables of interest. In light of these correlations, three latent factors were then extracted to reduce the dimensionality of the data by combining related measures. Specifically, I formed a divergent thinking factor from the measures of verbal and visual divergent thinking, a response inhibition factor from the Stroop and Emotional Stroop, and a self-report creativity measure from the ICAA-Act and the CAQ. Analysis then consisted of computing and comparing regressions for each of three resulting creativity measures (divergent thinking, convergent thinking, and self-report creativity), with measures of inhibitory control and personality as IVs.

Finally, moderation analyses were conducted to probe whether the relationship between inhibitory control and creativity is moderated by personality measures.

3.3.3 Descriptive statistics and zero-order correlations

Descriptive statistics for all variables of interest are shown in Table 4. Correlations are shown in Table 5. Note that in both cases values for AUT and Drawing creativity reflect the mean across raters.

Table 4

Descriptive statistics for all variables of interest

	M	*SD*	Min	Max
RAT	4.45	2.21	0.00	10.00
AUT Flu.	10.47	4.13	2.00	22.00
AUT Crea.	2.71	0.43	1.62	3.70
Draw Crea.	2.83	0.43	1.56	4.10
ICAA	8.64	4.25	0.17	23.33
CAQ	12.35	13.03	0.00	61.97
SMS	11.36	4.17	2.00	21.00
LI	0.11	0.35	-1.13	1.11
RIF	0.7	2.47	-6.00	7.00
Stroop	0.02	0.05	-0.06	0.20
Em. Stroop	0.02	0.04	-0.08	0.20
Openness	36.99	5.45	20.00	50.00
Intellect	36.19	6.15	21.00	49.00
Risk-taking	97.77	23.18	53.00	171.00
Gf	6.81	1.7	3.00	11.00

Note. RAT = Remote Associates Test; AUT = Alternative Uses Task; Flu. = Fluency score; Crea. = Creativity score; Draw = Drawing task; LI = Latent Inhibition; RIF = Retrieval Induced Forgetting; Em. Stroop = Emotional Stroop; ICAA = Inventory of Creative Achievements and Activities; CAQ = Creative Achievement Questionnaire; Gf = Intelligence.

Considering zero-order correlations, among task-based measures of creative thinking it was notable that RAT score and AUT fluency score were positively correlated ($r = .29$, $p < .001$), and AUT creativity and Drawing creativity were positively correlated ($p = .001$), while other correlations did not reach significance (ps > .054). It was also notable that the ICAA and CAQ were not significantly correlated with any task-based measure of creative thinking (ps > .073), though they did positively correlate with each other ($r = .49$, $p < .001$). These results are consistent with a multi-component model of creativity, in which the creative quality of divergent thinking responses are not necessarily related to the associative, insight processes involved in the RAT.

Among measures of inhibitory control, no significant correlations were found between the different forms of inhibition (i.e., latent inhibition, cognitive inhibition, and response inhibition). Specifically, LI score was not significantly correlated with either the RIF task or the Stroop or Emotional Stroop, while the RIF was also not significantly correlated with either the Stroop or Emotional Stroop (ps < .384). It was also notable that no task-based measures of inhibitory control were significantly related to SMS score (ps < .542). Stroop score was however correlated with Emotional Stroop score ($r = .34$, $p < .001$). While moderate in size, this correlation suggests the two tasks are likely to target the same form of inhibition (see Schmiedek et al., 2014). Overall, results are consistent with the existence of distinct forms of inhibitory control (Cipolotti et al. 2016; Diamond 2013; Engelhardt et al., 2008).

Table 5

Correlations between major variables of interest. AUT and drawing task scores are averaged over raters

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. RAT	-													
2. AUT Flu.	.29**	-												
3. AUT Crea.	.16	.08	-											
4. Draw Crea.	.09	-.05	.28**	-										
5. ICAA	-.02	-.01	.00	-.07	-									
6. CAQ	.04	.11	.15	.11	.49**	-								
7. SMS	.01	.17*	.08	-.07	.23**	.22**	-							
8. LI	.10	.08	.11	-.02	.13	.05	-.05	-						
9. RIF	.03	.04	.20*	.21**	-.14	-.05	.01	-.02	-					
10. Stroop	-.14	.05	.11	-.07	-.03	-.01	-.05	.02	.01	-				
11. Em. Stroop	-.12	.14	-.04	-.03	-.12	-.13	.01	.07	.00	.34**	-			
12. Openness	-.06	.08	.35**	.14	.25**	.25**	.14	.14	.07	.12	.09	-		
13. Intellect	-.06	.03	.11	-.02	.20*	.26**	.34**	.09	-.09	-.06	-.01	.16	-	
14. Risk-taking	-.21*	-.09	.08	-.09	.31**	.14	.24**	.01	-.03	.04	.00	.05	.19*	-
15. Gf	.13	.01	.22**	.16	.04	.01	.13	.05	-.10	-.18*	-.14	.05	.15	.07

Note. RAT = Remote Associates Test; AUT = Alternative Uses Task; Flu. = Fluency score; Crea. = Creativity score; Draw = Drawing task; LI = Latent Inhibition; RIF = Retrieval Induced Forgetting; Em. Stroop = Emotional Stroop; ICAA = Inventory of Creative Achievements and Activities; CAQ = Creative Achievement Questionnaire; Gf = Intelligence. * $p < .05$, ** $p < .01$.

Considering relationships between creative thinking and inhibitory control, SMS score showed small positive correlations with AUT fluency ($r = .17$, $p = .040$), and with ICAA ($r = .23$, $p = .004$) and CAQ ($r = .22$, $p = .007$). Interestingly, RIF score was positively correlated with AUT creativity ($r = .20$, $p = .015$) and drawing creativity ($r = .21$, $p < .010$). All other correlations between creative thinking and inhibitory control were non-significant (*p*s < .080).

Finally, considering relationships between creative thinking, inhibitory control, and measures of personality and intelligence, a positive correlation was found between Gf and AUT creativity ($r = .22$, $p = .008$), in line with past work (e.g., Benedek et al., 2014c; Frith et al., 2021a). A negative correlation was also found between Gf and the Stroop measure ($r = -.18$, $p = .026$), suggesting that those higher in Gf have greater response inhibition (and a smaller Stroop effect). Risk-taking showed an unexpected, small, negative correlation with RAT performance ($r = -.21$, $p < .011$), while openness showed a moderate positive correlation with AUT creativity ($r = .35$, $p < .000$), as is commonly reported (e.g., Kaufman et al., 2016; Oleynick et al., 2017; Silvia et al., 2008), but notably not drawing creativity ($r = .14$, $p = .093$). Finally, openness, intellect and risk-taking in general showed small to moderate correlations with self-report measures of creativity (i.e., ICAA and CAQ) and inhibition (i.e., SMS).

3.3.4 Estimating latent factors

To reduce the dimensionality of the data and form more reliable estimates of the constructs being examined, three latent factors were formed from the data, given the moderate to large correlations observed between the component measures in each case. Specifically, a response inhibition factor was computed as the mean of the z-scored values for the Stroop and Emotional Stroop. This new score was then inverted (multiplied by -1) so that higher scores reflect a lower Stroop effect and greater response inhibition. A self-report creativity factor was then formed by computing the mean of each participant's z-scored ICAA and CAQ scores. Finally, a divergent thinking factor was computed from the AUT and drawing creativity scores at the level of individual raters, using confirmatory factor analysis (CFA). This was done by first estimating lower-order measurement models for the drawing task and each cue of the AUT separately, and then estimating a higher-order divergent thinking factor from these three lower-order factors.

Descriptive statistics for creativity ratings, across the four raters, are shown in Table 6, while correlations between raters are shown in Table 7 for AUT creativity and Table 8 for drawing creativity.

Table 6

Descriptive statistics for creativity ratings

	M	*SD*	Min	Max
AUT1_R1	2.53	0.59	1.25	3.80
AUT1_R2	2.53	0.58	1.00	3.80
AUT1_R3	2.88	0.61	1.22	4.00
AUT1_R4	3.08	0.54	1.50	4.27
AUT2_R1	2.38	0.49	1.38	4.00
AUT2_R2	2.44	0.54	1.00	4.00
AUT2_R3	2.79	0.62	1.00	4.60
AUT2_R4	3.08	0.42	1.80	4.17
Draw_R1	2.43	0.52	1.40	3.71
Draw_R2	2.99	0.54	1.50	4.50
Draw_R3	2.80	0.50	1.63	4.50
Draw_R4	3.10	0.44	1.57	4.00

Note. AUT1 = AUT Box; AUT2 = AUT Rope; Draw = Drawing task; R1-R4 = Rater 1 – Rater 4.

Table 7

Correlations between AUT creativity ratings

	AUT1_R1	AUT1_R2	AUT1_R3	AUT1_R4	AUT2_R1	AUT2_R2	AUT2_R3
AUT1_R1	-						
AUT1_R2	.89**	-					
AUT1_R3	.81**	.81**	-				
AUT1_R4	.78**	.74**	.67**	-			
AUT2_R1	.60**	.56**	.46**	.55**	-		
AUT2_R2	.58**	.56**	.47**	.49**	.80**	-	
AUT2_R3	.45**	.44**	.46**	.37**	.47**	.41**	-
AUT2_R4	.46**	.36**	.36**	.42**	.56**	.52**	.42**

Note. AUT1 = AUT Box; AUT2 = AUT Rope; R1-R4 = Rater 1 – Rater 4.

Table 8

Correlations between drawing creativity ratings

	Draw_R1	Draw_R2	Draw_R3
Draw_R1	-		
Draw_R2	.61**	-	
Draw_R3	.65**	.70**	-
Draw_R4	.77**	.60**	.67**

Note. Draw = Drawing task; R1-R4 = Rater 1 – Rater

The first measurement model estimated a lower-order drawing creativity factor (Draw) formed of the four sets of ratings. The model showed good fit; χ^2 (2 df) 16.149 (p = .000; CFI = .959; RMSEA = .218; 90% CI [.128, .322]; SRMR = .033). The second model estimated a lower-order creativity factor for each AUT cue (AUT1 and AUT2; box and rope, respectively). Each was formed of the four sets of ratings for the cue. The model showed good fit; χ^2 (19 df) 32.909 (p = .025; CFI = .984; RMSEA = .070; 90% CI [.025, .109]; SRMR = .042).

Finally, a divergent thinking factor was estimated from these three lower-order factors. This was done with two models. In the first model (DT1), the divergent thinking factor was formed from the Draw factor and both AUT factors (see Figure 6). The model showed good fit; χ^2 (51 df) 75.900 (p = .013; CFI = .980; RMSEA = .057; 90% CI [.027, .082]; SRMR = .047). In the second model (DT2), however, the divergent thinking factor was formed from the Draw factor and just AUT1. This was done for several reasons. First, in the DT1 model, the Draw factor loads at only .31 on the higher-order factor, and thus contributes only slightly to the model. Removing one of the AUT factors from the model could lead to more equal loadings between the AUT and drawing task. In addition, correlations between raters for AUT2 were markedly lower than for AUT1 and Draw (see Figure 7). Indeed, the DT1 model showed higher variance among raters for AUT2, in particular raters R3 and R4, who had low loadings on AUT2. The DT2 model also showed good fit, and fit statistics were slightly better than for DT1; χ^2 (18 df) 34.219 (p = .012; CFI = .982; RMSEA = .077; 90% CI [.036, .116]; SRMR = .041). The loadings of the Draw and AUT1 factors onto the DT2 factor were more equal than for the DT1 model. Correlations and regressions are reported for both DT1 and DT2.

Figure 6

Confirmatory factor analysis model estimating DT1, formed of the lower order Draw, AUT1, and AUT2 factors

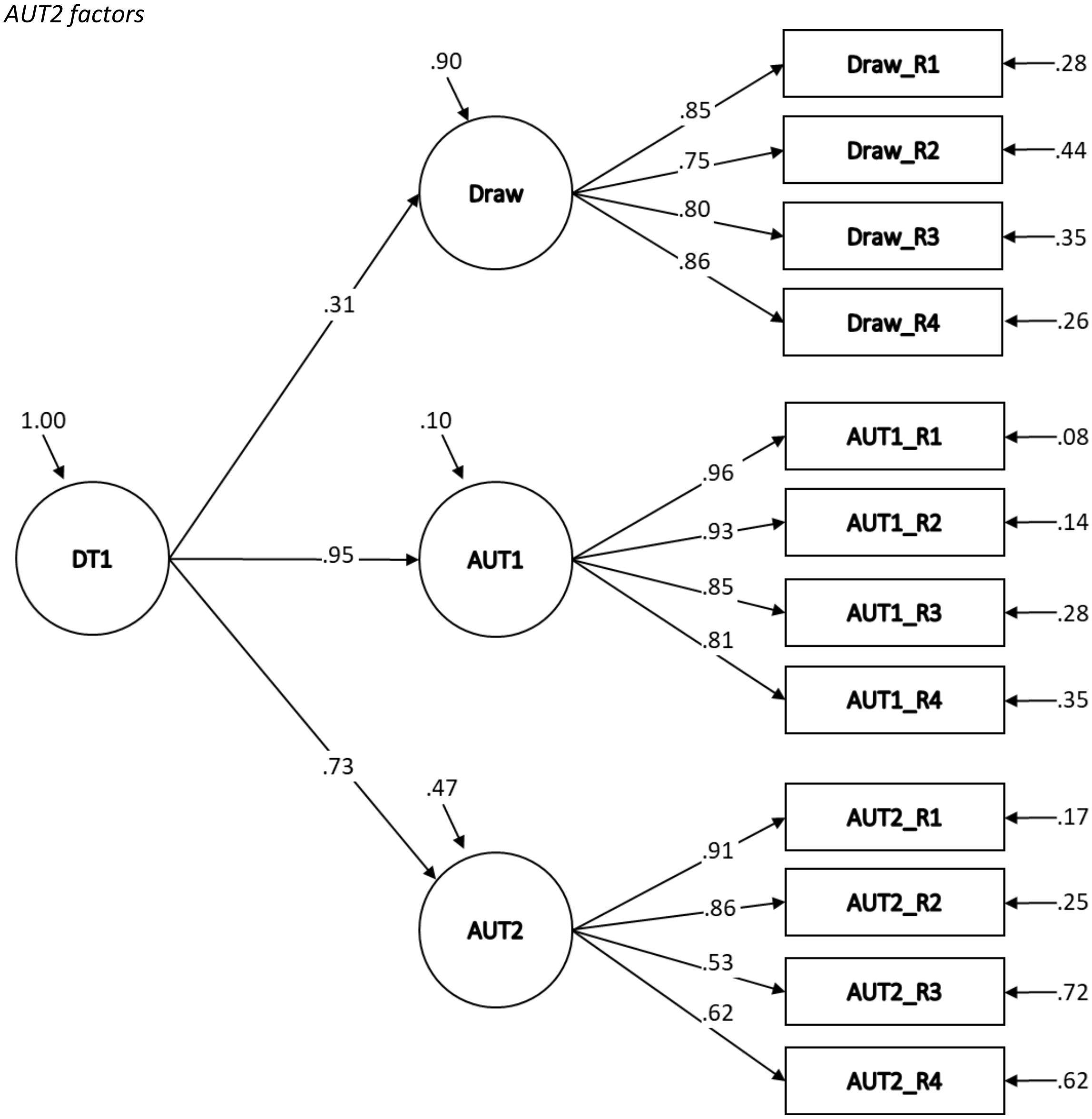
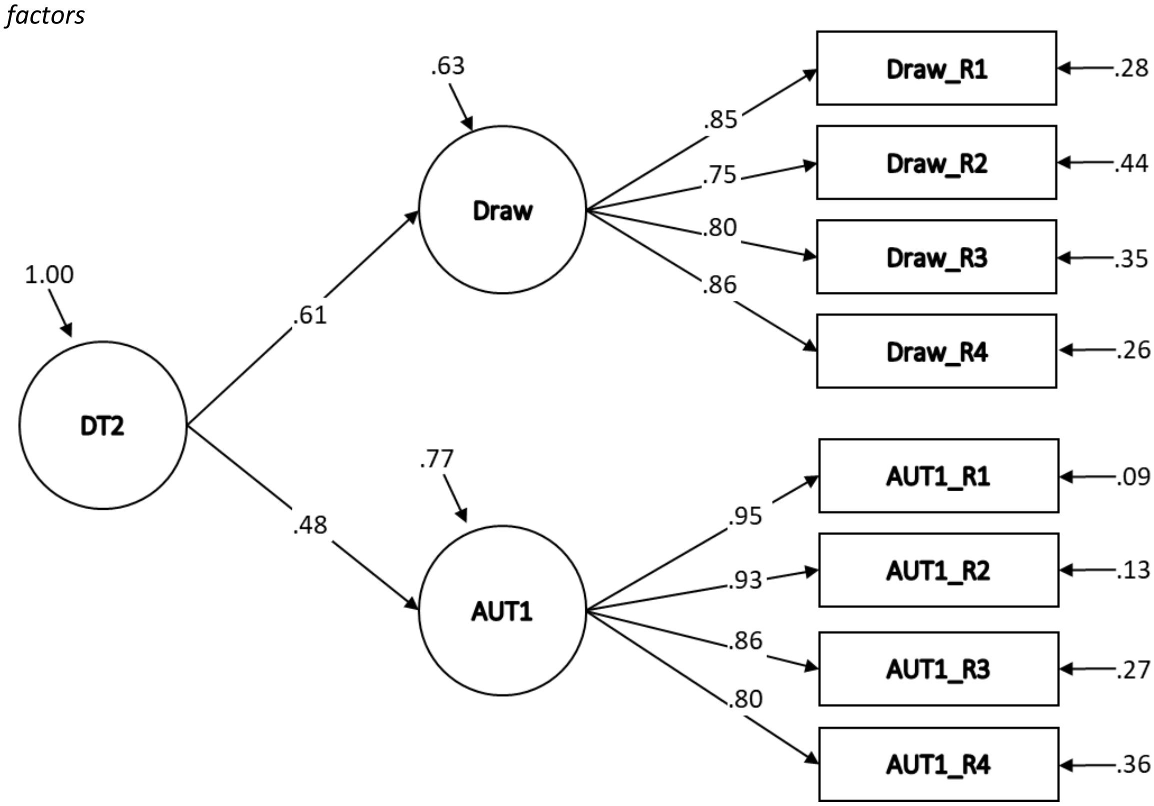


Figure 7

Confirmatory factor analysis model estimating DT2, formed of the lower order Draw and AUT1 factors



AUT fluency was excluded from further analyses since it does not reflect creative quality. Correlations between latent factors and other variables of interest are shown in Table 9. Correlations for the response inhibition and self-report creativity factors were relatively unchanged relative to those for their component variables (Stroop and Emotional Stroop, and ICAA and CAQ, respectively). Comparing the DT1 and DT2 factors, differences in relationships are small. Most notably, DT2, which has a larger contribution from the drawing task, has a stronger correlation with RIF, but a lower correlation with Openness, relative to DT1.

Table 9

Correlations between latent factors and other variables of interest

	1	2	3	4	5	6	7	8	9	10	11
1. RAT	-										
2. DT1	.13	-									
3. DT2	.11	.74**	-								
4. SelfRepC	.01	.06	.05	-							
5. SMS	.01	.05	-.04	.26**	-						
6. LI	.10	.11	.03	.10	-.05	-					
7. RIF	.03	.21**	.26**	-.11	.01	-.02	-				
8. RespInhib.	.16	-.01	.04	.10	.02	-.06	-.01	-			
9. Open.	-.06	.32**	.25**	.29**	.14	.14	.07	-.13	-		
10. Intel.	-.06	.11	.03	.26**	.34**	.09	-.09	.04	.16	-	
11. Risk.	-.21*	.06	-.02	.26**	.24**	.01	-.03	-.02	.05	.19*	-
12. Gf	.13	.22**	.21*	.03	.13	.05	-.10	.20*	.05	.15	.07

Note. RAT = Remote Associates Test; DT = Divergent thinking; SelfRepC = Self-reported creativity; SMS = Self-Monitoring Scale; LI = Latent Inhibition; RIF = Retrieval Induced Forgetting; RespInhib. = Response inhibition; Open. = Openness; Intel. = Intelligence; Risk. = Risk Taking; Gf = Fluid Intelligence. * $p < .05$, ** $p < .01$.

3.3.5 Hierarchical regressions

To more clearly examine how each of the three kinds of creativity assessed in the present study (divergent thinking, convergent thinking, and self-report creativity) vary in their relationships with inhibitory control, a series of hierarchical regressions were conducted. In each regression model, a creativity measure was included as a dependent variable, while predictors were inhibitory control measures (SMS, Response Inhibition, and RIF), kept constant across all regressions. LI was excluded from regressions since correlations between this measure and creativity measures did not approach significance. In addition, openness, intellect, risk-taking and Gf were included as control measures in block one in all regressions. Openness and Gf are often found to relate to divergent thinking (e.g., Frith et al., 2021a; Oleynick et al., 2017), while in the present study, intellect was significantly correlated with self-report creative achievement and risk-taking was significantly correlated with convergent thinking (RAT). Including these measures as control variables should reveal the contribution of inhibitory control measures to creative thinking over and above these additional variables.

A hierarchical regression model was constructed to examine the variance in DT1 explained by inhibitory control, over and above that accounted for by control variables (see Table 10). The total model explained 19% of the variance in DT1 (R^2 = .19, $F(7, 143)$ = 4.79, p < .001). Control variables accounted for 14% of the variance in DT1. Inhibitory control then accounted for an additional 5% of the variance, which was a significant contribution (p = .041). RIF was the only significant predictor of DT1, and importantly remained significant after controlling for openness and fluid intelligence.

Table 10

Summary of hierarchical regression predicting divergent thinking 1

Dependent	Predictor	R^2	ΔR^2	β	*t*	*p*
DT1	**Block 1**	.14	.14			
	Openness			.28	3.67	< .001
	Intellect			.06	0.75	.457
	Risk-taking			.04	0.46	.644
	Gf			.22	2.82	.005
	Block 2	.19	.05			.041
	SMS			-.05	-0.57	.567
	RespInhib.			-.01	-0.15	.880
	RIF			.22	2.88	.005

Note. DT = Divergent thinking; Gf = Fluid intelligence; SMS = Self-Monitoring Scale; RespInhib. = Response inhibition; RIF = Retrieval induced forgetting

A second hierarchical regression model was constructed to examine the variance in DT2 explained by inhibitory control, over and above that accounted for by control variables (see Table 11). The total model explained 18% of the variance in DT2 (R^2 = .18, $F(7, 143)$ = 4.40, p < .001). Control variables accounted for 10% of the variance in DT2. Inhibitory control then accounted for an additional 8% of the variance, which was a significant contribution (p = .005). Again, RIF remained a significant predictor of DT2 after controlling for openness and fluid intelligence (see Figure 8 for scatterplots of the relationships between RIF and DT1 and DT2). The stronger coefficient for RIF when predicting DT2 as compared to DT1 is likely due to the fact that DT2 loads more strongly onto the drawing task than the AUT, and the drawing task had a stronger correlation with RIF (see Table 9).

Table 11

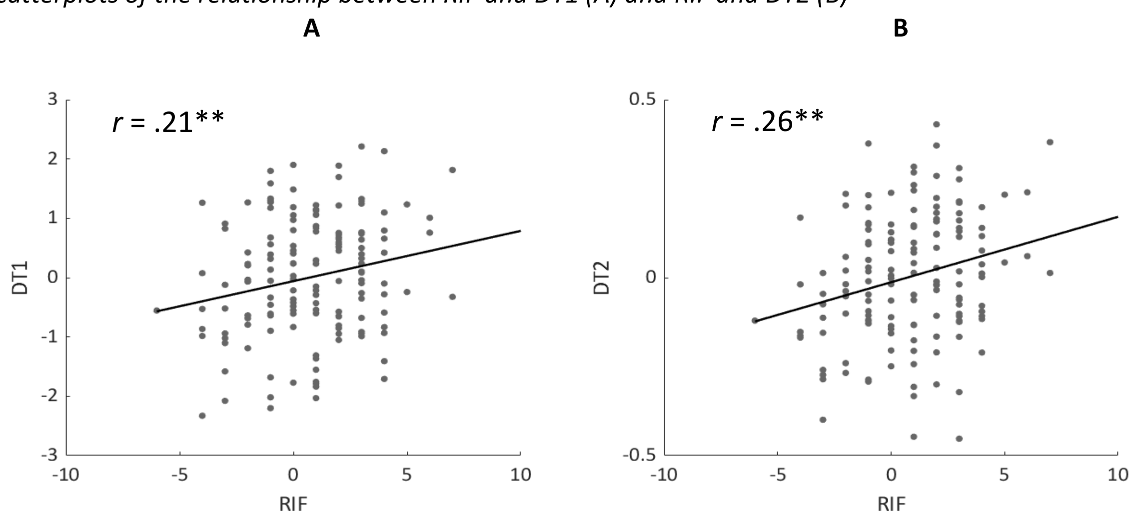
Summary of hierarchical regression predicting divergent thinking 2

Dependent	Predictor	R^2	ΔR^2	β	*t*	*p*
DT2	**Block 1**	.10	.10			
	Openness			.23	2.95	.004
	Intellect			.03	0.34	.738
	Risk-taking			-.02	-0.30	.763
	Gf			.23	2.88	.005
	Block 2	.18	.08			.005
	SMS			-.10	-1.26	.210
	RespInhib.			.03	0.34	.736
	RIF			.26	3.44	< .001

Note. DT = Divergent thinking; Gf = Fluid intelligence; SMS = Self-Monitoring Scale; RespInhib. = Response inhibition; RIF = Retrieval induced forgetting

Figure 8

Scatterplots of the relationship between RIF and DT1 (A) and RIF and DT2 (B)



Note. ** $p < .01$

A further hierarchical regression model was constructed to examine the variance in convergent thinking (RAT performance) explained by inhibitory control (see Table 12). The total model explained 9% of the variance in convergent thinking ($R^2 = .09$, $F(7, 143) = 1.93$, $p = .069$). Control variables accounted for 7% of the variance in convergent thinking. Inhibitory control then accounted for an additional 2% of the variance, which was not a significant contribution ($p = .403$).

No individual cognitive control measures contributed significantly to the model after including control variables, though response inhibition was the strongest predictor.

A final hierarchical regression model was constructed to examine the variance in self-reported creative achievement explained by inhibitory control (see Table 13). The total model explained 22% of the variance in self-reported creative achievement (R^2 = .22, F(7, 143) = 5.90, p = < .001). Control variables accounted for 18% of the variance. Inhibitory control measures then accounted for an additional 5% of the variance, which was a significant contribution (p = .036). However, no individual inhibitory control predictor contributed significantly to the model, though SMS and

Table 12

Summary of hierarchical regression predicting convergent thinking

Dependent	Predictor	R^2	ΔR^2	β	t	p
CT	**Block 1**	.07	.07			
	Openness			-.05	-0.57	.567
	Intellect			-.05	-0.56	.574
	Risk-taking			-.21	-2.58	.011
	Gf			.12	1.49	.138
	Block 2	.09	.02			.403
	SMS			.06	0.71	.481
	RespInhib.			.12	1.49	.140
	RIF			.03	0.40	.688

Note. CT = Convergent thinking; Gf = Fluid intelligence; SMS = Self-Monitoring Scale; RespInhib. = Response inhibition; RIF = Retrieval induced forgetting

response inhibition approached significance.

Overall, these results suggest that divergent thinking is related to inhibitory control, specifically cognitive inhibition (RIF), while convergent thinking and self-reported creative achievement are not related to inhibitory control.

Table 13

Summary of hierarchical regression predicting self-reported creative achievement

Dependent	Predictor	R^2	ΔR^2	β	*t*	*p*
SelfRepC	**Block 1**	.18	.18			
	Openness			.27	3.54	< .001
	Intellect			.13	1.64	.103
	Risk-taking			.19	2.53	.013
	Gf			-.08	-1.00	.317
	Block 2	.22	.05			.036
	SMS			.14	1.73	.086
	RespInhib.			.14	1.88	.062
	RIF			-.12	-1.59	.115

Note. SelfRepC = self-reported creative achievement; Gf = Fluid intelligence; SMS = Self-Monitoring Scale; RespInhib. = Response inhibition; RIF = Retrieval induced forgetting.

3.3.6 Moderation analyses

A further set of regressions were conducted to examine whether openness, intellect, or risk-taking were significant moderators of the relationship between inhibitory control and creative cognition. For each measure of creative cognition, moderation analyses focused on the most significant inhibitory control predictor and the most significant personality predictor.

In the case of DT1 and DT2, I examined whether the relationship between divergent thinking and RIF was moderated by openness, since this was also a significant predictor of divergent thinking (see Table 14). For DT1, the total model explained 14% of the variance in divergent thinking ($R^2 = .14$, $F(3, 147) = 8.17$, $p = < .001$), while for DT2, the total model explained 13% of the variance in divergent thinking ($R^2 = .13$, $F(3, 147) = 7.64$, $p = < .001$). An interaction between openness and RIF was not found to be a significant predictor of either DT1 or DT2 (*p*s > .082). In addition, for both models, including an interaction between openness and RIF caused the coefficient for RIF to become non-significant.

Table 14

Openness as a moderator of the relationship between divergent thinking and RIF

Dependent	Predictor	R^2	β	t	p
DT1		.14			
	Openness		.30	3.29	< .001
	RIF		.18	-0.81	.421
	Openness * RIF		.10	1.13	.259
DT2		.13			
	Openness		.22	2.14	.034
	RIF		.23	-1.34	.183
	Openness * RIF		.15	1.75	.082

Note. DT = Divergent thinking; RIF = Retrieval induced forgetting.

Openness remained a significant positive predictor of divergent thinking in both models. Likewise, I examined whether the relationship between convergent thinking and response inhibition was moderated by risk-taking (see Table 15). The total model explained 8% of the variance in convergent thinking (R^2 = .08, F(3, 147) = 4.03, p = < .009). An interaction between risk-taking and response inhibition was not found to be a significant predictor of convergent thinking (p = .198). Response inhibition remained a non-significant predictor of convergent thinking, while risk-taking remained a significant negative predictor.

Table 15

Risk-taking as a moderator of the relationship between convergent thinking and response inhibition

Dependent	Predictor	R^2	β	t	p
CT		.08			
	Risk-taking		-.21	-2.65	.009
	RespInhib.		.11	-0.90	.369
	Risk-taking * RespInhib.		.12	1.29	.198

Note. CT = Convergent thinking; RespInhib. = Response Inhibition.

Finally, I examined whether the relationship between self-report creative achievement and response inhibition was moderated by openness (see Table 16). The total model explained 10% of the variance in self-report creative achievement (R^2 = .10, F(3, 147) = 5.59, p = < .001). An interaction between openness and response inhibition was not found to be a significant predictor of self-report creative achievement (*p* = .991). Response inhibition remained a non-significant predictor of self-report creative achievement, while openness remained a significant positive predictor.

Table 16
Openness as a moderator of the relationship between self-report creativity and response inhibition

Dependent	Predictor	R^2	β	*t*	*p*
SelfRepC		.10			
	Openness		.31	3.89	< .001
	RespInhib		.14	0.25	.802
	Openness * RespInhib		.00	-0.01	.991

Note. CT = Convergent thinking; RespInhib = Response Inhibition.

In summary, no personality variables were found to be significant moderators of the relationship between inhibitory control and creative cognition, for any of the three forms of creative cognition examined in the present study.

3.4 Discussion

The present study examined the relationship between creative cognition and inhibitory control, measuring both as multi-faceted constructs. Creative cognition was examined with verbal and visual measures of divergent thinking (the AUT and a figural completion drawing task, respectively), a measure of verbal convergent thinking (the RAT), and self-report measures of real-world creative achievement (the CAQ and ICAA-Act). Inhibitory control was examined with two measures of response inhibition (the Stroop and Emotional Stroop), a measure of latent inhibition, a measure of cognitive inhibition (RIF), and a self-report measure of self-monitoring (SMS).

3.4.1 Overview of findings

In line with predictions, cognitive inhibition was more related to behavioral measures of creative cognition than response inhibition. Specifically, RIF was significantly and positively correlated with both verbal and visual divergent thinking measures, and was a significant predictor of divergent thinking as a latent factor. Indeed, RIF remained a significant predictor of divergent thinking even after accounting for openness and intelligence, reliable predictors of divergent thinking performance (Frith et al., 2021a; Oleynick et al., 2017). However, RIF was not found to be significantly related to convergent thinking or real-world creative achievement. By contrast, response inhibition was not found to be a significant correlate, or significant predictor, of any behavioral or self-report measures of creative cognition. These results indicate that cognitive inhibition may be a more relevant form of inhibitory control than response inhibition for creative cognition, and in particular, lab-based creative performance. This is in line with the notion that creative cognition involves the suppression of distracting or unoriginal semantic information, rather than the suppression of prepotent responses.

The finding that neither response nor cognitive inhibition were related to real-world creative achievement was also in line with predictions. It is possible that real-world creative endeavors or problems, that commonly extend over several days or even weeks, rely less on inhibitory control. In such contexts, time is less of a constraint, and so the need for efficient, fast cognition aided by inhibitory control is reduced (Benedek & Jauk, 2018; Chrysikou, 2018). Indeed, these contexts may even benefit from periods of mind-wandering and reduced inhibitory control to allow new associations to form between remote conceptual categories (Christoff et al., 2016; Fox & Beaty, 2018).

Contrary to predictions, and to previous research (Carson et al., 2003), latent inhibition was not found to be correlated with real-world creative achievement. In addition, latent inhibition was not found to be related to openness, as has also been found previously (Peterson et al., 2002). This finding may be due to the specific measure of latent inhibition used in this study. While previous studies have used a measure of latent inhibition involving auditory syllables and white noise, and visually presented yellow disks (Carson et al., 2003; Peterson et al., 2002), the present measure was based on a task developed by Granger and colleagues (2016), who were attempting to avoid contamination from effects such as learned irrelevance and conditioned inhibition (see also Evans, Gray, & Snowden, 2007). It could be that the difference in task is responsible for the lack of relationships found between latent inhibition, openness, and real-world creative achievement in this study.

Indeed, latent inhibition was also not found to be related to any other forms of inhibition. Moreover, none of the forms of inhibitory control examined in the present study were related to one another. This is in line with evidence suggesting that inhibitory control comes in distinct forms (Diamond, 2013; Friedman & Miyake, 2004; Gartner & Strobel, 2021), dependent on distinct neural regions (Cipolotti et al., 2016; Rodríguez-Nieto et al., 2022).

Turning to the present measures of creative cognition, it was notable that the measures of verbal and visual divergent thinking were moderately correlated. This suggests the existence of a domain-general divergent thinking construct that enables participants to generate creative ideas across domains (Beaty et al., 2016a; Chen et al., 2023; Christensen et al., 2021). Conversely, the fact that divergent thinking measures were not correlated with convergent thinking, as assessed by the RAT, suggests that the associative processes relevant to RAT performance do not contribute substantially to performance in divergent thinking tasks (Cortes et al., 2019), and vice-versa. These results support a model of creativity formed of multiple distinct sub-types (Colzato, Ritter, & Steenbergen, 2018; Cortes et al., 2019; Kuypers et al., 2016; Ma & Hommel, 2020; Shen et al., 2018). Moreover, the fact that behavioral measures of convergent and divergent thinking were not found to be positively related to real-world creative achievement was concerning, but not surprising given low latent correlations between behavioral measures of creative performance and self-reported creative achievement and engagement in creative activities (Jauk, Benedek, & Neubauer, 2014; Kaufman & Beghetto, 2009).

It was also surprising that a significant relationship was not found between divergent thinking and response inhibition, as found previously (Benedek et al., 2014c; Edl et al., 2014). One possibility is that the online nature of the present study, and the relatively large mean age of participants (33) had an effect on how the Stroop and Emotional Stroop were completed, and indeed on the relationship observed between divergent thinking and response inhibition. In addition, some of the research linking creative cognition to inhibitory control uses paradigms where fixation (i.e., unhelpful ideas regarding a problem) is deliberately induced in participants by the experimenter (e.g., Beaty et al., 2017a; Christensen et al., 2021; Koppel & Storm, 2014). This fixation then needs to be suppressed for participants to be able to access creative ideas and perform well on the task. It is possible that the relationship between inhibitory control and creative cognition in the absence of artificially-induced fixation is weaker than this research would suggest.

I did not find convergent thinking to be related to any measure of inhibitory control. While this is surprising given characterizations of convergent thinking as an analytic, evaluative process (e.g., Cropley, 2006; Lee & Therriault, 2013; Runco, 2014), it is in keeping with the notion that the RAT itself mostly relies on associative processes, without a substantial executive component (Marko et al., 2018). Indeed, the RAT is often used as a measure of insight (e.g., Kounios & Beeman, 2014; Tik et al., 2018), and was originally developed to assess associative processes (Mednick, 1962). As such, while satisfying the original definition of convergent thinking as problem solving with a single correct solution (Guilford, 1959), it may not be the best measure of convergent thinking as defined in more recent years.

Concerning the measures of personality, the positive relationships observed between openness and both behavioral divergent thinking and self-report creative achievement were expected and in line with prior research (Beaty et al., 2018; Kaufman et al., 2016; Oleynick et al. 2017). It was notable however that those higher in openness and risk-taking did not appear to have reduced inhibitory control abilities, as previous work has found (Dohmen et al., 2018; Peterson et al., 2002; Zabelina & Ganis, 2018). As such, it would seem that those higher in openness are not more open to new ideas simply because they cannot inhibit irrelevant information. Likewise, it is possible that those who prefer to take more risks may do so out of deliberate choice and not because they are unable to inhibit reckless behavior (Dohmen et al., 2018). It was also notable that those higher in self-monitoring (SMS), and intellect did not have higher scores of inhibitory control (though intellect and self-monitoring were positively related to one another), which may simply be an indication that behavioral measures do not always relate to self-report measures of the same construct (Dang, King, & Inzlicht, 2020).

The finding that risk-taking was negatively related to convergent thinking was surprising, but has been found elsewhere, for example by Shen and colleagues (2018). The authors of that study suggest a link between risk-avoidance, psychological safety, and convergent thinking, though it isn’t immediately clear how risk-avoidance would benefit the associative processing involved in the RAT. Finally, no personality measures were found to significantly moderate the relationship between inhibitory control and creative cognition. Taken as a whole, these findings suggest that while those higher in openness tend to have more creative ideas, they do not have reduced inhibitory control, and do not attain creative ideas or engage in creative activities due to a reduced ability to shut out distracting or non-task-relevant thoughts (e.g., Carson et al. 2003; Peterson et al., 2002). Likewise, those higher in intellect, while also engaging in more creative activities, may not have greater inhibitory control abilities, or may not use these abilities to perform better in creative tasks. Indeed, it is possible that individuals higher in these traits perform better in creative tasks and pursuits due to a greater ability to flexibly engage and disengage inhibitory control as and when needed (Gabora, 2018; Sowden et al., 2015; Zabelina & Robinson, 2010).

In summary, these findings suggest that creative cognition, in some instances, is related to greater inhibitory control. In particular, evidence was found that performance on lab-based measures of divergent thinking benefits from cognitive inhibition, the ability to suppress distracting concepts.

3.4.2 Limitations and future directions

As noted, this study is a departure from previous research in that it was an online study, and had a larger age range than is typical for creativity research studies, which tend to focus on undergraduate students (e.g., Beaty et al., 2014; Benedek et al., 2014c; Zabelina et al., 2016). Because of these factors, a future study could examine the same measures included here in an in-person experiment with a younger sample, to make results more comparable to those of previous studies in this field.

Moreover, while multiple measures of certain constructs were used in this study (e.g., divergent thinking, response inhibition, self-report creative achievement), for many constructs only a single measure was used. For example, as discussed, the RAT may not be the most appropriate measure of convergent thinking, and future research should use a range of creative problem solving tasks designed to tap convergent thinking (e.g., Lin & Lien, 2013). A study using multiple measures of all constructs of interest, and in particular convergent thinking, cognitive inhibition, and latent inhibition, could take the field much closer to a clearer understanding of the relationships between creative cognition and inhibitory control, using structural equation modelling.

CHAPTER 4: MECHANISMS OF CREATIVE COGNITION: THE IMPORTANCE OF CONTROL OVER WORKING MEMORY

4.1 Introduction

As discussed in Chapter 3, inhibitory control is an important contributor to creative cognition in at least some contexts, allowing individuals to suppress distracting and unoriginal ideas and increase their chances of forming creative associations. The notion that effective creative cognition requires inhibiting certain ideas from activating underscores the importance of WM, and suggests that access to WM must be carefully managed for optimal creative idea generation. Research into the link between creative cognition and WM capacity (WMC) sometimes reports a positive relationship (e.g., Benedek et al., 2014c; de Dreu et al., 2012; Hao, Yuan, Cheng, Wang, & Runco, 2015b; Lunke & Meier, 2016) and sometimes no relationship (e.g., Menashe et al., 2020; Smeekens & Kane, 2016). Indeed, a recent meta-analysis has concluded that while WMC is important for convergent thinking, it may not play a large role in divergent thinking (Gerver et al., 2023).

Nevertheless, control over WM may still be highly important for effective creative cognition. For example, managing the content of, and breadth of input to WM might enable participants to switch between states of broad, exploratory attention and narrow, exploitative attention (Dorfman et al., 2008; Herz, Baror, & Bar, 2020; Zabelina & Robinson, 2010; Zhang et al., 2020), or between narrow and broad conceptual representations (Gabora, 2010, 2018), as required by the current creative task or stage within a task. Indeed, control over WM might also underlie switching between idea generation and evaluation during creative cognition (Basadur, 1995; Ellamil et al., 2012; Kleinmintz et al., 2019), with each stage requiring very different approaches to managing WM. The generation of ideas might require a broader input to WM, where ideas can enter from a wider range of conceptual categories and WM content is refreshed frequently to allow more ideas to be considered. Meanwhile, the evaluation of ideas might require limiting input to a far narrower set of concepts that remain in WM for longer. Indeed, idea generation might involve a larger number of concepts activating in WM more shallowly, while idea evaluation involves a smaller number of concepts activating more deeply, so that individuals can better assess the details of a candidate creative idea (see also Gabora, 2018).

Control over WM is likely to involve all three of the executive functions of inhibition, shifting, and updating (Miyake et al., 2000). Inhibitory control is required to suppress distracting ideas from entering WM, and thus to keep processing resources free to operate on more creative ideas (Beaty et al., 2014, 2017; Benedek et al., 2014c). Shifting, meanwhile, may allow individuals to move from one set of ideas in WM to another, letting the right kinds of new information in to pursue fruitful ideas and associations (Gabora, 2018; Zabelina, 2010; Zhang et al., 2020). This could allow multiple categories of idea to be explored, and increase the chances of a creative association being formed. Likewise, WM updating should enable individuals to more efficiently refresh the contents of WM, suppressing older information and allowing new ideas to be explored (de Dreu et al., 2012; Gerver et al., 2023).

Understanding how WM is managed to promote optimal creative cognition would take us much closer to a mechanistic model of the processes that produce creative ideas. How exactly do cognitive processes interact to produce creative ideas, and do their interactions change in different contexts? For example, evidence suggests that spontaneous associative processes that spread activation through semantic memory are also important in creative cognition (Beaty & Kenett, 2023; Benedek & Jauk, 2018; Volle, 2018). It is possible that executive processes manage the activity of these associative processes primarily by managing the content and input of WM, thus influencing factors such as the speed and breadth by which semantic memory is explored (Beaty, Zeitlen, Baker, & Kenett, 2021b; Kenett et al., 2018a; Lopez-Persem et al., 2022; Volle, 2018). However, current research on the relationship between creative cognition, WMC, and the executive functions of inhibition, updating, and switching is inconclusive. This chapter focuses on an exploratory study, using a large battery of tasks to try to shed light on how executive functions and WM contribute to creative cognition, and in particular how they influence measures of creative cognition including the number, diversity, and creativity of ideas.

4.1.1 The role of executive functions in creativity

As discussed in Chapter 3, inhibitory control is likely to play a key role in certain forms of creative cognition, such as in-lab behavioral measures, with cognitive inhibition in particular benefiting the creativity of divergent thinking responses. The suppression of distracting thoughts might help to free up WM resources, allowing individuals to focus on the most creative ideas and explore the most promising associations.

How exactly executive switching benefits creative cognition is not immediately clear. Researchers often discuss switching in the context of creative performance, for example suggesting that more creative individuals may switch more frequently between different conceptual spaces (Nijstad et al., 2010; Zhang et al., 2020), narrow- and broad-focus states (Gabora, 2010; Zabelina & Robinson, 2010), and generative and evaluative modes of thought (Ellamil et al., 2012; Finke et al., 1992; Ward, Smith, & Vaid, 1997). In addition, various studies have examined switching in creative cognition, for example finding that switching between categories of idea mediates the relationship between intelligence and creativity (Nusbaum & Silvia, 2011), that the number of category switches a person makes may relate to a trait-level bias towards flexibility or persistence (Mekern et al., 2019b), and that forcing participants to switch between different creative tasks can improve their creative performance (Lu et al., 2017).

However, it remains unclear how these various forms of creative switching might relate to classical executive switching (or shifting; Diamond, 2013). Only a handful of studies have examined relationships between creative cognition and shifting, which is typically measured as the ability to switch between different executive tasks (e.g., Benedek et al., 2014c; Krumm et al., 2018; Pan & Yu, 2018; Zabelina et al., 2019). For example, in a study where both executive shifting and creative cognition were measured with three different behavioral measures, the authors found a positive relationship between the two at the latent level (Pan & Yu, 2018). Moreover, executive shifting was found to be more relevant to factors such as the number of ideas generated and the number of categories explored than the creative quality of ideas. However, another study by Krumm and colleagues (2018) found that shifting was positively related to creative quality in both verbal and visual divergent thinking tasks, and this relationship remained after accounting for intelligence. By contrast, other research has found no relationship between shifting and creativity at the latent level (Benedek et al., 2014c). Indeed, a study by Zabelina et al., (2019), found no relationship between executive shifting and either the number or quality of generated ideas in a divergent thinking task.

While it might be expected that individuals with stronger executive shifting abilities would attain higher flexibility scores (by exploring a broader range of conceptual categories) in creative tasks, few studies have examined shifting and flexibility, and it is unclear whether the processes involved in executive shifting are also involved in creative switching. For example, in executive shifting paradigms switches are typically cued by the experimenter, whereas in creative tasks switches tend to be initiated freely by the participant. However, it is possible that those who are better able to cope when forced to switch executive tasks tend to also make more self-motivated switches in creative contexts.

Considering relationships between WM updating and creative cognition, results are also inconclusive. Updating refers to the ability to maintain and update relevant information in WM, and as typically measured (e.g., through N-back tasks), updating is so closely related to measures of WMC (e.g., complex span tasks) that many researchers argue they are identical constructs (Schmiedek, Hildebrandt, Lövdén, Wilhelm, & Lindenberger, 2009; Schmiedek et al., 2014; Wilhelm, Hildebrandt, & Oberauer, 2013). A study by De Dreu and colleagues (2012) found that increasing WM load in participants lead to reduced RAT performance, and that those with greater WMC produce more creative musical improvisations and both more ideas (higher fluency score) and more creative ideas (higher creativity quality, or simply higher creativity score) in a verbal divergent thinking task. However, more recent research has found mixed results, with some studies finding that updating relates to creative quality (Benedek et al., 2014c; Stolte et al., 2020), and others finding that it relates only to fluency, and not to creative quality itself (Hao et al., 2015b; Zabelina et al., 2019). A further study by Krumm and colleagues (2018) found positive relationships between updating and creative quality, but these relationships did not remain significant after accounting for intelligence.

Indeed, other research has found that updating is unrelated to verbal or visual divergent thinking, but is related to verbal convergent thinking as measured by the RAT (de Vink et al., 2021; see also Gerver et al., 2023). By contrast, Lunke and Meier (2016) found that WM updating was related to verbal divergent thinking, but not convergent thinking or self-report creative achievement. Finally, other studies have found no link between WM updating and divergent thinking as measured by metaphor generation (Menashe et al., 2020) or the AUT (Smeekens & Kane, 2016). As such, there do not seem to be reliable findings regarding the connection between WM updating and creative cognition. A recent review has argued that updating most likely benefits flexibility and fluency, but may not benefit creativity itself (Palmiero et al., 2022). Indeed, a recent meta-analysis of 43 studies examining creativity and WM reports that WM may benefit convergent thinking, but does not appear to benefit creative quality in divergent thinking tasks (Gerver et al., 2023).

To summarize, while inhibitory control likely aids creative cognition by suppressing distracting and unoriginal ideas, there are no solid conclusions regarding how shifting and updating benefit creative cognition. It is possible, however, that shifting is related to more frequent switches in creative tasks (higher flexibility), while updating promotes idea fluency in creative tasks. Further research is needed to unpack how exactly executive functions impact creative cognition, and whether they contribute to creative factors such as the number of ideas generated, the number of conceptual categories explored, and the ability to switch between broad and narrow attention states (Gabora, 2010; Zabelina & Robinson, 2010; Zhang et al., 2020) or generative and evaluative modes of thought (Ellamil et al., 2012; Kleinmintz et al., 2019).

4.1.2 The present study

In the present, exploratory study, a large battery of tasks was employed to better understand how executive functions benefit creative cognition, and how they interact with more spontaneous, associative processes during creative thought. Specifically, the study is most interested in how control over WM can affect factors such as the breadth by which semantic memory is traversed (as might be measured by the semantic distance between consecutive responses), and the number of semantic categories explored. The study also aims to understand how WM control can impact the number of ideas that are generated (fluency), and overall creative performance.

Building on the study discussed in Chapter 3, a measure of cognitive inhibition (RIF) is included, together with a measure of executive switching, a measure of WM updating, and a measure of

WMC (though the latter two measures may target the same underlying processes (Schmiedek et al., 2014). Verbal measures of divergent and convergent thinking are also employed, with measures of verbal fluency and chain association to target associative processes. Finally, various self-report measures relevant to creative cognition and control over WM are included, including real-world creative achievement, and scales assessing attention control, ADHD, and the ability to switch between associative and analytical modes of thought.

In addition to examining fluency and creative quality in divergent thinking tasks, I also make use of automated measures of semantic distance including SemDis (Beaty & Johnson, 2021) and the Bidirectional Encoder Representations from Transformers model (BERT; Devlin, Change, Lee, & Toutanova, 2019), to assess the size of associative leaps between responses in divergent thinking and associative tasks. This enables us to examine factors such as the speed and breadth by which individuals traverse semantic memory, which should provide a more detailed understanding of the ways in which executive functions and control over WM might contribute to creative cognition.

4.2 Methods

4.2.1 Participants

Participants (*N* = 200; 102 females; mean age = 28.0, *SD* = 4.8) were recruited from Prolific. Participation was contingent on a Prolific approval rating of 90% or above and a minimum of 50 previously completed studies. Fluency in English was also required. Informed consent was given prior to data collection. Ethical approval for the study was given by the Local Ethics Committee of the Department of Psychology at Goldsmiths, University of London.

4.2.2 Materials

With the exception of the ICAA (which was hosted on Qualtrics), all tasks were coded in Psychopy and PsychoJS (Peirce et al., 2019). Screen color for all tasks was gray.

Creative / associative thought

Our measures of creative thinking included two typical verbal measures of creative performance (one a measure of creative idea generation, and one a measure of associative problem solving), and a self-report measure of creative achievement. These were in addition to two measures of associative thought likely to involve semantic clustering and switching processes (a chain association task and a verbal fluency task).

Alternative Uses Task

The AUT was used as a measure of verbal creative idea generation. The task was identical to that described in Chapter 3, with the following exceptions. There were four cues (Box, Rope, Shoe, Brick), and participants had 2 minutes per object to generate as many creative uses as they could. Ideas were later rated for creativity by three independent raters on a 1 (not at all creative) to 5 (very creative) scale (Silvia, et al., 2009), and processed using automated measures of semantic distance to create scores for creative switching and overall semantic breadth (see Data Processing section below).

Remote Associates Test

The compound RAT (Bowden & Jung-Beeman, 2003) was used as a measure of associative problem-solving. This task was identical to that used in Chapter 3.

Inventory of creative activities and achievements

The ICAA was used as a self-report measure of creative achievement and engagement in creative activities. See the previous study for details on the content and scoring of the activities subscale of the ICAA (ICAA-Act). For the Achievement subscale of the ICAA (ICAA- Ach), participants mark the levels of achievement they have reached in eight domains including “music”, “literature”, and “science and engineering”. In each domain participants are shown 11 items ranging from “I have never been engaged in this domain” to “I have already sold some of my work in this domain”. Participants tick all the levels of achievement they have reached. Items in each domain are weighted from 0 to 10, and weighted scores are summed across items to produce a domain-specific score. For the present purposes, scores were then summed across domains to produce a domain-general creative achievement score.

Chain association

The Forward Flow task (a chain free association task) was used as a measure of associative processing (Gray et al., 2019). Participants were shown a single cue word and asked to type the first word that came to mind in response to the cue and press ‘enter’. They were then shown the word they had just typed, and had to again think of the first word that came to mind. This continued until they had entered 19 words. This process was repeated for three different cue words: “table”, “bear”, and “candle” (as used by Gray et al., 2019;see also Beaty et al., 2021b). Participants were instructed to type only single words and to avoid proper nouns. Responses were later processed for Forward Flow score following Beaty et al., (2021b) and the SemDis platform (see Data Processing section, below). In addition to the calculation of forward flow score, responses were also processed through automated means to assess the semantic breadth of responses.

Verbal fluency

As an additional measure of associative memory processes, three verbal fluency tasks were used. Participants were given 60s per task to generate and type as many words as they could that fell into the following categories: “words beginning with M”, “words with five letters”, and “first names”. These tasks were selected from a prior study (Silvia et al., 2013), and chosen so that the categories involved would not overlap with those used in the RIF and Keep Track tasks. In each task, participants were shown the target category, together with a white text entry box, and the following brief reminder of the instructions, at the top of the screen: “Type as many words as you can that are in the category shown. Press ENTER after each word”. A countdown timer was also displayed at the bottom right of the screen. Each task was scored for the number of valid responses (e.g., excluding repetitions and incorrect responses). Responses to the categories “words beginning with M” and “words with five letters” were further processed to calculate the semantic breadth of responses.

Executive measures

The measures of executive function included a measure of executive switching, a measure of WM updating, a measure of cognitive inhibition, and a measure of WMC. In addition, self-report questionnaires were included to assess attentional control, ADHD, and mode-shifting.

Inhibition

As a measure of cognitive inhibition, the RIF task from Chapter 3 was used. This measure of inhibitory control was found in Chapter 3 to be the most relevant to creative cognition. No changes were made to this task.

Shifting

To assess executive shifting, the odd/even-high/low task (Liu & Yeung, 2020; Pan & Yu, 2018) was used, which involves switching between two distinct tasks involving the same kind of stimulus (a single number between 1 and 9, excluding 5). Participants were told “You will be shown a series of numbers. Sometimes you will need to think whether the number is odd or even, and sometimes you will need to think whether the number is less than or greater than 5”. Task type was cued via the shape the number appeared inside. If the number appeared within a square, participants had to indicate whether it was odd ('F' key; left index finger) or even ('J' key; right index finger). If the number appeared within a diamond, participants had to indicate whether it was less than ('F' key) or greater than 5 ('J' key). Participants were told to respond as quickly and accurately as possible.

Trials proceeded as follows: a 0.5s blank screen was followed by a central white fixation cross for 0.5s. This was followed by the presentation of the number in the center of the screen within a square or a diamond. The diamond was simply the square rotated by 45 degrees. Participants then had up to 4s to make their response before the trial ended. In practice trials (but not real trials) a brief feedback message (“incorrect”) was displayed after incorrect trials, for 1.5s.

Participants first completed short sets of practice trials (8 trials each) for each task individually (odd/even followed by high/low). They then completed a short practice (12 trials) where both tasks appeared together in a random order. Reminders of the instructions were given before each practice. Finally, participants completed 129 trials of both tasks together, where 64 trials were “switch” trials (i.e., they followed a trial from a different task), and 64 were “stay” trials (i.e., they followed a trial from the same task). The order of trials was the same across participants, and defined pseudo-randomly while meeting the following conditions: an equal number of trials from both tasks, and an equal number of switch and stay trials, in an unpredictable, non-repetitive sequence. Analysis ignored the first trial and focused on the difference in RT between correct switch trials and correct stay trials (see Data Processing section).

Updating

To assess WM updating, the Keep Track task was used (Friedman et al., 2016; Zabelina et al., 2019). This task requires participants to keep track of the last members of four categories in a stream of words. Trials proceeded as follows: following a white fixation cross (1s), a list of four category words was displayed left to right along the bottom of the screen (5s). These category words then remained on screen while a sequency of 12 category-member words were displayed for 1s each with a 0.25s interval. The order of appearance of the words (in terms of which category they belong to) was unpredictable (e.g., all the words of one category might appear in the first half of the sequence). At the end of the sequence, a 1s blank screen was followed by the recall phase: each category was shown one at a time together with a white text input box. Participants were required to type the last word shown in the category and press ‘enter’. The next category was then shown.

Participants first completed a single practice trial with just three categories (furniture, names, tools). They then saw a reminder of the instructions, before completing eight real trials with four categories each, selected from a total of six possible categories (instruments, countries, vegetables, clothing, sports, animals). In real trials, the sequence of 12 words thus contained three words per category, selected from 12 possible category members. The dependent measure was the proportion of words recalled across all trials (out of a possible 32 words).

Working memory capacity

As a measure of WMC, the reading span task (RST; Daneman & Carpenter, 1980; Farmer, Fine, Misyak, & Christiansen, 2017; Hicks, Foster, & Engle, 2016; Van Den Noort, Bosch, Haverkort, & Hugdahl, 2008) was used. This complex span task was thought to be more likely to target processes relevant to verbal creative thinking than non-verbal alternatives (e.g., Smeekens & Kane, 2016; Unsworth, Redick, Heitz, Broadway, & Engle, 2009; Wagner, Shaffer, Ivanson, & Jones, 2021). Participants were shown a series of sentences, some of which were semantically valid (e.g., “Spring is her favorite time of year because flowers begin to bloom”) and some of which were semantically invalid (e.g., “The judge gave the boy community sweat for stealing the candy bar”). Participants had to judge the semantic acceptability of the sentence and indicate whether it made sense (‘J’ key; right index finger) or not (‘F’ key, left index finger), while attempting to remember the final word of the sentence.

The task proceeded as follows. Participants first received instructions relating to the semantic judgement task, and completed a brief practice sequence containing three sentences. They were then instructed that they had to simultaneously try to remember the final word of each sentence, while keeping their accuracy on the semantic judgement task above 85%. Participants then completed a second practice containing two sequences of three sentences. At the end of each sequence, they were asked to recall the final word of each sentence in the sequence and type them in order of appearance. During this second practice, participants’ mean RT for the semantic judgement task was computed. This mean plus 2.5 SDs was used as the time limit for the semantic judgement task, for that participant. Finally, participants saw a reminder of the instructions before completing the real trials. These consisted of 36 sentences organized into sequences of 3, 4, 5, or 6 sentences (2 sequences of each possible length). The order of sequences and sentences was randomized. If a participant’s RT in a trial exceeded the time limit for that participant, the trial ended and was counted as incorrect. This served to encourage participants to respond quickly and made cheating (e.g., writing down sentence-final words) more difficult.

In each trial, sentences were presented in white font in the center of the screen, together with a reminder of the keys (“F = False, J = True”). Once participants made their response, a 0.2s blank screen was followed by the next sentence. After a sequence of sentences, a white text-entry box appeared with the instruction to “Enter all the final words from the previous [X] sentences, in the order they appeared. Type them all in one box, with a SPACE between each word, and press ENTER when finished." X was replaced with the number of sentences in the preceding sequence. After pressing ‘enter’, participants were shown their current judgement accuracy and the correct sentence-final words from the preceding sequence, as feedback. Participants then pressed ‘enter’ again when ready to begin the next sequence.

Sentences were taken from a larger set used by Hicks et al. (2016). However, while Hicks and colleagues (2016) required participants to remember single letters presented between sentences, given the online nature of the present study participants were asked to remember sentence-final words (e.g., Farmer et al., 2017; Daneman & Carpenter, 1980) as a precaution against cheating. To that end, sentences were chosen to such that their final words did not differ greatly in length (see also Van de Noort et al., 2008). Specifically, all final words were a single syllable and a similar number of letters (M = 3.92, SD = 0.65), while the number of letters (M = 66.11, SD = 4.56) and words (M = 13.08, SD = 1.00) in each sentence were also controlled.

The dependent variable in the task was the number of words remembered in the correct order of appearance (Unsworth et al., 2009; Van den Noort et al., 2008).

Attention Control Scale

As a self-report measure of attentional control, the Attention Control Scale (ATTC; Derryberry & Reed, 2002) was used. The scale consists of 20 items (e.g., "My concentration is good even if there is music in the room around me") that probe participants' ability to regulate their attention. Participants mark how often each item statement is true for them, on a four-point Likert scale from 1 (almost never), to 4 (always). 11 items are reverse-scored. The ATTC yields one total scale and two subscales (attention shifting and attention focusing). Scores are calculated as the sum across the respective items. The present study examined only the total ATTC scale.

ADHD self-report scale

As an additional self-report measure of attentional control, the ADHD self-report scale (ASRS; Kessler et al., 2005) was used. This 18-item scale probes symptoms related to ADHD, and has a high diagnostic accuracy (Brevik, Lundervold, Haavik, & Posserud, 2020). Participants mark how often various symptoms are true for them (e.g., "How often do you have difficulty unwinding and relaxing when you have time to yourself?"), on a five-point Likert scale from 0 (never) to 4 (very often). The ASRS contains one total scale and two subscales (inattention and hyperactivity-impulsivity). Scores are calculated as the sum of the respective items. In the present study only the total ADHD scale was examined.

Mode-shifting index

As a final self-report measure of attentional control, in this case related to switching ability, the Mode-Shifting Index (MSI; Pringle & Sowden, 2017) was used. The 11-item scale probes the ability to shift between associative and analytic modes of thought, which has been suggested to be highly relevant to creative thinking (Bristol & Viskontas, 2006; Sowden et al., 2015; Zabelina & Robinson, 2010). Participants mark how true each statement (e.g., "I am good at both figuring things out logically and going with my instincts when deciding on a course of action") is for them, on a five-point Likert scale ranging from 1 (completely false) to 5 (completely true). The MSI contains items probing two facets of mode-shifting: mode-shifting awareness and mode-shifting competence, which are examined separately in the present study.

Additional Measures

In addition to the above measures, I include the Cattell pattern completion task (Cattell & Cattell, 1961) as a measure of fluid intelligence, and the Openness/Intellect subscale of the BFAS (DeYoung et al., 2007) to assess openness and intellect. These measures were unchanged from the study described in Chapter 3.

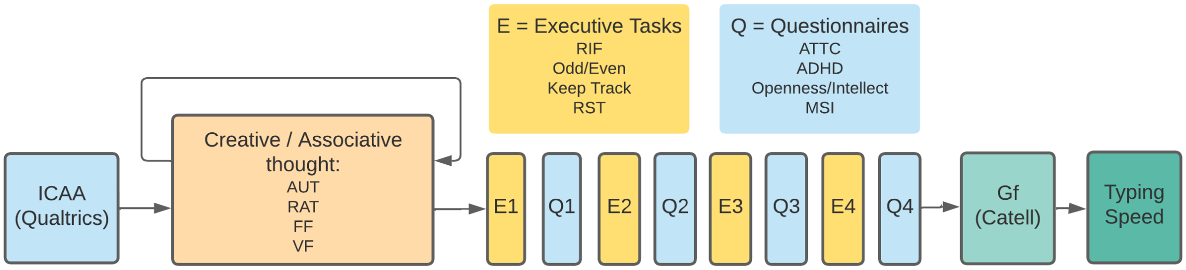
4.2.3 Procedure

The experimental procedure was as follows (see Figure 9). First, the ICAA was completed in Qualtrics. Participants were then directed to Pavlovia (https://pavlovia.org/), where the main experiment was hosted.

Participants first completed the experimental tasks related to creative thinking and associative thought (i.e., the AUT, RAT, FF, and VF tasks). These were completed in one of four counter-balanced orders. Next, participants completed the four measures of executive function (RIF, odd/even-high/low, Keep Track, and RST), again in one of four counter-balanced orders. To reduce fatigue, executive tasks were interleaved with the five questionnaires in the study (ATTC, ADHD, Openness/Intellect, MSI), which always appeared in a fixed order. Finally, participants completed the Cattell pattern completion task and the typing speed task.

Figure 9

Experimental Procedure (left to right)



Note. Participants completed the ICAA, before completing creative/associative tasks in one of four orders. They then completed executive tasks in one of four orders. Executive tasks were interleaved with questionnaires. Except for the ICAA, all tasks were coded in Psychopy (Pierce et a., 2019) and hosted on Pavlovia (https://pavlovia.org/).

4.3 Results

4.3.1 Participant exclusions

Eight participants were excluded entirely due to poor engagement (very low scores across multiple tasks). In addition, some participants' data for individual tasks was excluded. Specifically, two participants were excluded from the typing speed task, and four participants from the FF task, due to misunderstanding the task instructions. Finally, 16 participants were excluded from the executive switching task due to a total error rate greater than 30%.

4.3.2 Data Processing

Additional processing was carried out for several tasks. For the executive switching task, incorrect trials and those following an error were excluded from analysis (11.42% of the data). Mean participant accuracy in the task was 91.72% (*SD* = 4.72%). In addition, RTs that differed by more than 2 SDs from the individual mean for each participant and condition (switch vs stay) were removed (an additional 4.43% of the data). Task score for each participant was then calculated as mean switch RT minus mean stay RT.

Data from the verbal, generative tasks in the study (AUT, FF, VF) were also subjected to additional processing to calculate automated measures of semantic distance. Several measures were calculated depending on the specific task in question. Importantly, two separate methods were used to calculate semantic distance. The first, which was used for the FF and VF (where responses are single words) used a latent factor extracted from five separate semantic models, using the SemDis platform (Beaty & Johnson, 2021), and the multiplicative model option. The second, used for AUT responses, was the semantic distance calculated using the BERT model (Devlin et al., 2019). BERT makes use of context-dependent word embeddings, and so should provide better estimates of semantic distance in the case of longer responses, such as AUT responses. In both cases, responses were first cleaned by removing punctuation and stop words, using the SemDis platform's "Remove filler and clean" method.

For the FF task, two automated measures of semantic distance were calculated. First, the forward flow measure itself was calculated (Beaty et al., 2021b; Gray et al., 2019). Here, for each response, the average semantic distance between the response and its preceding responses is calculated. Next, this value is then averaged across all responses in a trial (typically 19 words minus any invalid responses) to produce the forward flow score for that trial. Notably, forward flow score was calculated using SemDis, and did not make use of LSA as done in the original study by Gray and colleagues (2019). In addition to the standard forward flow score, SemDis was used to calculate semantic breadth, as the average semantic distance between pairs of consecutive responses (i.e., between each response and its immediately preceding response). This was found by summing the semantic distance between all pairs and dividing by the number of pairs, and provides a measure of the typical size of the associative jumps made by a participant in a given task.

For the VF tasks, only semantic breadth was calculated, again using SemDis, and only for two prompts: "words beginning with M", and "words with 5 letters".

For the AUT, all measures of semantic distance used the BERT model, and not SemDis. Semantic breadth was calculated together with two additional measures. First, similar to semantic breadth, the semantic distance between all pairs of consecutive responses was calculated, for each participant and for each cue. Then, for each cue separately, but across all participants, a threshold value was found that distinguished the lowest 20% of semantic distances. 'Stay' responses were then defined as responses with a semantic distance to their preceding response that was lower than this threshold (while ‘switch’ responses fell above this threshold; see Fernández-Fontecha & Ryan, 2023, for a similar method of defining switch and stay responses). From this data, each participants’ average number of switches (across cues) was computed as an automated measure of the number of category switches (autoSwi). Finally, an automated creativity score (autoCrea) was calculated by computing the average semantic distance between each response and the cue word, for each participant across all responses to all cues. This was included primarily as a more direct means of assessing the relationship between human-rated creativity and automated measures of creative performance.

As noted, responses in the AUT were rated for creativity by three independent human raters, recruited via Prolific. Inter-rater reliability was in the excellent range, with an ICC of .93 (.90 – .94).

4.3.3 Analyses

Analyses explored the relationships between measures of creative thinking and measures of executive functions, with Pearson correlations.

4.3.4 Descriptive statistics

Descriptive statistics for all variables of interest are shown in Table 17. Note that the sample size is slightly lower for the FF and Shifting variables, due to participant exclusions for these tasks.

Table 17
Descriptive statistics for all variables

	N	*M*	*SD*	Min	Max
AUT Fluency	192	7.82	3.53	2.00	22.50
AUT Creativity	192	2.56	0.38	1.72	3.55
AUT autoCrea	192	0.70	0.05	0.47	0.80
AUT autoSwi	192	0.68	0.09	0.30	0.90
AUT SemBre	192	0.74	0.05	0.57	0.83
RAT	192	4.68	2.09	0.00	9.00
VF	192	16.50	4.06	5.67	25.00
VF SemBre	192	0.00	0.03	-0.18	0.06
FF	188	-0.02	0.02	-0.08	0.04
FF SemBre	188	-0.14	0.04	-0.23	0.01
ICAA Act.	192	7.57	4.29	0.00	21.33
ICAA Ach.	192	44.98	38.41	0.00	188.00
Inhibition	192	0.96	2.11	-4.00	6.00
Shifting	176	0.18	0.14	-0.14	0.57
Updating	192	19.79	5.30	3.00	32.00
WMC	192	24.59	8.49	7.00	36.00
Openness	192	37.29	5.98	19.00	49.00
Intellect	192	35.31	6.83	16.00	50.00
MSIc	192	15.63	2.37	5.00	20.00
MSIa	192	25.31	3.74	13.00	35.00
ATTC	192	50.68	9.18	31.00	73.00
ADHD	192	50.46	10.94	18.00	86.00
Gf	192	7.18	1.50	4.00	11.00

Note. AUT = Alternative Uses Task; Flu. = fluency score; Crea. = human-rated creativity score; SemBre = semantic breadth; autoSwi = automated switching score; autoCrea. = automated creativity score; RAT = Remote Associates Test; VF = verbal fluency; FF = Forward Flow; ICAA = Inventory of Creative Achievements and Activities; Act. = Activities subscale; Ach. = Achievements subscale. WMC = working memory capacity; MSIc = Mode Shifting Index, competence; MSIa = Mode Shifting Index, awareness; ATTC = Attention Control Scale; ADHD = ADHD self-report scale; Gf = fluid intelligence.

4.3.5 Correlations

I report correlations between variables in three sets: correlations among creative and associative measures, correlations among executive functions, intelligence, and questionnaires, and correlations between these two sets.

Correlations among creative and associative measures

Correlations among creative and associative measures are shown in Table 18. AUT fluency was negatively related to AUT human-rated creativity (r = -.22, p = .003), and automated measures of creativity (r = -.23, p = .002) and semantic breadth (r = -.22, p = .002). These results suggest that those who generate more ideas tend to generate fewer creative ideas (or rather, that more creative ideas take longer to form). AUT fluency was also positively related to verbal fluency (r = .30, p < .001), suggesting that the generation of creative uses and category members share similar processes, at least in terms of the number of responses generated. Human-rated AUT creativity was positively related to the automated measure of AUT creativity (r = .53, p < .001), suggesting that semantic distance as measured using the BERT model is an effective proxy for human-rated creativity (Beaty DSI).

Table 18

Correlations among creative and associative measures

	1	2	3	4	5	6	7	8	9	10	11
1. AUT Fluency	-										
2. AUT Crea.	-.22**	-									
3. AUT autoCrea.	-.23**	.53**	-								
4. AUT autoSwi	.13	-.07	-.14	-							
5. AUT SemBre	-.22**	.43**	.71**	-.02	-						
6. RAT	.17*	.25**	.19**	.01	.25**	-					
7. VF	.30**	.09	.22**	.00	.21**	.32**	-				
8. VF SemBre	.03	.02	.04	-.14	.06	.19**	-.01	-			
9. FF	.02	.10	.13	-.05	.01	.00	.04	.16*	-		
10. FF SemBre	-.02	.13	.14	-.07	-.08	-.09	-.19*	.22**	.65**	-	
11. ICAA Act.	.16*	.14	.01	-.05	.04	.06	.00	-.02	.11	.07	-
12. ICAA Ach.	.13	.14	.05	-.02	.07	.03	.07	-.04	.05	.01	.67**

Note. AUT = Alternative Uses Task; Crea. = human-rated creativity score; autoCrea. = automated creativity score; autoSwi = automated switching score; SemBre = semantic breadth; RAT = Remote Associates Test; VF = verbal fluency; FF = Forward Flow; ICAA = Inventory of Creative Achievements and Activities; Act. = Activities subscale; Ach. = Achievements subscale. * p < .05, ** p < .01.

Interestingly, the number of switches a person made in the AUT was not significantly related to any other creative or associative measure (ps > .054). However, AUT semantic breadth, or the average distance between consecutive responses was positively related to human-rated creativity

($r = .43$, $p < .001$). Indeed, the measure of switching used is derived from the semantic breadth measure, and is simply the number of times a participant made an associative jump, between pairs of consecutive responses, that was in the top 80% of associative jumps made by all participants. It is possible that counting the number of larger jumps in this manner fails to approximate human definitions of clustering and switching, while the average associative jump size (semantic breadth) provides a better assessment of creative processes.

RAT performance was positively related to AUT fluency ($r = .17$, $p < .020$), human-rated AUT creativity ($r = .25$, $p < .001$), and automated measures of creativity ($r = .19$, $p = .009$) and semantic breadth ($r = .25$, $p < .001$). Contrary to the study discussed in Chapter 3, a positive relationship between verbal divergent and verbal convergent thinking was thus found. These results also suggest that the present automated measures of creative switching and creative quality do indeed tap into creative cognition. RAT performance was also positively related to verbal fluency score ($r = .32$, $p < .001$), which in turn was positively related to automated measures of creativity ($r = .22$, $p = .002$) and semantic breadth ($r = .21$, $p = .004$), though not human-rated creativity ($r = .09$, $p = .205$). These relationships might indicate that the automated measures of creativity, which are based on the distance between each response and the cue (for creativity), and between each response and the previous response (for semantic breadth), assess mainly associative processes of the kind involved in the RAT and VF, while human-rated creativity taps into an additional element not involved in VF.

Our other associative measures (FF and semantic breadth in the FF and VF tasks) were not significantly correlated with many other measures, though they were positively related to each other (ps < .026). ICAA score for both the activities and achievement subscales were not significantly related to almost any behavioral measures of creativity or association-making, though ICAA activities was slightly positively related to AUT fluency ($r = .16$, $p = .033$).

Correlations among executive functions and questionnaires

Correlations among executive functions and questionnaire measures are shown in Table 19. Relations among executive functions were low: only WM updating and WMC were significantly correlated ($r = .39$, $p < .001$), which was unsurprising given prior research arguing that they assess the same construct (Schmiedek et al., 2014).

Notably, there were also few significant correlations between executive functions and questionnaires, though WMC was found to be positively related to openness (*r* = .17, *p* = .018), and both mode-switching competence (*r* = .20, *p* = .005) and awareness (*r* = .17, *p* = .019). Moreover, both updating (*r* = .20, *p* = .006), and WMC (*r* = .20, *p* = .006), were positively related to intelligence, which was not significantly related to inhibition or shifting.

Table 19

Correlations among executive functions and questionnaires

	1	2	3	4	5	6	7	8	9	10
1. Inhibition	-									
2. Shifting	.03	-								
3. Updating	-.10	-.05	-							
4. WMC	-.10	-.11	.39**	-						
5. Open	.06	-.03	.13	.17*	-					
6. Intel	.06	-.01	.01	.06	.36**	-				
7. MSIc	.02	-.02	.05	.20**	.30**	.36**	-			
8. MSIa	.08	.00	.09	.17*	.32**	.04	.34**	-		
9. ATTC	-.04	-.09	-.06	.06	.06	.41**	.26**	-.10	-	
10. ADHD	.13	.06	.00	-.01	.13	-.25**	-.16*	.26**	-.62**	-
11. Gf	.01	.04	.20**	.20**	-.01	.04	-.03	-.04	-.05	-.03

Note. WMC = working memory capacity; MSIc = Mode Shifting Index, competence; MSIa = Mode Shifting Index, awareness; ATTC = Attention Control Scale; ADHD = ADHD self-report scale; Gf = fluid intelligence. * *p* < .05, ** *p* < .01.

Considering questionnaires, mode-shifting competence and awareness were positively related to each other (*r* = .34, *p* < .001), and to openness (*r* = .30, *p* < .001; *r* = .32, *p* < .001, respectively). Only mode-shifting competence was significantly related to intellect (*r* = .36, *p* < .001), however.

It was also notable that intellect and mode-shifting competence were positively related to attention control (*r* = .41, *p* < .001; *r* = .26, *p* < .001, respectively), and negatively related to the ADHD scale (*r* = -.25, *p* < .001; *r* = -.16, *p* < .031, respectively), while mode-shifting awareness was negatively (but not significantly) related to attention control (*r* = -.10, *p* = .152), and positively related to ADHD (*r* = .26, *p* < .001). These results suggest that those who are more aware of mode-shifting actually believe themselves to be poorer at controlling their attention. As would be expected, attention control was negatively related to ADHD (*r* = -.62, *p* < .001).

Correlations between creative and associative measures and executive functions and questionnaires

Correlations between measures of creativity and associative processing, and measures of executive functions and questionnaires, are shown in Table 20. Very few significant relationships were found between measures of AUT performance and executive functions, though a weak positive relationship was observed between shifting and the automated measure of creativity ($r = .16$, $p = .033$). Critically, the finding from Chapter 3, where RIF was found to be positively related to divergent thinking performance, was not replicated.

Table 20

Correlations among executive functions and creative and associative measures

	Inhib.	Shift.	Updat.	WMC	Open.	Intel.	MSIc	MSIa	ATTC	ADHD	Gf
AUT Fluency	.07	.06	.13	.06	.10	.02	-.13	.00	-.06	.23**	.09
AUT Crea.	.01	-.02	.12	.10	.24**	.11	.10	.13	-.08	.09	.06
AUT autoCrea	.10	.16*	.10	.00	.09	.11	.05	.04	-.07	.03	.13
AUT autoSwi	.11	-.09	-.02	-.01	-.05	-.05	.06	.10	.10	.02	.04
AUT SemBre	.13	.11	.04	-.01	.11	.11	.01	.07	-.04	.06	.15*
RAT	-.04	.07	.21**	.12	.21**	.09	-.05	.17*	-.15*	.19**	.20**
VF	.10	.02	.31**	.19**	.08	.04	.03	.18*	-.16*	.13	.32**
VF SemBre	.12	.10	-.04	-.09	.00	.00	-.08	-.11	-.05	.08	.03
FF	.07	.11	-.05	-.11	.10	.06	.01	-.04	-.12	.11	-.05
FF SemBre	.11	.07	-.16*	-.21**	.07	.00	-.01	-.04	-.12	.10	-.21**
ICAA Act.	.00	.02	.06	.20**	.26**	.18*	.20**	.20**	.06	.19**	.10
ICAA Ach.	.05	-.18*	.01	.07	.27**	.16*	.14	.22**	-.03	.12	.10

Note. AUT = Alternative Uses Task; Crea. = human-rated creativity score; autoCrea. = automated creativity score; autoSwi = automated switching score; SemBre = semantic breadth; RAT = Remote Associates Test; VF = verbal fluency; FF = Forward Flow; ICAA = Inventory of Creative Achievements and Activities; Act. = Activities subscale; Ach. = Achievements subscale. Inhib. = Inhibition; Shift. = Shifting; Updat. = Updating; WMC = working memory capacity; Open. = Openness; Intel. = Intellect; MSIc = Mode Shifting Index, competence; MSIa = Mode Shifting Index, awareness; ATTC = Attention Control Scale; ADHD = ADHD self-report scale; Gf = fluid intelligence. * $p < .05$, ** $p < .01$.

Aside from the AUT, WM updating was found to correlate positively with RAT ($r = .21$, $p = .003$) and VF performance ($r = .31$, $p < .001$), while WMC was positively relate to VF ($r = .19$, $p = .009$) and showed a non-significant positive trend with the RAT ($r = .12$, $p = .112$). Together, these results suggest that updating and WMC may support associative processes that underlie the retrieval of

RAT solutions and category members (de Vink et al., 2021; Gerver et al., 2023). Meanwhile, both updating (r = -.16, p = .031) and WMC (r = -.21, p = .003) were negatively related to FF semantic breadth, possibly indicating that greater WM updating is related to persistence within a semantic category rather than the exploration of new categories (de Dreu et al., 2012).

Moving beyond executive functions, openness was positively related to RAT performance (r = .21, p = .003) and human-rated AUT creativity (r = .24, p = .001), a common finding (Oleynick et al., 2017). However, openness was not significantly related to the automated measure of AUT creativity (r = .09, p = .215), suggesting a limit to the use of this automated measure to assess creative abilities. It is possible that this measure does not reflect certain key processes in creative thinking, which underlie the commonly-found relationship between openness and AUT performance.

Both openness and intellect were positively related to real-world creative achievement as assessed by the ICAA (both activities and achievements; ps < .026). Measures of AUT performance also showed little relationship with executive questionnaires and intelligence, except for positive correlations between AUT fluency and ADHD (r = .23, p = .001), and between AUT semantic breadth and intelligence (r = .15, p = .034). It was notable that no relationship was found between human-rated AUT creativity and intelligence, which is commonly found (Frith et al., 2021a) and indeed was found in the study in Chapter 3.

Both RAT and VF performance were positively related to mode-switching awareness (r = .17, p = .021; r = .18, p = .013, respectively), intelligence (r = .20, p = .006; r = .32, p < .001, respectively), and ADHD (r = .19, p = .008; r = .13, p < .001, respectively), while being negatively related to attention control (r = -.15, p = .034; r = -.16, p = .024, respectively). Together, these results suggest that the associative processes involved in the RAT and VF relate to intelligence and mode-switching, but not to attention control as assessed by the ATTC. This may reflect the fact that the attention control scale primarily targets the ability to shut out distracting thoughts and shift between tasks. Those with greater RAT and VF performance may believe they have trouble shutting out distracting thoughts (i.e., reduced inhibitory control) while possessing a greater ability to update WM and retrieve associative information.

4.4 Discussion

The present study was conducted to examine whether control over WM is relevant to creative cognition. Researchers have suggested that creative cognition involves switching between broad, exploratory states and narrow, exploitative states (Zabelina & Robinson, 2010; Zhang et al., 2020), between narrow and broad conceptual representations (Gabora, 2018), and between generation and evaluation (Ellamil et al., 2012, Kleinmintz et al., 2019), which may all be processes that depend on control over WM. Indeed, control over WM in creative cognition could allow distracting ideas to be suppressed, conceptual categories to be switched between, and WM content to be refreshed easily to allow new and original ideas to activate.

Factors such as how often participants switch between narrow and broad states, or between generation and evaluation, are difficult to assess directly. However, control over WM could influence factors such as the breadth by which semantic memory is traversed (as might be measured by the semantic distance between consecutive responses), as well as the number of conceptual categories explored in creative tasks. WM control could also impact the number of ideas that are reported overall (i.e., fluency), as well as measures of overall creative performance including RAT score and human-rated creativity in the AUT. Currently, however, research into the relationship between creative cognition and executive functions has produced very mixed findings (Benedek et al., 2014c; de Dreu et al., 2012; Hao et al., 2015b; Krumm et al., 2018; Pan & Yu, 2018; Stolte et al., 2020; Zabelina et al., 2019). There is little consensus in the literature regarding how exactly executive functions including inhibition, shifting, and updating contribute to creative cognition.

In this exploratory study, measures of each of the three executive functions of inhibition, shifting, and updating were included, together with a measure of WMC. Measures of convergent and divergent creative cognition (the RAT and AUT, respectively) were also included, together with measures of associative processes including the FF task and VF tasks. Finally, the study included measures of real-world creative achievement and engagement in creative activities (ICAA), a measure of intelligence, and self-report measures of openness, intellect, mode-shifting, attention control, and ADHD. To assess elements of creative cognition including the number of categories explored and the semantic breadth of responses, several recent methods of calculating semantic distance were used, including SemDis (for VF and FF responses; Beaty & Johnson, 2021) and the BERT model (for AUT responses; Devlin et al., 2019).

4.4.1 Review of findings

I found significant correlations among different creative and associative measures, suggesting the measures used were valid and that online participants engaged well with the tasks. Specifically, it was found that AUT fluency was negatively related to measures of AUT creative quality (suggesting that more creative ideas take longer to form) and positively related to RAT performance and VF score (suggesting that shared associative processes enable AUT fluency, and VF and RAT performance). Indeed, significant correlations were also found between RAT performance and semantic breadth in the AUT and VF tasks. Correlations between RAT performance and human-rated and automated measures of creativity in the AUT were also significant, again underlining a possible overlap between divergent and convergent thinking. Finally, a strong correlation was found between human-rated and automated measures of creativity in the AUT, suggesting that the BERT model is an effective method of estimating creative performance in this task (see Johnson et al., 2022).

Correlations among executive measures were surprisingly low. Indeed, only updating and WMC were significantly correlated with each other. Moreover, only updating and WMC were related to intelligence, and only WMC was related to questionnaires assessing WM-relevant factors such as mode-shifting.

Crucially, correlations between creative and associative measures and executive functions were also low. Indeed, significant correlations were only found for updating and WMC with the RAT and VF, suggesting that updating is important for the associative processes that operate in these tasks (Gerver et al., 2023; Palmiero et al., 2022). Critically, the finding from Chapter 3, where cognitive inhibition as measured by the RIF contributed significantly to divergent thinking performance, was not replicated. This was despite using exactly the same measure of RIF, and a very similar version of the AUT (only the cues themselves were different). Weak negative correlations were found between one measure of semantic breadth, in the FF task, and updating and WMC, which may provide some tentative evidence that those with greater WMC persist longer in single categories and do not shift as often (de Dreu et al., 2012).

Aside from executive functions, no significant correlations were found between AUT performance and self-report measures, besides from small correlations between ADHD and AUT fluency (as found previously in some studies; Boot, Nevicka, & Baas, 2020; Stolte et al., 2022), and between AUT creativity and openness (Oleynick et al., 2017). RAT and VF performance was positively related to intelligence and mode-shifting awareness while being slightly negatively related to self-reported attention control, which may suggest that these tasks benefit from updating ability and intelligence while being negatively impacted by inhibition (as assessed by the attention control scale).

4.4.2 Limitations and future directions

While the present research was exploratory, it was expected that more relationships would be found between executive functions and different aspects of creative cognition. The study was unable to produce more concrete findings regarding the relationships between control over WM and creative cognition than previous research (Gerver et al., 2023; Palmiero et al., 2022). Creative cognition presumably must involve some form of control over WM to enable the generation of creative ideas, the suppression of uncreative ideas, the retrieval of semantic information from memory, the formation of new associations, and switching between semantic categories or between generative and evaluative states. However, it is possible that the measures of executive function used in the present study do not assess the same WM control processes that underlie performance in creative tasks.

One issue for the present study is that data were collected online, which may have impacted participant engagement. While participants with very low performance were excluded from the switching task – and in eight cases, from the entire study – participant engagement with measures of executive function may have been considerably lower than in laboratory-based studies. This in turn may have affected the relationships observed between executive functions and creative cognition. Indeed, it has been found that engagement with demanding tasks can be lower for online studies than in-person studies, though this can be mitigated by providing performance-based rewards (Bianco, Mills, de Kerangal, Rosen, & Chait, 2021).

Further research, conducted in person, and including several measures of each construct (e.g., inhibition, updating, visual and verbal divergent thinking, etc.), could shed further light on the relationships between executive functions and creative cognition. More fine-tuned measures of creative cognition, that can probe factors such as switches between generation and evaluation, the time dynamics of idea retrieval, or the structure of an individual's semantic memory (Kenett, 2019; Kenett et al., 2018a), may be better placed to examine the processes underlying creative cognition. Such research could then examine the relations between creative cognition and control over WM using more sophisticated techniques than pure correlations, such as structural equation modeling (e.g., Benedek et al., 2014c; Frith et al., 2021a). Moreover, executive processes may not contribute evenly to creative cognition in all participants. For example, some participants might favor creative strategies that lean more on free associative processes, while others favor analytic strategies (Barr, 2018; Zhang et al., 2020). Taking into account individual differences in the relationships between executive functions and creative cognition may be possible using hierarchical mixed effects models (e.g., Acar, Runco, & Park, 2019).

Computational modelling could also provide a more effective means of examining how executive functions and associative processes interact to produce creative ideas, and how they might interact differently in different contexts. For example, a model of verbal creative cognition could be created with specific components that reflect WM, and control over WM through inhibition, WM updating, and shifting, as well as associative processes such as the rate at which activation spreads through memory. Parameters governing the behaviors of these processes could then be adjusted to fit empirical measures of executive functions and creative performance, potentially for each participant individually. This would enable researchers to test different causal pathways between cognitive processes, such as inhibitory control, and creative outcomes. This possibility, and the importance of greater computational modeling in general for NCR, will be explored in more detail in the next chapter.

CHAPTER 5: THE IMPORTANCE OF COMPUTATIONAL MODELING FOR NEUROCOGNITIVE CREATIVITY RESEARCH

5.1 Introduction

Creativity has traditionally been considered an important yet somewhat mysterious ability, and even after considerable research into the cognitive and neural basis of creative cognition there exists considerable variation in how creativity is conceived, operationalized, and assessed across fields (Hennessey & Amabile, 2010; Plucker, 2022; Plucker, Beghetto, & Dow, 2004; Puryear & Lamb, 2020).

As discussed in previous chapters, NCR covers a diverse range of research areas, and has begun to uncover how creative cognition relates to numerous cognitive and psychological factors including attention (Liu & Peng, 2020; Zabelina, 2018), memory (Benedek, Beaty, Schacter, & Kenett, 2023; Kenett et al., 2018; Madore, Addis, & Schacter, 2016; Storm, Angello, & Bjork, 2011), executive control (Benedek et al., 2014c; Camarda et al., 2018a; Chrysikou, 2019), and reward processing (Beversdorf, 2019; Boot et al., 2017; Lin & Vartanian, 2018). NCR has also made considerable progress in identifying the neural correlates of creative cognition, for example finding that greater creative performance relates to enhanced EEG alpha waves (Agnoli et al., 2020; Fink et al., 2018; Rominger et al., 2019; Stevens & Zabelina, 2020), and greater fMRI connectivity between large-scale brain networks (Beaty, Cortes, Zeitlen, Weinberger, & Green, 2021; Chen, Beaty, & Qiu, 2020; Mayseless, Eran, & Shamay-Tsoory, 2015; Sunavsky & Poppenk, 2020; see also Chapter 2).

However, it remains unclear how exactly these neural and psychological correlates lead to the production of creative ideas. Despite the remarkable progress of NCR, our theoretical understanding of creative cognition is still in its infancy. Over recent decades, the cognitive theories that guide NCR have evolved from more abstract accounts, such as the distinction between convergent and divergent thinking (Guilford, 1959, 1967), to more specific accounts that describe how creative ideas can emerge from, for example, spontaneous and controlled processes (Benedek et al., 2023; Benedek & Jauk, 2018; Volle, 2018) and flexible and persistent meta-control states (Nijstad et al., 2010; Zhang et al., 2020). In addition, significant efforts have been made to formalize and standardize the ontology used by NCR researchers (Gabora, 2018; Kenett et al., 2020; Simonton, 2013, 2022; Sowden et al., 2015). However, considerable work remains to move the field away from loosely defined verbal accounts toward mechanistic theories of creative cognition, complete with causal hypotheses regarding the cognitive operations that produce creative ideas.

This chapter argues that the wider adoption of computational modeling can help greatly in achieving this aim. Computational modeling involves formalizing a theory into a set of algorithmic operations (Farrell & Lewandowsky, 2015; Maia et al., 2017). This process requires the theory to be fully described in explicit terms, which can expose assumptions that might otherwise remain hidden, and lends considerable clarity, rigor, and reproducibility to the development of theories and hypotheses (Farrell & Lewandowsky, 2015; Guest & Martin, 2021). Computational models also allow causal hypotheses to be formulated and tested, helping researchers to establish relationships between neurocognitive factors and creative behavior (Blohm et al., 2020; Wiggins & Bhattacharya, 2014). Indeed, calls for greater modeling within psychology as a whole are growing (Blohm et al., 2020; Guest & Martin, 2021; Smaldino, 2020), yet modeling is rarely used in NCR. Meanwhile, though computational creativity is itself a growing field (e.g., Carnovalini & Rodà, 2020; Gatti, Stock, & Strapparava, 2021; Mekern, Hommel, & Sjoerds, 2019a) with its own annual conference (the International Conference on Computational Creativity), it has developed in relative isolation from NCR, with little cross-pollination between the two fields. Increased collaboration could lead to both a clearer understanding of human creativity and more human-like artificial creative systems (Chateau-Laurent & Alexandre, 2021; Dipaola, Gabora, & McCaig, 2018; Gobet & Sala, 2019). Critically, however, very few computational models exist that both embody a theoretical account from NCR and can perform (and thus, be validated on) common lab-based creativity tasks.

First, I provide an overview of recent cognitive theories of creativity. I then consider some limitations of purely verbal theories and how NCR would benefit from the increased adoption of computational modeling. Next, I discuss recent computational models of creativity, exploring several models that aim to account for performance in common lab-based creative tasks. Finally, I outline a pathway toward greater computational modeling within NCR, considering ways in which existing models might be improved (including a greater focus on modeling multiple creative tasks) and examining an example of model development.

5.2 The theories that guide NCR

Guiding NCR are a range of theoretical accounts, providing a conceptual scaffold for researchers to interpret data and develop further hypotheses. These accounts range from being relatively abstract to quite specific in terms of the cognitive processes they describe. For example, an older but highly influential account is Wallas' (1926) four-stage model, which describes the creative process as involving distinct stages of preparation, incubation, inspiration, and verification. This account is broadly suggestive of the processes that might produce creative ideas and can be seen as a precursor to more recent and specific theories.

Another older account (and one that still retains tremendous popularity among NCR researchers) is the distinction between convergent and divergent thinking. These terms were first coined by Guilford (1950, 1959) as two of the (initially) five major intellectual abilities in his Structure of the Intellect model (Guilford, 1967). Guilford defined both kinds of thinking in terms of the number of solutions they produce, with divergent thinking defined as "thinking in different directions" to produce a "variety of responses", and convergent thinking defined as producing "one right answer" (Guilford, 1959). While both modes of thought were described as ways to generate new information from old information, Guilford linked divergent thinking to creativity and convergent thinking to the ability to solve intelligence tests (but see more recent evidence linking divergent thinking to intelligence; Frith et al., 2021a; Karwowski et al., 2016). It is worth noting that the Structure of Intellect model was later criticized due to issues with the factor analytic evidence used to support it, and the model has little support today (Jensen, 1998; Mackintosh, 1998; Undheim & Horn, 1977).

In the years since Guilford, the divergent and convergent thinking constructs have gradually evolved and been reinterpreted, with researchers now arguing that both play important roles in creative cognition (Basadur, 1995; Brophy, 2001; Caughron, Peterson, & Mumford, 2011; Cropley, 2006; Jung et al., 2013; Runco, 2012, 2014b). Indeed, many researchers have shifted away from defining divergent and convergent thinking in terms of the number of solutions they produce, toward defining divergent thinking as a generative process that produces novel ideas, and convergent thinking as an evaluative process that selects and refines ideas (Basadur, 1995; Brophy, 2001; Cropley, 2006; Lee & Therriault, 2013). These generation-evaluation definitions of divergent and convergent thinking can be seen in numerous recent NCR articles (e.g., de Vink et al., 2021; Eskine, Anderson, Sullivan, & Golob, 2020; Gabora, 2018; Jung et al., 2013; Kleinmintz et al., 2019; Lee & Therriault, 2013), although Guilford's original definitions (many solutions vs. a single solution) also remain popular (e.g., Gilhooly, Fioratou, Anthony, & Wynn, 2007; Lu, Akinola, & Mason, 2017; Radel et al., 2015; Runco, 2010; Shamay-Tsoory, Adler, Aharon-Peretz, Perry, & Mayseless, 2011; Volle, 2018). This reinterpretation of divergent and convergent thinking has its roots in another common framework for conceptualizing creativity, which suggests that creative ideas arise from iterative cycles of generation and evaluation (Basadur, 1995; Ellamil et al., 2012; Finke et al., 1992; Jung et al., 2013; Kleinmintz et al., 2019). A prominent theory of this kind is the blind variation and selective retention (BVSR) model, first suggested by Campbell (1960) and later expanded upon by Simonton (2013, 2022). BVSR argues that creative cognition involves cycles of relatively undirected (or partially sighted; Simonton, 2013) processes to produce multiple ideas, and directed processes that select the best idea to develop further.

Among the most popular frameworks for understanding creative cognition that have emerged in recent decades are dual-process accounts. These argues that creative cognition emerges from the interactions of spontaneous, associative processes and controlled, analytic processes (Allen & Thomas, 2011; Barr, 2018; Benedek et al., 2023; Benedek & Jauk, 2018; Sowden et al., 2015; Tubb & Dixon, 2014; Volle, 2018). The account is based on wider dual-process theories of cognition (e.g., Evans, 2008; Evans & Stanovich, 2013; Kahneman, 2011), which describe two broad categories of processes which might be termed Type 1 and Type 2 (Evans & Stanovich, 2013). Type 1 processes are typically described as associative, fast, unconscious, and implicit, while Type 2 processes are described as controlled, slow, conscious, explicit, and dependent on WM (Evans, 2008; Evans & Stanovich, 2013; Tubb & Dixon, 2014). NCR researchers have discussed the overlaps between dual-process associative and controlled processes, divergent and convergent thinking, and generation and evaluation (Benedek & Jauk, 2018; Goldschmidt, 2016; Sowden et al., 2015), with some highlighting differences between the accounts (e.g., Sowden et al., 2015; Tubb & Dixon, 2014), and others concluding that they are broadly synonymous (e.g., Benedek & Jauk, 2018; Goldschmidt, 2016). Indeed, many NCR articles now define divergent and convergent thinking in terms of associative and controlled processes (e.g., Augello et al., 2016; Cortes et al., 2019; Drago & Heilman, 2012), producing a third interpretation of Guilford's original constructs.

The accounts discussed so far are, for the most part, relatively imprecise, leaving considerable room for interpretation. For example, describing creative cognition as involving divergent and convergent thinking, or cycles of generation and evaluation, does not greatly constrain the space of possible cognitive mechanisms that might underlie creativity. However, as the findings of NCR have grown, more specific theories of creative cognition have emerged. One example is the BVSR theory (Simonton, 2013, 2022), which defines its variational and selective processes in formal mathematical terms. Another is the contextual focus theory (Gabora, 2010, 2018) which builds on suggestions that creative cognition involves switching between narrow and broad attentional states (Bristol & Viskontas, 2006; Dorfman et al., 2008; Gabora, 2010; Herz, Baror, & Bar, 2020; Zabelina & Robinson, 2010) to define divergent thinking as the broadening of conceptual representations to include more abstract and associative information, and convergent thinking as the narrowing of representations to only the most relevant information (Gabora, 2010, 2018).

Researchers have also suggested more specific cognitive mechanisms corresponding to the associative and controlled processes described by the dual-process account of creative cognition (Benedek et al., 2023; Barr, 2018; Benedek & Jauk, 2018; Volle, 2018). Drawing on evidence linking creative cognition to performance on free-association and verbal fluency paradigms, researchers have suggested that associative creative processes may include the automatic spreading of activation through semantic memory (Kenett et al., 2018a; Volle, 2018). Meanwhile, evidence linking creative cognition to intelligence and executive functions has led to suggestions that controlled creative processes may include strategic search processes (Avitia & Kaufman, 2014; Benedek & Neubauer, 2013; Forthmann, Bürkner, Szardenings, Benedek, & Holling, 2019a; Lebuda & Benedek, 2023; Silvia, Beaty, & Nusbaum, 2013), and the inhibition of distracting or unoriginal thoughts (Beaty et al., 2017a; Camarda et al., 2018a; Volle, 2018).

Another more specific account distinguishes between two opposing strategies for producing creative ideas: flexibility and persistence. The former involves switching between conceptual spaces to attain more diverse ideas and may depend on striatal dopamine pathways, while the latter involves the persistent exploration of one conceptual space and may depend on prefrontal dopamine pathways (Mekern et al., 2019b; Nijstad et al., 2010; Zhang et al., 2020). The account has strong similarities to the distinction between exploration and exploitation in creative cognition (Hart et al., 2017; Lin & Vartanian, 2018), and is primarily supported by measures of clustering (i.e., the generation of similar ideas) and switching (i.e., the generation of ideas from different conceptual categories) in divergent thinking and cognitive search tasks (Mekern et al., 2019b).

5.3 How NCR can benefit from the wider adoption of computational modeling

NCR has made considerable progress in uncovering a broad range of cognitive, psychological, and neural correlates of creative cognition, guided by theories ranging from older, broader accounts to more recent and specific accounts. However, a precise, mechanistic understanding of creative cognition remains elusive. The increased adoption of computational modeling can help greatly towards this goal. While verbal theories are a useful and necessary part of science, they are more ambiguous and open to interpretation than formal computational models, which require all elements of a theory to be explicitly defined (Farrell & Lewandowsky, 2015; Fried, 2020; Guest & Martin, 2021; Smaldino, 2020). Defining theories in explicit and formal terms makes them more falsifiable and easier to compare in terms of their predictions and assumptions. NCR should continue to move towards more specific cognitive theories supported by computational models.

For clarity, by “computational model”, I refer to dynamic computational models that aim to embody a particular cognitive theory of creativity by representing how creative ideas arise from cognitive processes. As such, I am not referring to statistical models of human fMRI (e.g., Beaty et al., 2018b; Sunavsky & Poppenk, 2020), EEG (e.g., Rosen et al., 2020; Stevens & Zabelina, 2020) or behavioral data (Beaty & Johnson, 2021; Harada, 2020; He et al., 2020; Zioga, Harrison, Pearce, Bhattacharya, & Di Bernardi Luft, 2020). Equally, I do not include machine learning models that generate novel or interesting products but in ways that do not seek to emulate human cognition, such as Google DeepDream (Suzuki, Roseboom, Schwartzman, & Seth, 2017), and GPT3 (Floridi &

Chiriatti, 2020). Here I examine in more detail the issues that can affect purely verbal accounts, including more recent and specific accounts, and how computational modeling can provide greater clarity, rigor, and reproducibility to the development of cognitive theories (Farrell & Lewandowsky, 2015; Guest & Martin, 2021).

5.3.1 The limitations of verbal theories

At the less specific end of the spectrum of theoretical accounts of creative cognition is the distinction between convergent and divergent thinking. As noted, researchers have defined these constructs in several distinct ways since they first appeared. The first definition separates the two constructs based on the number of ideas or solutions they produce (Guilford, 1959) (i.e., one solution in convergent thinking, but multiple solutions in divergent thinking). A later definition focused on divergent thinking as idea generation and convergent thinking as idea evaluation (Basadur, 1995; Brophy, 2001; Cropley, 2006; Lee & Therriault, 2013). Finally, a third definition draws on dual process theories of cognition to define divergent thinking as an unconscious, associative process and convergent thinking as a conscious, analytic process (Augello et al., 2016; Cortes et al., 2019; Drago & Heilman, 2012; Gabora, 2010).

The existence of multiple definitions of divergent and convergent thinking suggests that they are likely to be conceptualized very differently across NCR researchers. Indeed, previous researchers have commented on the apparent contradictions that can emerge due to these varying definitions (e.g., Cortes et al., 2019; Dietrich, 2019; Gabora, 2018; Lee & Therriault, 2013). Moreover, none of these definitions are particularly precise. This can make it difficult to develop specific process-level hypotheses regarding these constructs, such as how divergent and convergent thinking might be differentially impacted by WM capacity. The definitional ambiguity of these constructs also makes it difficult to model them computationally, as to do so one would first have to translate one of their broad definitions into a specific set of processes (e.g., Gabora, 2018; Zhang et al., 2020). Whichever processes are chosen could differ greatly from those chosen by another researcher, so any conclusions drawn about these processes need not necessarily apply to the broader constructs. In essence, the reinterpretable nature of divergent and convergent thinking makes them difficult to study or falsify since any specific hypothesis can be easily dissociated from the construct.

Research into divergent and convergent thinking is also affected by inconsistencies between the definitions of these constructs and the tasks used to assess them. For example, convergent thinking is commonly assessed with the Remote Associates Test (RAT; e.g., de Vink et al., 2021; Nielsen, Pickett, & Simonton, 2008; Shang, Little, Webb, Eidels, & Yang, 2021; Zhang et al., 2020), in which participants are shown three unrelated words and must generate a response word that relates to all three. While RAT problems have one correct solution (consistent with the original conception of convergent thinking), they require generating numerous candidate solutions in an associative manner (Cortes et al., 2019), contrary to later definitions of convergent thinking as an analytic, evaluative process (Cropley, 2006; Runco, 2014). Indeed, the RAT was originally developed as a measure of associative processes (Mednick, 1962) and continues to be used as a measure of unconscious insight (e.g., Kounios & Beeman, 2014; Tik et al., 2018; see also Barr, 2018; Benedek & Jauk, 2018).

Meanwhile, divergent thinking is typically assessed with the Alternative Uses Task (AUT; Guilford, 1959, 1967), which requires participants to think of unusual uses for a given object. Since the AUT involves producing multiple ideas, and undoubtedly involves generative and associative thinking, it might appear to satisfy all three definitions of divergent thinking. However, the AUT is also widely considered to engage evaluative and analytic processes to ensure that the ideas generated are task-relevant and original (Beaty et al., 2014; Cortes et al., 2019; Gilhooly et al., 2007; Nusbaum & Silvia, 2011; Volle, 2018), processes commonly associated with convergent thinking (Cropley, 2006; Sowden et al., 2015). Indeed, both the AUT and RAT are now thought to involve a mixture of associative and controlled processes (Cortes et al., 2019). Given the difficulties in assessing divergent and convergent thinking, their varying definitions, and the fact that they must be translated into more specific accounts when researchers attempt to model or hypothesize about their underlying processes, NCR might seek to replace these constructs with more precise subtypes of creativity defined in terms of more established cognitive processes, such as memory, attention, and cognitive control (Barbot, Hass, & Reiter-Palmon, 2019; Benedek & Fink, 2019; Farrell & Lewandowsky, 2015; Kaufman et al., 2016; Plucker, 2022; Wiggins & Bhattacharya, 2014).

As noted, more recent theoretical accounts of creative cognition go much further in suggesting specific mechanisms that might produce creative ideas. Besides BVSR (Simonton, 2022), another recent extension of the generation-evaluation account describes several possible neural and cognitive mechanisms that may underlie both kinds of process (Kleinmintz et al., 2019). Meanwhile, an extension of dual-process accounts has suggested how creative ideas might arise from specific associative and controlled processes operating on a semantic network (Volle, 2018). In addition, several recent review articles have provided in-depth descriptions of the roles of distinct associative (Beaty & Kenett, 2023), memory (Benedek et al., 2023), and metacognitive processes (Lebuda & Benedek, 2023) in creative cognition. Researchers have also proposed neurocognitive mechanisms that might underlie new conceptions of convergent and divergent thinking, relating them to focused and defocused mental representations (Gabora, 2010, 2018) and flexible and persistent meta-control states (Hommel & Wiers, 2017; Nijstad et al., 2010; Zhang et al., 2020). The latter account may soon form the basis of a computational model. Finally, a recent review of the neural underpinnings of divergent thinking, abstraction, and improvisation has argued that all three can arise from dopaminergic novelty-seeking processes, in a framework that may soon be implemented computationally (Khalil & Moustafa, 2022).

For the most part, however, these are still verbal accounts, and thus they retain a degree of ambiguity that can make them difficult to falsify and leaves them open to reinterpretation. Another key issue for verbal theories is that they can be difficult to compare in terms of their predictions or internal consistency. Despite recent efforts (Kenett et al., 2020), there is no commonly accepted ontology for conceptualizing creativity (Kenett et al., 2020; Puryear & Lamb, 2020; Saggar, Volle, Uddin, Chrysikou, & Green, 2021). Researchers tend to employ different accounts to guide their research (Abraham, 2013; Hennessey & Amabile, 2010; Wiggins & Bhattacharya, 2014), and it is not always clear to what extent these accounts are synonymous or overlapping. For example, it is unclear whether associative and controlled processes are synonyms for constructs like generation and evaluation and implicit and explicit thought, or in fact underlie them. Another example is the overlap between theories of flexibility vs. persistence (Nijstad et al., 2010; Zhang et al., 2020) and exploration vs. exploitation (Hart et al., 2017; Lin & Vartanian, 2018), which both distinguish between the tendency to shift between conceptual spaces and the tendency to exploit a single conceptual space. Similarities also exist between accounts linking different forms of creativity to different forms of attention (Gabora, 2010, 2018; Zabelina et al., 2016; Zabelina & Robinson, 2010). However, without formal models, it is difficult to say whether these theories are broadly equivalent or describe fundamentally different kinds of operation.

5.3.2 The benefits of modeling

The benefits that computational modeling can bring to psychology and neuroscience have been discussed at length in several excellent recent articles (Blohm et al., 2020; Borsboom et al., 2021; Fried, 2020; Guest & Martin, 2021; Maia et al., 2017). A computational model is the explicit formalization of a theory in equations and algorithms (Farrell & Lewandowsky, 2015; Maia et al., 2017), and therefore requires that every aspect of a theory be precisely defined. More precise theories, that describe more specific cognitive processes or operations, are more easily communicated and testable since they make clearer predictions about what should be observed under certain conditions. By contrast, imprecise or ambiguous theories provide no clear mapping to empirical research questions and can be redefined continually, potentially leading different researchers to have very different interpretations of the theory. While NCR is already working toward more rigorous and specific theories (Benedek & Fink, 2019; Gabora, 2018; Volle, 2018; Zhang et al., 2020), the process of translating a theory into a computational model is an excellent way to make it more precise. For example, building a model based on the dual process account would force researchers to be extremely specific about what associative and controlled processes are, how they produce creative ideas, and how they might vary in different creative contexts.

The detail required by computational modeling can also reveal weak points, dubious assumptions, or outstanding questions in theories (Blohm et al., 2020), which can then direct empirical work. For example, modeling creative cognition as involving cycles of generation and evaluation would involve deciding how frequently the model should switch between the two modes. Researchers might also consider whether movement along a continuum between generation and evaluation (or even simultaneous generation and evaluation) is preferable to a binary switch. These decisions might inform, and be informed by, empirical research (e.g., Goldschmidt, 2016; Kleinmintz et al., 2019).

In addition, modeling provides a way to demonstrate and test hypotheses for how variation in a neurocognitive factor leads to variation in behavioral outcomes. Indeed, creative cognition is a particularly high-level construct, and there are likely to be a large number of factors that can impact creative outcomes, including a person's attention, memory, cognitive control, and personality (Beaty et al., 2014; Benedek & Fink, 2019; Oleynick et al., 2017). With modeling, these factors can be represented as sets of operations within a computational system, enabling researchers to examine the causal pathways by which they can impact creative performance. For example, researchers might hypothesize that individuals higher in the personality trait openness to experience produce more creative ideas by engaging in broader attentional states (Gabora, 2010, 2018). This hypothesis might then be embodied in a computational model by defining "openness" as a set of parameters governing the propensity to use broad instead of narrow conceptual representations. The hypothesis can then be tested by adjusting the parameters reflecting openness and observing whether the changes in simulated creative outcomes are in line with those observed among human participants with varying openness scores.

Moreover, modeling several contrasting theories can provide researchers with a more concrete basis for comparing their empirical predictions, internal consistency, and theoretical complexity (with less complex models being favorable; Farrell & Lewandowsky, 2015), allowing researchers to combine similar theories and select or reject opposing theories. As noted, there appear to be strong similarities between several accounts of creative cognition, such as those that describe generative and evaluative states (Jung et al., 2013; Kleinmintz et al., 2019), and those that describe associative and controlled processes (Benedek & Jauk, 2018; Volle, 2018), but it is hard to say whether these accounts are equivalent. Translating each account into a computational model could reveal opposing predictions about the role of a particular factor in creative cognition, or might instead indicate that the two accounts are referring to the same underlying mechanisms.

Ultimately, modeling results in more fleshed-out, transparent, and comparable theories (Guest & Martin, 2021). For a more specific example of how computational modeling can bring clarity to verbal theories, consider a creative search task in which participants must think of unusual members of a category (e.g., "uses for a brick", or simply "fruits"). Researchers might debate the processes that govern performance on this task, such as spontaneous association-making, attention, and cognitive control. To provide a concrete foundation for this debate, the task could be modeled as an iterative search through an n-dimensional space, with dimensions representing properties that vary across concepts (e.g., the size or exoticness of fruits). Concepts (i.e., fruits or possible task solutions) could be distributed across this space, with the strength of associations between concepts defined by the Euclidean distance between them (smaller distance = stronger association). Common items (e.g., apple, pear) could be clustered around the center, with more unusual items nearer the periphery of the space. Cognitive processes could then be modeled as operations on this space, such as spontaneous processes spreading activation from the center outward and controlled processes strategically pushing activation along one dimension (e.g., thinking of exotic locations to access more unusual fruits; Benedek & Neubauer, 2013).

Once a basic model of a task is implemented, it can serve as a starting point for further models embodying different theories. In the current example, researchers who emphasize associative processes in creative search might adjust certain parameters of the model to reflect this. Others might simulate WM by limiting the number of concepts able to activate at once, or simulate processing speed, attention, or mind-wandering by adding other features. Examining and comparing how these different models fit empirical human data could then help to improve our understanding of the processes underlying creative search (Wilson & Collins, 2019). Of course, evaluating model performance against human data requires reliable and valid measures of the underlying construct, and even then, alternative models may be equally supported by empirical data. As such, models of creative performance might also be compared in terms of their internal consistency and complexity, while researchers continue to develop more fine-tuned assessments of creativity (e.g., Barbot, 2018; Hart et al., 2017, 2022).

5.4 Existing computational models of creativity

Having discussed the theoretical accounts that guide NCR and how these might benefit from the increased adoption of computational modeling, I now consider some recent computational models of creativity, and the steps that might be taken to improve these and better integrate them with NCR. Computational models of human creative cognition come in two main forms: broader models and cognitive architectures that focus on creativity as a general feature of cognition (e.g., Hélie &

Sun, 2010; Wiggins, 2020), and narrower models that aim to simulate human performance in specific lab-based creative tasks (e.g., Olteţeanu & Falomir, 2016; Schatz et al., 2018).

Examples of broader models include recent attempts to model conceptual blending - the creative association of ideas or features from two distinct conceptual spaces (Falomir & Plaza, 2020; Schorlemmer & Plaza, 2021), and the simulation of both individual and cultural creativity using autocatalytic networks (Gabora, Beckage, & Steel, 2022; Gabora & Steel, 2020). Other examples include the Copycat (Hofstadter & Mitchell, 1994) and Metacat systems (Marshall, 2006), which focus on simulating analogical thought. Meanwhile, the CLARION cognitive architecture draws on Type 1 and Type 2 processes (Evans & Stanovich, 2013) to model creative thinking as the outcome of both associative, implicit processes and rule-based, explicit processes (Hélie & Sun, 2010). Researchers have also adapted the ACT-R cognitive architecture to simulate aspects of creativity including conceptual blending (Guhe, Smaill, & Peace, 2010). Finally, the IDyOT model, inspired by theories of predictive intelligence (Clark, 2013; Friston, 2010) and global workspace theory (Baars, 1988), focuses on cognition as the hierarchical prediction of perceptual input, with creativity emerging from the system "free-wheeling" in the absence of an external stimulus (Wiggins, 2020).

Although informative, the generality of these broad-focus models means that they are not best placed to model the cognitive theories of NCR, which typically focus on how humans perform specific lab-based creative tasks. For example, Copycat and Metacat operate on a limited set of abstract symbolic concepts, far removed from a human-like associative memory. Meanwhile, CLARION has only modeled elements of cognition relevant to incubation and insight, and must be set up and trained in a specific way for each task. Finally, IDyOT focuses on the perception and generation of sequential information such as music. Critically, these models lack the specific input/output components needed to simulate standard laboratory-based measures of creativity.

By contrast, narrow-focus models aim to simulate the cognitive processes that operate in specific creative tasks (e.g., Kajić, Gosmann, Stewart, Wennekers, & Eliasmith, 2017; Olteţeanu & Falomir, 2016; Schatz et al., 2018). NCR would arguably benefit most from increased modeling of this kind, since NCR and the theories that guide it focus mainly on lab-based creativity, and the performance of such narrow-focus models could be readily compared to large amounts of human data. While such models lack the flexibility needed to account for performance across multiple tasks, they have demonstrated how relatively simple operations on associative memory structures can lead to human-like creative performance on tasks such as the AUT and RAT.

To consider the structure of these narrow-focus models in more depth, one example comes from Kajić et al. (2017), who developed a spiking neural network model of the RAT. The model utilized a distributed memory architecture where each simulated neuron could be part of several concept representations. Words were represented as vectors encoded in neural activity, with word associations defined using the Free Association Norms dataset (Nelson, McEvoy, & Schreiber, 2004). When retrieving solutions, RAT cues were activated in sequence, with only one cue able to activate associations at any one time. Competing associations inhibited each other, and activation gradually decayed over time until a solution was reached. The model produced behavior comparable to human participants in terms of the number of RAT problems it could solve, the number of responses it generated, and the similarities between its responses. By examining the model parameters most relevant to performance, the researchers concluded that two main cognitive processes underlie RAT performance: one that generates potential responses and one that filters responses.

In contrast to the neural-level model of Kajić et al. (2017), Olteţeanu and Falomir (2015) developed a cognitive-level model of RAT performance in which concepts were represented as sets of associations to other concepts. The model's memory was constructed from a database of unique 2-word phrases (i.e., 2-grams), with the strengths of associations between words (i.e., associative strength) defined by the frequency of their co-occurrence in 2-grams. When solving RAT problems, all three cues and their associated concepts were activated in memory simultaneously (again in contrast with the sequential activation employed by Kajić and colleagues, 2017). Solutions were then selected from the most strongly activated associated concepts. While the authors did not directly compare the model to humans in terms of the number of RAT problems it could solve, model performance suggested that the difficulty of RAT items relates to both the strength of associations between cues and solutions, and the number of associations each cue word has (known as "fan"). Since these properties impact how activation spreads automatically between ideas in memory, these findings emphasize the role of automatic associative processes in the RAT.

Building on this work, Schatz, Jones, and Laird (2018) developed a model of the RAT using the Soar cognitive architecture. The authors tested two versions of the model. A baseline model simply searched memory for words that linked to all three cue words. By contrast, a second “free recall model” used spreading activation, which propagated through memory from the three cue words according to both associative strength and fan. The authors also tested two knowledge bases for the model: one formed of 2-grams (following Olteţeanu & Falomir, 2015) and one based on a larger corpus not limited to 2-grams and including several kinds of word association. The authors found that the “free-recall” model and the more sophisticated knowledge base produced the most human-like performance in terms of the number of RAT problems solved, highlighting the important roles of memory structure and associative processes in modeling RAT performance.

Models of the AUT are rare, but one attempt comes from Olteţeanu and Falomir (2016). The model used a knowledge base of 70 objects, each composed of a set of features (manually added by the authors), in a hierarchical memory. These features enabled the simulation of several cognitive strategies that people are known to employ when thinking of unusual uses for objects in the AUT (Gilhooly et al., 2007), including object replacement (matching the cue object to the typical uses of another object with similar features) and object decomposition (breaking the object into components and generating uses for these). The model did not aim to model memory retrieval processes such as spreading activation, but served as a proof-of-concept that matching features of cue objects (and components of objects) to features of other objects can produce solutions to AUT problems.

Another recent model of creative idea generation, this time focusing on free association, comes from Lopez-Persem et al. (2022). The model included separate modules for exploration, valuation, and selection. The exploration module simulated activation spreading through a semantic network using random walks biased by associative strength (defined using a database of word associations). The valuation module then calculated the value of activated ideas based on their novelty and appropriateness (estimated as linear and quadratic functions of the associative strength between each idea and the cue word). Finally, the selection module selected a word from among activated ideas according to their value. The authors then adjusted parameters of the model, and compared the resulting changes in performance to the performance of human participants. They found that certain model parameters were more relevant to the performance of individual modules than others, indicating the processes that may underlie these different components of creative cognition. For example, the exploration module performed well (i.e., matched human performance well) using just associative strength, and was not improved by considering the value of ideas, which only played a role in the subsequent valuation stage. The performance of the exploration module was also unaffected by whether human participants were asked to produce the first response that came to mind or an original but still associated response. These findings indicate that the initial activation of ideas during exploration does not depend on how valuable ideas are, and does not vary depending on the specific task being performed. By contrast, the selection module performed better when considering appropriateness more among first responses, and value more among original responses.

In each of these studies, the authors found evidence that particular computational model structures and parameters can mimic human performance on creative tasks, in some cases finding that certain structures and parameters perform better than others. In this way, models can provide considerable insight into the cognitive operations that underlie performance in creative tasks. However, despite the progress of these models, and the benefits that models of this kind could bring to NCR, computational modeling of creativity is currently conducted largely separately from empirical research. The researchers who build models rarely overlap with those involved in empirical work, and models are rarely mentioned by NCR. One method to increase integration between the two fields would be to improve the value of models to empirical researchers. For example, with some exceptions (e.g., Lopez-Persem et al., 2022; see also Augello, 2016), the models discussed have not explicitly aimed to embody a particular cognitive theory from NCR in a way that would enable researchers to examine the theory's predictions or to test new hypotheses. Indeed, several clear steps could be taken to improve future models of creativity, to increase their ability to simulate human cognition and maximize their explanatory value to NCR.

5.5 Future steps for computational models of creative cognition

I have argued that NCR would benefit greatly from the increased adoption of computational modeling. To this end, the neurocognitive theories that guide NCR should, where possible, be formally defined in computational models that can simulate performance in typical lab-based tasks. Hypotheses can then be developed with the aid of computational models, with models adjusted on the basis of empirical data. This approach would bring considerable clarity to our understanding of creative cognition, allowing researchers to rigorously compare different theories and make inferences about underlying processes. Such integration between NCR and computational modeling would, in turn, aid the development of artificial creative systems (Chateau-Laurent & Alexandre, 2021; Wiggins & Bhattacharya, 2014) since a more algorithmic understanding of human creative cognition could inform models of autonomous creativity (Dipaola et al., 2018; Veale & Pérez y Pérez, 2020).

In addition to a heavier focus on modeling theories from NCR, future models of specific creative tasks should aim to meet several additional criteria (see also Mekern et al., 2019a). As already noted, it is highly important that computational models can simulate performance on common creative tasks, to allow model output to be compared to human data. This provides a means to evaluate the structure of the model, and the cognitive theories and hypotheses that the model intends to represent. Different models of the same task can also be compared in terms of how well they fit human data (Guest & Martin, 2021; Wilson & Collins, 2019). I have suggested that smaller, narrow-focus models may be best placed to simulate creative performance on lab-based tasks, though the option also exists to adapt larger cognitive architectures, such as Soar and ACT-R, for this purpose (e.g., Schatz et al., 2018).

Indeed, future models should ideally aim to simulate performance on multiple creative tasks. This is needed to explain how the same cognitive processes can produce creative ideas in different contexts. The first step here would likely be to simulate performance across different verbal tasks, since tasks in different modalities, such as musical composition and drawing paradigms, would require modality-specific components (e.g., memory with visual and auditory representations). Since there is considerable diversity even amongst verbal tasks, which include free-association, metaphor tasks, insight problem-solving in the RAT, and strategic search in the AUT, modeling performance in just some of these tasks would be a good starting point.

Models might also seek to adopt more complex and human-like memory structures. While several studies have modeled human semantic memory as a static network (see, e.g., Kenett et al., 2018a;

Rotaru, Vigliocco, & Frank, 2018), with nodes representing concepts, and edges representing associations, in reality, human memory is far more complex and dynamic. Building more complexity into a model's memory (or “knowledge base”) provides it with more information about concepts and their relationships, enabling more nuanced cognitive processes to be simulated. For example, a simple network in which concepts are represented in a single layer and linked by only a single kind of association does not allow the simulation of search processes that might restrict activation to only one type of concept (e.g., objects), or to concepts that possess a particular property (e.g., roundness) rather than simply being associated with that property.

The benefits of more sophisticated memory structures have already been seen in a model of the RAT, in which a larger memory network with multiple kinds of association produced more human-like behavior than a smaller and simpler network (Schatz et al., 2018). Other examples of more complex memory structures include distributed and hierarchical memory. In distributed memory, concepts are represented as patterns of activity across multiple nodes, where each node can form part of multiple concept representations. This provides a more natural and biologically plausible basis for spreading activation, which now moves between concepts that share nodes (Kajić et al., 2017). In hierarchical memory (e.g., Olteţeanu & Falomir, 2016; Wiggins, 2020), concepts in each layer are represented as sets of concepts in lower layers, which serve as features or properties of higher-level concepts. In both cases, richer conceptual representations provide a basis for more complex and flexible processes to operate on memory.

Other critical goals for future models include the simulation of individual differences and context effects (see also Mekern et al., 2019a). While simulating creative performance allows models to be evaluated in relation to other models, the capacity to model individual differences in a given psychological or cognitive factor (e.g., WM capacity or response inhibition) goes a step further, enabling researchers to develop and test causal hypotheses for how variation in the factor leads to variation in creative performance. To do this, the factor must first be embodied in the model as a set of parameters. These parameters can then be modified, leading to changes in simulated creative outcomes. If these changes align with individual differences observed among human participants (who also vary in the designated factor), then the modeled causal pathway is supported. Indeed, different versions of a model can be designed to reflect contrasting hypotheses regarding how a factor affects creative outcomes. This gives researchers a powerful tool to compare two or more causal hypotheses by examining which model set-up best fits human data.

Finally, modeling context effects allows the conceptual representations stored in a model to be adjusted in response to the current context or sensory input. Concepts in human memory are not equally active at all times, but rather become more activated in certain environments or after certain stimuli. Simulating context effects would thus lead to more realistic models, and might involve allowing activated concepts (such as cue words in the AUT and RAT) to modify the associations, weights, or features that define inactive concepts, thus changing their representations.

5.6 Towards greater integration between NCR and computational modeling

Progress toward a more precise, mechanistic understanding of creative cognition cannot be made by modeling alone, but will require the cooperation of theorists, modelers, and experimenters (Dongen et al., 2022; Hitchcock, Fried, & Frank, 2022; Wiggins & Bhattacharya, 2014). How might greater integration between NCR and computational modeling look? I would argue that any research group that proposes a theory of creative cognition should aim to produce a computational model to demonstrate their thinking explicitly. Such models would make theories more rigorous and complete, and could highlight questions for future research. Following the recommendations of Barton et al. (2022), these models should be easily reproducible, with publicly available code that is accessible to those with minimal modeling experience, allowing them to be adapted by other researchers who wish to develop their own hypotheses. As noted, it is also important that future models can simulate performance on common creative tasks, to allow models to be readily compared to both human data and the performance of other models. While I have focused on models of the AUT and RAT, NCR makes use of a large number of other tasks, including metaphor tasks (Beaty, Silvia, & Benedek, 2017b; Benedek et al., 2014a), drawing tasks (Ellamil et al., 2012; Rominger et al., 2018), musical improvisation (Pinho et al., 2014; Rosen et al., 2020), and story writing (Fink, Reim, Benedek, & Grabner, 2020; Prabhakaran, Green, & Gray, 2014). NCR should ideally aim to model all of these tasks computationally to improve our understanding of the cognitive processes that enable creative performance in these different contexts.

5.6.1 Designing a model

To show more clearly how theories can be represented in formal models and how modeling can inform empirical research and theoretical debate, I now outline how a more complex model might be built, based on dual-process accounts (Figure 10). A simple starting point would be a semantic network, where nodes are words and edges are associative links, which could be constructed from human free-association data (e.g., Kenett et al., 2018a; Schatz et al., 2018) or distributional semantics methods (e.g., Rotaru et al., 2018). The next step is to examine the literature for theoretical processes that might be represented as operations on this network. For example, the spontaneous and deliberate processes described by dual process theories might conceivably be modeled as collections of several computational elements and mechanisms (Table 21).

Spontaneous processes are often described as propagating through memory, reinterpreting information, and activating distant concepts (Benedek & Jauk, 2018; Volle, 2018), and so could be modeled via the structure of memory itself, the automatic spreading of activation through memory, and the spontaneous activation of tangential (i.e., non-task-relevant) ideas. Deliberate processes, meanwhile, are described as inhibiting unoriginal or distracting ideas (Beaty et al., 2017a; Camarda et al., 2018a; Chrysikou, 2019) and directing thought to fulfill strategies (Forthmann et al., 2019b; Gilhooly et al., 2007; Nusbaum & Silvia, 2011). As such, modeling deliberate processes might involve specifying mechanisms that can prevent certain ideas from activating and inhibit certain associative pathways to guide thought in particular directions (Volle, 2018).

Table 21

Summary of cognitive mechanisms that might feature in a computational model of verbal creativity

Broader cognitive construct	Specific feature or mechanism	Example from the literature
Spontaneous Associative Processes	Memory structure	Semantic memory structure relates to creative ability (Kenett et al., 2018a).
	Automatic spreading of activation between concepts	Free association and verbal fluency relate to creative performance (Beaty et al., 2014; Marron et al., 2018).
	Spontaneous activation of tangential or task-unrelated ideas	In the absence of cognitive control, distraction and mind-wandering can occur (Fox & Beaty, 2018; Zabelina, 2018).
Deliberate Control Processes	Inhibition of unoriginal and distracting ideas	Less original and distracting ideas require suppression (Camarda et al., 2018a; Lloyd-Cox et al., 2021). Inhibition relates to creative ability (Benedek et al., 2012, 2014c; Kaur et al., 2021).
	Strategic search processes	Strategic search occurs in the AUT (Gilhooly et al., 2007; Silvia et al., 2013). Search can vary between more flexible and persistent strategies (Lin & Vartanian, 2018; Nijstad et al., 2010).
	Control over WM input	Creativity relates to the breadth of attentional focus (Gabora, 2010; Zabelina, 2018), and WM updating and shifting (Benedek et al., 2014c; Krumm et al., 2018; Zabelina & Ganis, 2018).
Working Memory	A finite set of currently active concepts	WM capacity impacts creative thought (Fugate et al., 2013; Lee & Therriault, 2013). Context effects play a role in creative thought (Gabora, 2018).

To be modeled effectively, these processes seem to require additional features. For example, guiding thought to fulfill strategies suggests the existence of multiple kinds of associative pathway, which could be modeled either with a hierarchical or distributed memory, or by defining the part-of-speech of words (e.g., verbs, nouns) and using these to define different kinds of association. In the context of the AUT, this latter option could allow the simulation of the strategy of object replacement (where the cue object performs the typical use of another object; Gilhooly et al., 2007) by directing activation first along noun-adjective-noun associative pathways (to find an object with similar properties; e.g., brick -> heavy -> hammer) and then noun-verb pathways (to find uses; e.g., hammer -> pound a nail). More importantly, the notion that ideas can be distracting, and require inhibition to allow more relevant or original ideas to activate, implies that active concepts occupy a finite WM, access to which must be managed by cognitive control. Indeed, WM is not often discussed in significant depth by dual-process accounts of creative thought, yet in the context of modeling appears central to the need for controlled mechanisms.

As discussed in detail in Chapter 4, researchers within NCR have suggested that creative performance involves adjusting attention between narrower and broader states (Dorfman et al., 2008; Gabora, 2010; Zabelina, 2018; Zabelina & Robinson, 2010) and shifting between exploratory and exploitative search strategies (Mekern et al., 2019b; Nijstad et al., 2010). Such processes might be simulated by adjusting input to WM. For example, broad or exploratory attentional states might be simulated as a wider input to WM, where activation flows more freely, and tangential ideas can activate spontaneously. By contrast, narrow or exploitative attentional states might involve limiting WM input to only closely related ideas (see Figure 10). Embodying different attention-based theories of creativity in models of this general sort would allow them to be more rigorously compared. Alternatively, if a single model could simulate the behavioral outcomes discussed by different theoretical accounts, that would strongly suggest that the theories are consistent and could be combined into one. Indeed, it is hypothetically possible that all creativity-relevant control processes, including inhibition, adjustment of attentional breadth, and switching between generative and evaluative modes, are based on adjusting WM input, a possibility that could be investigated empirically.

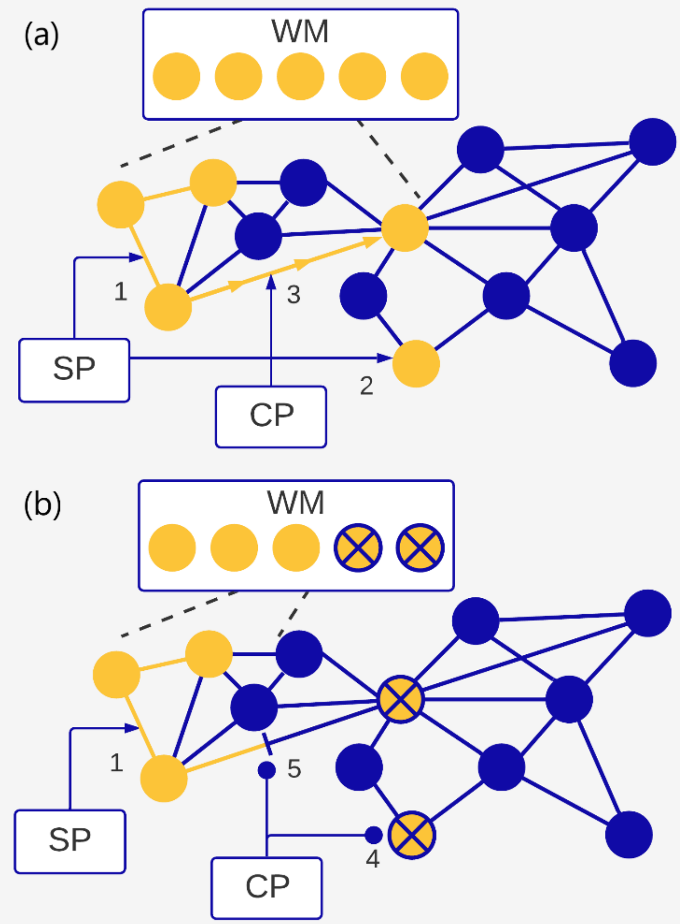


Figure 10

Diagram of an example dual-process computational model of creative cognition.

Note. Semantic memory is represented as a network of concept nodes (yellow = active; blue = inactive). Creative performance depends on a combination of spontaneous processes (SP) and controlled processes (CP). Active concepts in working memory (WM) form the current context and can bias the representation of other concepts. Dashed lines indicate the breadth of WM input.

(a) In broad focus attentional states, associative processes, including spreading activation (1), and spontaneous activation of tangential concepts (2), combine with strategic controlled processes that can force activation in specific directions (3), to produce a broader input to WM.

(b) In narrow focus attentional states, cognitive control can suppress distracting concepts (4) and inhibit specific associative pathways (5) to constrain WM input to the most relevant ideas.
Different creative tasks may require different attentional states and different combinations of processes.

In principle, such a model could meet many of the requirements for future models noted earlier. Active concepts in WM could form the current context, modifying conceptual representations in memory by changing their associative weights. Individual differences could be simulated by varying parameters governing specific features or operations in the model (e.g., WM capacity or the strength of inhibition). Finally, performance on multiple creative tasks might be achieved using spreading activation to complete RAT problems (e.g., Schatz et al., 2018) and the activation of specific associative pathways to perform strategic idea generation in the AUT. Moreover, such a model could be developed in concert with empirical studies such as the ones described in Chapters 3 and 4, for example with model parameters being trained on measures of associative and executive processes, and model output tested on how closely it simulates creative outcomes. Different model structures could also be tested to examine different causal hypotheses regarding, for example, how control over WM impacts creative performance.

5.6.2 Implementing a model

Once the structure of a model has been outlined, implementing it computationally requires several additional steps. The first step is to construct the memory base of the model, which in the current example is the semantic network. Regardless of whether this is based on human free association data or distributional semantics methods, researchers would have to make several decisions, such as how many words to include, whether to exclude prepositions, articles, and quantifiers, whether to combine singular and plural forms of words, whether to exclude associations below a certain strength threshold, and so on. Researchers also have the option to create multiple semantic networks and tailor each one to an individual participant (Benedek et al., 2017; He et al., 2020).

Once a memory base is constructed, the next step is to choose which processes to model and how to simulate them. For example, associative processes could be modeled as spreading activation alone, or as both spreading activation and the spontaneous activation of tangential concepts. Each approach requires specifying parameters that determine, for example, how quickly or distantly activation should spread through memory, or how often tangential ideas should activate. Similar decisions need to be made to simulate components such as WM or cognitive control processes (e.g., how strongly inhibition can suppress distracting ideas). These parameters can be selected based on existing hypotheses or left open and later adjusted to fit participant data, as described below.

In addition, researchers need to decide how to manage model input and output. For example, in the verbal model described above, one option is to simulate input by activating cue words strongly in memory (e.g., Kajic et al., 2017; Schatz et al., 2018). Activation may then propagate outwards from these cue words to other concepts. The process of selecting concepts as responses for output also requires careful consideration. In tasks like the RAT, this might involve selecting the most strongly activated concept (e.g., Olteţeanu & Falomir, 2015). However, tasks like the AUT may require more sophisticated evaluation and selection processes, potentially based on a specified trade-off between proximity to the cue word (which improves the usefulness of the response) and distance from the cue word (which improves the novelty).

Finally, researchers need to consider how the model will update over time to simulate cognition. One approach is to update the model in discrete time steps. At each time step, activation might spread to new concepts, while the activation of previous concepts gradually decays. Further, each update might involve control processes switching to inhibit different concepts or pushing activation in a different direction. Once all these factors and decision points have been implemented in the code, the model is ready to simulate task performance. As discussed, spreading activation alone might be sufficient to model performance on tasks such as chain association and the RAT (e.g., Lopez-Persem et al., 2022; Schatz et al., 2017). However, simulating performance on the AUT might require a slightly different model setup depending on the particular strategy used, such as object replacement or object decomposition (Gilhooly et al., 2007).

Once the initial model is developed computationally, researchers can refine it and its parameters to fit human data better. One option is to build a model with a specific structure (i.e., with certain components linked by causal pathways) based on theories and hypotheses, and then fit the parameters governing model behavior to human data. For example, the distance traveled by spreading activation processes could be set based on a certain weighting of participants' verbal fluency or chain association data. Researchers could train the parameters of the model using data from one group of participants and then test its ability to predict the creative outcomes of another group. Different hypotheses can then be tested by building different versions of the model with varying causal structures, for example by modifying the process by which inhibition operates (as opposed to how strongly it operates). After testing and training, different model versions can be compared in terms of how well their performance predicts human data. Another option is to specify both the structure of the model and its parameters based on preexisting theories. Different hypotheses, for example regarding how much impact inhibition should have on creative outcomes, can then be tested by defining several sets of parameters and assessing their fit to human data (Lopez-Persem et al., 2022).

This brief sketch of model development clarifies how theories of creative cognition can be translated into formal models. It also demonstrates the potential of modeling to identify new research avenues and the importance of cognitive factors, such as WM, that may have been overlooked in verbal accounts. Importantly, this example highlights that modeling inevitably requires making many reasonable assumptions to “fill the gaps” left by verbal accounts. Verbal theories rarely describe all the details necessary to implement a computational model, leaving the modeler to decide factors such as how exactly to structure semantic memory or simulate inhibition processes. For each of these decisions, alternatives are possible, and so ideally multiple models should be constructed by different research groups and their performances compared (Poile & Safayeni, 2016; Wilson & Collins, 2019). It is crucial to note that the design and implementation of the model discussed here may differ substantially from models focused on the neural level or based on alternative theories of creative cognition, such as flexibility vs. persistence (Mekern et al., 2019b; Zhang et al., 2020). This also highlights the importance of building and comparing multiple models of each creative task.

5.7 Concluding remarks

NCR has greatly increased our understanding of creative cognition and its relations to psychological phenomena, including memory, attention, and cognitive control (Beaty et al., 2021a; Benedek & Fink, 2019; Chrysikou, 2019; Kenett et al., 2018a; Kleinmintz et al., 2019; Volle, 2018). However, the field remains far from a mechanistic understanding of creativity complete with causal hypotheses for how cognitive processes produce creative ideas and how such processes interact differently in different tasks and individuals. The increased adoption of computational modeling can significantly advance the field and bring it closer to this goal. The verbal theories that guide NCR (and psychology in general) are intrinsically more open to interpretation, more difficult to falsify, and less transparent than formal models (Farrell & Lewandowsky, 2015; Fried, 2020; Guest & Martin, 2021; Smaldino, 2020). By contrast, embodying these theories in computational models can help make them more complete, accessible, and comparable. Modeling forces researchers to exchange abstract constructs for concrete definitions of cognitive processes as operations in a computational system (Benedek & Fink, 2019; Wiggins & Bhattacharya, 2014). Moreover, computational modeling can allow the complex pathways that produce creative ideas to be predicted effectively.

For its part, though several computational models of creativity exist, they have been developed in relative isolation from empirical research, and surprisingly few are well-suited to modeling the cognitive theories of NCR in a way that can be easily compared to human performance. Since a clearer understanding of human creativity could lead to more creative artificial systems, further integration and collaboration between computational modeling and NCR stands to benefit both fields greatly (Chateau-Laurent & Alexandre, 2021; Dipaola et al., 2018; Veale & Pérez y Pérez, 2020; Wiggins & Bhattacharya, 2014). Indeed, among all areas of cognitive neuroscience, NCR may benefit especially well from computational modeling. After all, creativity is a complex and heterogeneous construct, and its underlying processes undoubtedly vary greatly depending on the specific task, domain, and other contextual and interpersonal factors. Ultimately, science seeks to establish cause and effect relationships, and to truly advance, NCR needs clear hypotheses about how the same cognitive processes operate in different contexts, explicitly demonstrated in computational models.

Chapters 3 and 4 described two studies examining how creative cognition relates to inhibitory control, and more generally to executive functions and control over WM. These studies were correlational in nature, and thus can only assess shared variance between creative cognition and more basic executive processes. However, computational modeling could provide researchers with a far more sophisticated tool for examining these relationships. For example, researchers could construct a model where control over WM plays a critical role in the production of creative ideas; a model embodying several causal hypotheses regarding how executive functions contribute to creative cognition in different contexts. By training parameters of the model using collected data on executive functions, and testing how the model performs on creative tasks compared to other models and to human participants, researchers can provide support for one set of hypotheses over another. If a certain causal pathway seems promising given simulations, empirical research with experimental interventions could be conducted, for example to confirm whether increasing inhibitory control affects specific aspects of creative performance but not others.

Greater use of computational modeling could thus help to increase the testability of theories and the development of causal hypotheses, in turn highlighting promising avenues for future research. Indeed, the use of computational modeling need not be limited to examining the roles of executive processes in creative cognition. Factors such as an individual’s personality and preference for novelty as opposed to usefulness in creative ideas may also be important determinants of their creative process. These factors could also, with some careful interpretation, be represented in computational models of creative cognition.

Indeed, while considerable research in NCR has focused on the generation of creative ideas, relatively little has explored the evaluation of creative ideas. The factors that affect idea evaluation, a critical element of the creative process, will be explored in more detail in the following chapter.

CHAPTER 6: EVALUATING CREATIVITY: HOW IDEA CONTEXT AND RATER PERSONALITY AFFECT CONSIDERATIONS OF NOVELTY AND USEFULNESS

6.1 Introduction

This chapter turns to an often neglected component of the creative process: evaluation. In particular, I consider how and why individuals might vary in how they consider novelty and usefulness when evaluating a creative idea, and whether their considerations of these factors depend on the specific task the idea was generated in.

The most commonly accepted definition of creativity is the "standard definition" (Runco & Jaeger, 2012), which states that to be creative, an idea must be both novel and useful. Though the precise terminology can vary (e.g., novelty may be referred to as originality or uniqueness, while usefulness may be referred to as appropriateness, relevance, or effectiveness), the twin criteria of novelty and usefulness have formed principal components of numerous definitions of creativity dating back at least 70 years (Amabile, 1982; Plucker et al., 2004; Stein, 1953). The definition is not without conceptual issues (see Corazza, 2016; Martin & Wilson, 2017), and some have suggested additional requirements including surprise (Boden, 2007; Simonton, 2018), discovery (Martin & Wilson, 2017), and aesthetics and authenticity (Kharkhurin, 2014). However, especially within cognitive psychology and neuroscience, the standard definition continues to provide a theoretical foundation for vast amounts of creativity research, and to serve as a guide when raters evaluate the creativity of ideas, products, or responses.

If a creative idea is (at minimum) both novel and useful, it seems likely that when evaluating the creativity of an idea, raters would make their final judgement based on a certain weighting of its perceived novelty and usefulness. However, surprisingly little research has investigated how these components contribute to evaluations of creativity, and the factors that can modify these contributions. While some research suggests that novelty is far more important to creativity than usefulness (Caroff & Besançon, 2008; Diedrich et al., 2015; Han et al., 2021; Runco & Charles, 1993), other findings indicate that the contributions of novelty and usefulness may depend on the context in which the idea was generated and the nature of the problem it is intended to solve (Acar et al., 2017; Long, 2014; Runco et al., 2005).

Meanwhile, although researchers have examined how individual differences, including expertise (Long, 2014), emotion (Lee et al., 2017; Mastria et al., 2019), and uncertainty (Mueller, Melwani, & Goncalo, 2012), can influence evaluations of overall creativity, little is known about how these differences might affect considerations of novelty and usefulness. Personality, particularly the Big-Five trait openness/intellect, is likely to be an important factor here, since it determines how receptive individuals are to new and unusual ideas (Kaufman et al., 2016; Oleynick et al., 2017), potentially driving them to consider novelty more than usefulness when they evaluate creativity. However, it remains unknown how factors such as the nature of the creative task and the personality of the rater can affect how novelty and usefulness contribute to evaluations of creativity. Providing answers to these questions is of central importance to our understanding of how creativity is evaluated, defined, and perceived, and may inform the development of subjective creativity assessments that can account for variance across raters (Barbot et al., 2019; Myszkowski & Storme, 2019). As a brief but important note, this study is concerned with the evaluation of exogenous ideas (i.e., ideas generated by others) as opposed to the evaluation of one's own ideas, which is likely to be a related but distinct evaluative process (Karwowski, Czerwonka, & Kaufman, 2020; Rodriguez, Cheban, Shah, & Watts, 2020; Runco & Smith, 1992).

6.1.1 Assessing creativity and its components

While creativity can be assessed through self-report methods that focus on creative achievements and activities (e.g., Carson et al., 2005; Diedrich et al., 2018; Kaufman, 2019), lab-based creativity tests typically require participants to produce creative responses or products, such as musical improvisations (Pinho et al., 2014), drawings (Rominger et al., 2018), or short stories (Prabhakaran et al., 2014), which are then evaluated by a panel of raters. When it comes to evaluating creativity as a single, holistic construct, the gold-standard method within psychology is the consensual assessment technique (CAT; Amabile, 1982; Baer & McKool, 2014; Kaufman, Lee, Baer, & Lee, 2007; see also Cseh & Jeffries, 2019), in which several expert judges rate the creativity of each idea on a Likert scale. Ratings are then averaged across raters.

As mentioned earlier, creativity has two essential components – novelty and usefulness. Novelty refers to the unusualness, uniqueness, and originality of an idea and can be assessed either through subjective ratings (e.g., Acar et al., 2017; Diedrich et al., 2015; Silvia, 2008) or through objective measures such as the statistical infrequency of the idea among the current sample (Plucker, Qian, & Wang, 2011; Runco et al., 2005; Wilson, Guilford, & Christensen, 1953). By contrast, usefulness refers to the feasibility, appropriateness, and value of an idea, which in the majority of tasks can be determined only by subjective assessment (Acar et al., 2017; Diedrich et al., 2015; Runco et al., 2005).

6.1.2 How novelty and usefulness contribute to evaluations of creativity: the role of idea context

How do novelty and usefulness contribute to evaluations of creativity, and is one component more important than the other? Novelty and usefulness ratings are often negatively correlated (Caroff & Besançon, 2008; Diedrich et al., 2015; Runco & Charles, 1993), so an optimally creative idea may have to balance a trade-off between novelty and usefulness. To date, however, only a handful of studies have examined how novelty and usefulness contribute to evaluations of creativity. The majority of this research has found that the perceived creativity of an idea depends more on its novelty that on its usefulness, in contexts including AUT ideas (Acar et al., 2017; Diedrich et al., 2015; Runco & Charles, 1993), advertisements (Caroff & Besançon, 2008; Storme & Lubart, 2012), and product designs (Han et al., 2021). For example, Diedrich et al. (2015) asked 18 participants to rate the novelty, usefulness, and creativity of around 5000 ideas produced in both the AUT and a figural-completion drawing task. They found that creativity ratings were far more strongly related to novelty ratings (with β estimates ranging between .75 and .81) than usefulness ratings (β estimates between .26 and .32). They also found a significant interaction between novelty and usefulness, whereby usefulness was less related to creativity among common (i.e., non-novel) ideas and far more related to creativity among novel ideas.

However, some findings suggest that the contributions of novelty and usefulness to evaluations of creativity may depend on the context in which the idea is produced. Runco and colleagues (2005) examined ideas for both realistic problems (with potential application to the real-world) and unrealistic problems (unlikely to be encountered in the real world). Ideas for realistic problems were rated as more useful than ideas for unrealistic problems, while ideas for unrealistic problems were rated as more novel. While relations with creativity were not examined, these findings indicate that certain contexts may elicit a different consideration of novelty and usefulness when raters evaluate creativity. For example, usefulness may have a minimal impact on evaluations of creativity in contexts where it is less relevant (such as with adverts, artworks, and AUT ideas) but may draw far more consideration in the context of genuine real-world problems. This possibility is further supported by a qualitative study, which found that when raters evaluated the creativity of scientific ideas, novelty and usefulness were considered equally important criteria (Long, 2014).

A further suggestion that the relationships between novelty, usefulness, and creativity might depend on the context of the creative idea comes from Acar et al. (2017), who examined how four factors, including novelty and usefulness, contributed to judgments of creativity. In their study, 776 participants completed ratings for both AUT ideas and real-world creative products. The authors again found novelty to be more related to creativity than usefulness, but also found evidence that the relationship between usefulness and creativity may depend on the context of the idea. However, the study focused on variance at the rater level, examining ratings for only 12 ideas (all of which had high prior ratings of creativity), and the results were inconclusive as to which context displayed the greater relationship between usefulness and creativity. To my knowledge, no study has provided definitive evidence regarding how the context of ideas can affect the contributions of novelty and usefulness to evaluations of creativity.

6.1.3 Individual differences in the evaluation of creativity and its components

In addition to the context of the idea, individual differences between raters are also likely to influence the contributions of novelty and usefulness to evaluations of creativity. Understanding differences in the evaluation of creativity is highly important to creativity research for at least two reasons. First, creativity research relies heavily on subjective assessments of creativity, and so understanding the interpersonal factors that cause variation in these assessments is key to developing strong and reliable measures. Indeed, the most common subjective assessment method, the CAT, has recently been criticized for not accounting for variation across raters (Barbot et al., 2019; Myszkowski & Storme, 2019). The limitations intrinsic to subjective assessments of creativity are well-known, and have stimulated the development of objective assessments including distributional semantics methods (Acar et al., 2021; Beaty & Johnson, 2021) and machine learning techniques (Cropley & Marrone, 2021; Edwards, Peng, Miller, & Ahmed, 2021). However, such methods can often assess only the novelty of ideas, not the usefulness (Beaty & Johnson, 2021), and the field will likely continue to rely on subjective assessments of creativity for the foreseeable future.

Second, a better understanding of creative evaluation could lead to a better understanding of creative generation. The production of creative ideas is often argued to involve iterative cycles of generation and evaluation (e.g., Basadur, 1995; Finke, Ward, & Smith, 1992; Lubart, 2001; cf. Campbell, 1960; Simonton, 2013), and research suggests that more thorough evaluation during the production of ideas can lead to better creative performance (Gibson & Mumford, 2013; McIntosh, Mulhearn, & Mumford, 2021; Watts, Steele, Medeiros, & Mumford, 2019). Moreover, given the close ties between generation and evaluation, differences in how people evaluate ideas may relate to differences in how people generate ideas. For example, individuals who favor novelty over usefulness when evaluating the ideas of others may show the same preferences when generating their own products or responses (a possibility supported by Caroff & Besançon, 2008). As such, a clearer understanding of differences in the evaluation of creativity may lead not only to more nuanced creative assessment techniques but also to a clearer understanding of differences in creative performance.

A considerable body of work has examined how differences in the evaluation of creative ideas relate to factors including culture (Ivancovsky, Shamay-Tsoory, Lee, Morio, & Kurman, 2019; McCarthy, Chen, & McNamee, 2018; Simonton, 1999; Sternberg, 2018), intelligence (Karwowski et al., 2020; Storme & Lubart, 2012), musical training (Kleinmintz, Goldstein, Mayseless, Abecasis, & Shamay-Tsoory, 2014; Kleinmintz et al., 2019), emotion (Mastria et al., 2019), and uncertainty (Lee et al., 2017; Mueller et al., 2012). Of particular note, research suggests that positive emotion may relate to higher creativity ratings (Mastria et al., 2019), while uncertainty relates to lower creativity ratings (Lee et al., 2017; Mueller et al., 2012). It has also been found that prevention focus (a tendency to minimize loss) is related to greater accuracy when evaluating usefulness and reduced accuracy when evaluating novelty, compared to promotion focus (a tendency to maximize reward; Herman & Reiter-Palmon, 2011). These findings suggest that more negative, uncertain, and avoidance-oriented states may lead raters to favor practicality over creativity, shunning novel ideas that may be associated with greater risk. By contrast, more positive, certain, and promotion-oriented states might lead raters to be more receptive to creative and novel ideas. In line with this research, it seems likely that an individual's personality and preference for risk-taking might also impact how they evaluate creativity, and indeed how they weigh novelty and usefulness when evaluating creativity.

Research into the link between personality and creativity has a rich history (Batey & Furnham, 2006; Feist, 1998). In particular, the Big Five trait openness/intellect has been found to relate to greater scores on virtually all forms of creativity assessment (Batey & Furnham, 2006; Feist, 1998; Kaufman et al., 2016; Oleynick et al., 2017). Openness/intellect is typified by imagination and artistic and intellectual curiosity, and may be assessed as a single construct or in terms of its twin aspects of openness and intellect (Kaufman et al., 2016; Oleynick et al., 2017). Among possible reasons for the link between greater openness/intellect and greater creativity is that those higher in the trait tend to seek out novelty and complexity, and are motivated by a recurrent desire to enlarge their experience (DeYoung, Peterson, & Higgins, 2005; Kaufman et al., 2016; McCrae & Ingraham, 1987; Oleynick et al., 2017).

Given this characterization, it seems possible that individuals with higher openness/intellect scores might be more receptive to creative ideas, and may place more importance on novelty and less on usefulness when evaluating creativity. It is also possible that openness and intellect, examined separately, are associated with different weightings of novelty and usefulness. For example, Kaufman et al. (2016) found that while openness predicts creative achievement in the arts, intellect predicts creative achievement in the sciences. As such, one might expect openness to relate to a greater consideration of novelty and intellect to relate to a greater consideration of usefulness when participants evaluate creativity. However, while some research has investigated how openness/intellect relates to the evaluation of creativity overall (Ceh, Edelmann, Hofer, & Benedek, 2022; Silvia, 2008), very little is known about how differences in openness/intellect relate to differences in how novelty and usefulness are weighted during the evaluation of creativity.

An individual's willingness to take risks might also affect how they evaluate creative ideas. By definition, creative ideas are different from the norm, and as their novelty increases, they may be less likely to be appropriate or useful (as is indicated by the negative relationship often found between novelty and usefulness; Caroff & Besançon, 2008; Diedrich et al., 2015; Runco & Charles, 1993). As such, individuals who are more willing to take risks might be more willing to pursue creative ideas, and may place more weight on novelty than usefulness when assessing creativity. The relationship between risk-taking and creativity is not as clear-cut as for openness/intellect, with some studies finding a positive relationship (Dewett, 2007; Glover & Sautter, 1977) and others finding no relationship (Erbas & Bas, 2015; Shen et al., 2018). More recent research suggests that it may be social risk-taking (and not risk-taking in other domains) that relates to greater creativity (Bonetto et al., 2021; Tyagi et al., 2017). However, it remains unknown how risk-taking affects the evaluation of creative ideas and the importance assigned to novelty and usefulness.

6.1.4 The present research

Empirical and theoretical work suggests that creative ideas are both novel and useful. However, while some research indicates that novelty is more important than usefulness to evaluations of creativity, it remains unknown how the contributions of these components depend on the nature of the creative task and how applicable it is to the real world. In addition, despite the importance of subjective assessments to creativity research, it is unclear how individual differences among raters can affect their evaluations of creativity and the importance they assign to novelty and usefulness.

To investigate these outstanding questions, this study followed a hierarchical, mixed-effects design (with ratings nested within participants) to examine how idea context and rater personality can affect the contributions of novelty and usefulness to evaluations of creativity. Participants rated the novelty, usefulness, and creativity of ideas from two contexts: AUT ideas and genuine suggestions for social development projects (subsequently referred to as "Projects"). Following these ratings, participants completed questionnaires assessing openness/intellect and risk-taking traits. Relationships between idea ratings and personality scores were then examined using both single-subject maximum likelihood estimation (SSMLE) and linear mixed-effects models (LMEMs).

I had several predictions, in line with the hypothesis that when evaluating creativity, raters would weigh the novelty and usefulness of an idea differently depending on their personality traits and the idea's context (i.e., real-world relevance). Concerning context, it was predicted that among AUT ideas, creativity ratings would be more related to novelty ratings than usefulness ratings (as found previously; Diedrich et al., 2015; Runco & Charles, 1993; Storme & Lubart, 2012). However, consistent with the notion that usefulness is a more important component of creativity in the context of more realistic problems (Long, 2014; Runco et al., 2005), it was also predicted that creativity ratings would be more related to usefulness ratings among Projects than among AUT ideas.

Concerning personality traits, it was predicted that openness and risk-taking would both be associated with a stronger relationship between novelty and creativity, among idea ratings in both contexts. This would be consistent with the notion that individuals who are more open to new ideas, and more likely to take risks, are more driven toward novelty and so value novelty more when evaluating creativity. No specific predictions were made regarding how intellect would moderate relationships; however, the study aimed to examine whether higher intellect scores would be associated with a stronger relationship between usefulness and creativity, given research linking intellect to creative achievement in the sciences, but not in the arts (Kaufman et al., 2016).

6.2 Methods

6.2.1 Participants

Using G*power software (version 3.1; Faul, Erdfelder, Lang, & Buchner, 2007), it was calculated that a sample size of 111 was required for a 95% power to detect correlations of r = .03 or greater. As such, 121 healthy human adults (88 females; mean age = 31.3 years, SD = 14.3) were recruited for the study. 36 were recruited from Goldsmiths, University of London and did not receive any financial incentive, while 85 were recruited via Prolific and were paid a small cash incentive. Among paid participants, participation was contingent on a Prolific approval rating of 90% or above and a minimum of 40 previously completed studies. Fluency in English was required for participants in both samples due to the nature of the task, which involved evaluating the creativity of verbal ideas. Among both paid and non-paid participants, informed consent was given prior to data collection. Ethical approval for the study was given by the Local Ethics Committee of the Department of Psychology at Goldsmiths, University of London.

6.2.2 Materials

Idea ratings: AUT responses.

AUT ideas were 48 suggested uses for one of two objects: “table” and “shoe”. The ideas were carefully selected from a total of 1866 responses produced by participants in a prior study (Luft et al., 2018), to ensure an even distribution in terms of creative quality. Each idea had been rated for creativity on a scale from 1 to 10 by three raters. For the present study, scores were averaged across these raters to produce one creativity score per idea. Ideas were then spelling-corrected, and repeated items were removed. Next, histograms of idea creativity were examined for each object. Ideas for both objects were highly skewed, with very few ideas scoring above 8 in creativity. To produce more even distributions, ratings of 9 or 10 were recoded as 8. Ideas were then separated into four bins, each corresponding to a rating of 1-2, 3-4, 5-6, and 7-8. For each object, 48 ideas were pseudorandomly selected (for a total of 96), such that 12 ideas came from each rating bin. These were then manually checked, and inappropriate or very similar ideas were removed, leaving 24 ideas per object (48 in total). Finally, ideas were rephrased for succinctness.

Idea ratings: social development Projects.

Projects were 10 suggestions for urban planning projects that might “restore vibrancy in cities and regions facing economic decline”. During a prior study (Pétervári, 2018), Projects had been selected from an open-source platform (OpenIDEO, 2011) from among entrees into a competition, and reduced to two-paragraph descriptions. Participants in this prior study (N = 80) rated their willingness to invest in each Project on a scale from 0 to 100, which was assumed to indicate the

Project's overall quality. For the present study, 10 Projects were selected from a total of 15, due to time constraints and the longer length of the Project descriptions compared to the AUT ideas. This was achieved by removing the 5 Projects with the most variable ratings, which increased the uniformity of the quality scores across Projects.

***Openness/Intellect*.**

The Openness/Intellect subscale of the Big Five Aspect Scale (BFAS; DeYoung et al., 2007) was used to assess openness and intellect (see Chapter 3).

***Risk-taking*.**

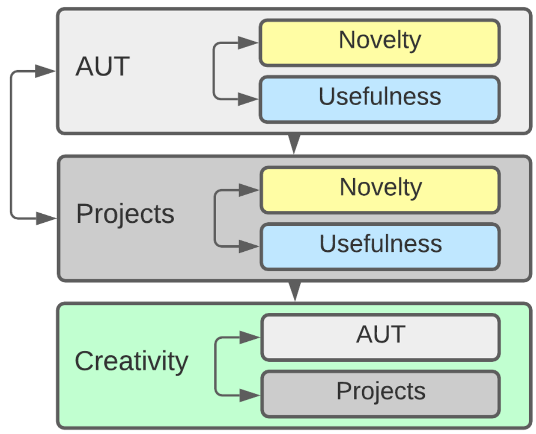
The Domain Specific Risk-taking Scale (DSRS; Blais & Weber, 2006) was used to assess risk-taking (see Chapter 3).

6.2.3 Procedure

All data was collected using Qualtrics software. Participants completed idea ratings first, and personality measures second. Idea rating trials were organized into blocks by idea context (i.e., AUT or Projects), and by property (i.e., novelty, usefulness, or creativity). Participants completed blocks in one of four orders to counterbalance the order of contexts and properties. Specifically, half of the participants completed AUT ratings first, while half completed Projects ratings first. Within these groups, half of the participants completed novelty ratings first, while the other half completed usefulness ratings first. All participants completed ratings for overall creativity last, though the order of AUT ideas and Projects varied within creativity ratings (see Figure 11). Within each block (e.g., novelty ratings for AUT ideas) trials were randomized.

Figure 11

Order of rating blocks (top to bottom)



Note. The order of contexts (i.e., AUT ideas or Projects) and properties (i.e., novelty or usefulness) were counterbalanced. Double-ended arrows denote interchangeability dependent on counterbalancing conditions. Creativity ratings were always completed last.

Participants were initially told only that they would be "evaluating ideas". No instructions regarding novelty, usefulness, or creativity were given until participants began the corresponding block. As such, participants were naive to the fact that they would be rating creativity until after they had completed both novelty and usefulness ratings. Upon starting each block, participants were told they would be asked to rate the novelty, usefulness, or creativity of either "ideas for how to use common, everyday objects" or "real proposals for urban planning projects". Participants were then given further instructions to help them consider the property in question. Specifically, for novelty, usefulness, and creativity respectively, they were told to think about: "how novel, unusual, or unexpected each idea is"; "how useful, effective, or practical each idea is"; or "how creative each idea is". Since instructions pertaining to creativity often ask participants to focus on originality, novelty, usefulness, or appropriateness (Acar et al., 2019), and since these components were being rated separately in this study, creativity was deliberately left open to interpretation, with minimal additional instructions. Participants then completed two (Projects) or five (AUT) practice ratings before seeing the same instructions again and beginning the real trials. Instructions were repeated to emphasize the points participants should consider in their ratings.

Within each trial, participants were shown a single line of instruction (e.g., “How NOVEL is this idea for how to restore vibrancy in cities and regions facing economic decline?”, or “How USEFUL is this idea for how to use a table?”), together with the idea itself, and a scale from 1 (not at all) to 7 (very). After finishing all ratings, participants completed questionnaires assessing openness/intellect and risk-taking.

6.2.4 Analyses

Analyses made use of both SSMLE and LMEMs. LMEMs can account for the dependence of multiple data points from a single individual (here, ratings for different ideas), modeling them as random effects (Singmann & Kellen, 2019). This allowed us to model unique relationships between novelty, usefulness, and creativity for each participant, while simultaneously estimating group-level effects (McNeish & Kelley, 2019). By contrast, SSMLE (Katahira, 2016) is a more intuitive approach that involves fitting a standard linear regression for each participant separately. While this approach is known to be generally less powerful than LMEMs (see Stein’s paradox; Efron & Morris, 1977; Katahira, 2016), SSMLE provides distributions of predictor estimates (e.g., for novelty and usefulness) which can then be compared for significant differences, while correlations can be computed between parameter estimates and individual differences (e.g., openness). The two forms of analysis have different assumptions, and so using both together can provide a richer understanding of the examined relationships, as well as an indication of the robustness of findings (see Steegen, Tuerlinckx, Gelman, & Vanpaemel, 2016).

SSMLE was conducted first, and separately for AUT ideas and Projects, to compare the relative importance of novelty and usefulness when evaluating creativity in both contexts. Regressions were fitted for each participant individually, with creativity as the dependent variable and novelty and usefulness as joint predictors (i.e., novelty and usefulness were simultaneously present in each regression). Prior to computing regressions, creativity, novelty, and usefulness ratings were z-scored within participants. The standardized beta coefficients for novelty and usefulness were then used in further analyses, to compare the coefficients between idea contexts, and to examine relationships between coefficients and personality measures.

Following the SSMLE analyses, a series of LMEMs were computed to further examine the relationships between creativity, novelty, and usefulness ratings, and to test whether these relationships were significantly moderated by context and participants' personality scores. In addition, the study aimed to test for a significant interaction between novelty and usefulness, as has been found previously (Diedrich et al., 2015). Three LMEMs were computed, all of which had creativity rating as the dependent variable. These models were constructed by successively adding effects to create more complex versions of the model, comparing each model to the previous, simpler model via likelihood ratio testing (e.g., Wilken, Forthmann, & Holling, 2020). This should reveal whether each added effect contributes significantly to model fit. Models were computed using custom MATLAB scripts and the fitlme function. As with SSMLE, creativity, novelty, and usefulness were z-scored within participants. In addition, personality scores were z-scored across participants.

6.3 Results

Of 121 participants, data for nine were removed due to these participants failing attention checks or responding randomly. One additional participant's data was removed from all analyses involving the Projects ratings due to incomplete data for this part of the study. The final sample sizes were thus 112 for the AUT data and 111 for the Projects data.

To check for differences between paid (N = 76) and non-paid (N = 36) samples, a series of independent samples t-tests were conducted. No significant differences were found between paid and non-paid participants, either in terms of novelty, usefulness, or creativity ratings (among either AUT ideas or Projects) or in terms of personality measures (ps >.235).

6.3.1 Descriptive statistics

Descriptive statistics and zero-order correlations for participants' personality scores and novelty, usefulness, and creativity ratings are shown in Table 22. Here, idea ratings are averaged within participants to produce a single score for each rating block and each participant.

Table 22

Means, standard deviations, and correlation coefficients for personality measures and participant-level idea ratings

	Mean	*SD*	1	2	3	4	5	6	7	8	9
1. Openness	38.63	5.47	-								
2. Intellect	37.11	5.79	.32**	-							
3. Risk General	93.88	22.33	-.04	.18	-						
4. Risk Social	30.81	5.21	.19*	.31**	.47**	-					
5. AUT Nov.	4.03	0.60	.02	.12	.00	-.10	-				
6. AUT Use.	3.81	0.57	-.03	-.14	-.04	.06	-.09	-			
7. AUT Crea.	3.94	0.66	.10	.13	.01	-.13	.51**	.03	-		
8. Proj. Nov.	4.57	0.81	.03	.03	-.11	.13	.25**	.18	.31**	-	
9. Proj. Use.	4.67	0.75	.02	-.06	.07	.14	.05	.31**	.15	.49**	-
10. Proj. Crea.	4.88	0.79	.15	-.07	.05	.12	.10	.13	.31**	.60**	.61**

Note. Risk General = general risk-taking; Risk Social = social risk-taking; Nov. = novelty; Use. = usefulness; Crea. = creativity; Proj. = Projects. * p <.05., ** p <.01.

Creativity was positively related to novelty, among both AUT (r = .51, p < .001) and Project ratings (r = .60, p < .001). By contrast, creativity was positively related to usefulness only among Project ratings (r = .61, p < .001), not AUT ratings (r = .03, p = .758). In addition, novelty and usefulness ratings were positively correlated only among Project ratings (r = .49, p < .001). While correlations between personality measures and participants' mean ratings were of secondary interest in this study (which is primarily interested in how personality measures moderate relationships between creativity ratings and novelty and usefulness ratings), it was notable that no personality measures were significantly correlated with mean ratings for novelty, usefulness, or creativity (ps > .126). Within personality measures, social risk-taking was robustly correlated with intellect (r = .60, p = .001) and weakly correlated with openness (r = .19, p = .048). Meanwhile, general risk-taking was weakly and not significantly correlated with intellect (r = .18, p = .063), and did not correlate with openness (r = -.04, p = .709).

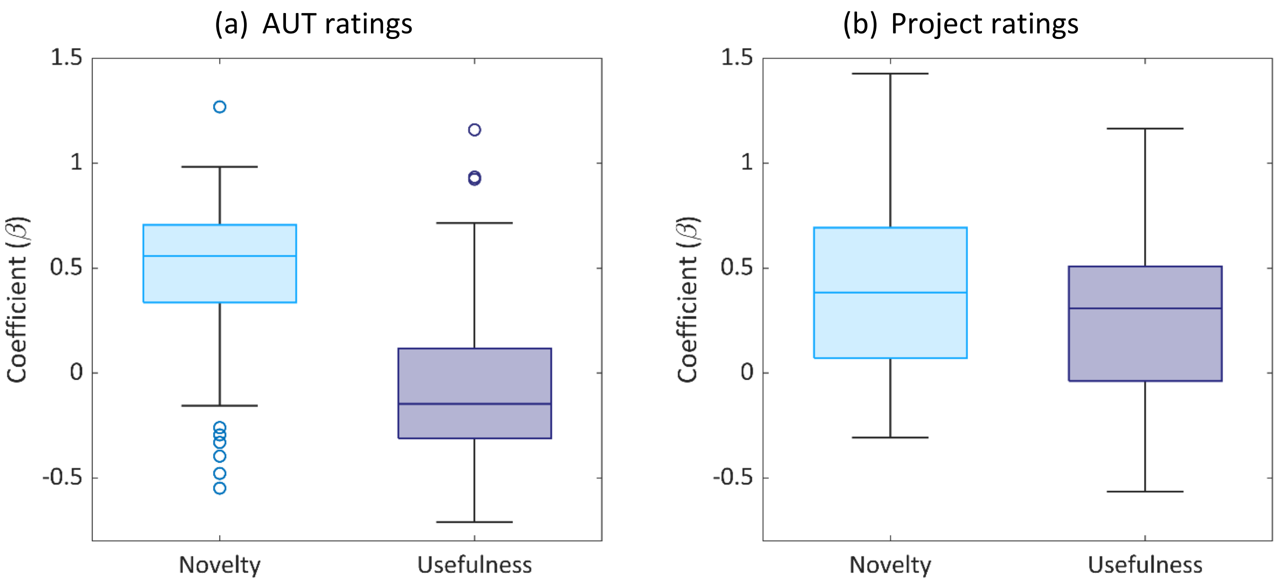
6.3.2 Single-subject maximum likelihood estimation

SSMLE was conducted for AUT ideas and Projects separately, to estimate standardized coefficients for novelty and usefulness for each participant individually. Differences between coefficients within and across contexts, and relationships between coefficients and personality measures were then examined. Since the statistical significance of individual participant estimates is not of interest to this study, significance values for individual estimates are not included here.

Across all participants, within AUT ideas, coefficients had a mean of 0.48 (*SD* = 0.33) for novelty, and 0.08 (*SD* = 0.33) for usefulness. With Projects, coefficients had a mean of 0.38 (*SD* = 0.39) for novelty, and 0.24 (*SD* = 0.38) for usefulness. Boxplots summarizing the distributions of these coefficients are presented in Figure 12.

Figure 12

Boxplots showing means and ranges for standardized novelty and usefulness coefficient estimates across all participants, for AUT ratings (a), and Projects ratings (b)



A series of between-participants t-tests were conducted to test for significant differences between novelty and usefulness coefficients, both within and between idea contexts (AUT ideas and Projects). In all t-test results, Cohen's d_{av} is reported as a measure of effect size (Lakens, 2013). Results are summarized in Table 23. Novelty coefficients were significantly larger than usefulness coefficients among both AUT ratings and Projects ratings. Comparing across idea context, novelty coefficients were significantly higher among AUT ratings than Projects ratings. By contrast, usefulness coefficients were significantly higher among Projects ratings than AUT ratings. Together, results suggest that novelty plays a greater role in evaluations of creativity than usefulness in both contexts, but is more important in the context of AUT ideas. In addition, results indicate that usefulness is far more important to evaluations of creativity among urban planning projects than among AUT ideas.

Table 23
Results of t-tests comparing novelty and usefulness coefficients within and between task types

	t (d.f.)	*p*	Cohen's d_{av}
AUT: Novelty β > Usefulness β	13.63 (111)	.000	1.29
Projects: Novelty β > Usefulness β	2.35 (110)	.020	0.22
Novelty β: AUT > Projects	2.39 (110)	.018	0.23
Usefulness β: AUT < Projects	7.43 (110)	.000	0.71

Next, I examined whether the weightings given to novelty and usefulness relate to aspects of participants' personalities. Correlations between participant personality scores and novelty and usefulness coefficients, for ideas in both contexts, are shown in Table 24.

Table 24
Correlations between novelty and usefulness coefficient estimates and personality scores

Task	Coefficient	Openness	Intellect	Risk General	Risk Social
AUT	Novelty β	.23*	.22*	-.03	-.01
	Useful β	.04	.09	.03	-.03
Projects	Novelty β	-.03	-.15	-.14	-.03
	Useful β	.20*	.16	.01	.02

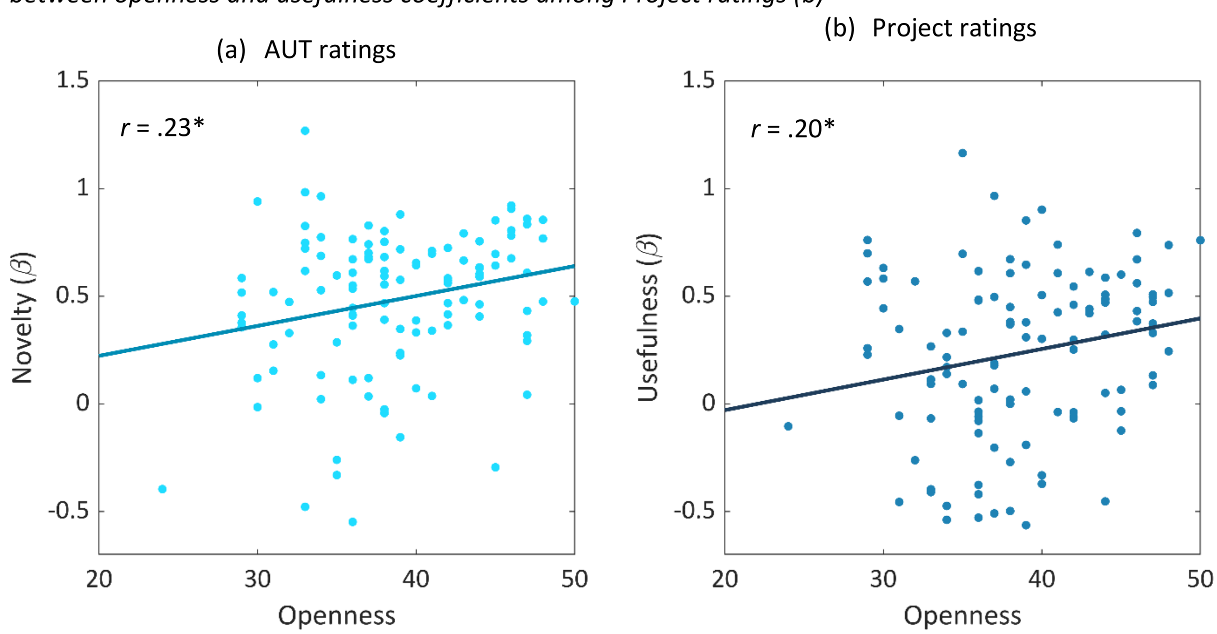
Note. Risk General = general risk-taking; Risk Social = social risk-taking.
* $p < .05$.

Among AUT ratings, novelty coefficients were significantly and positively correlated with both openness ($r = .23$, $p = .015$) and intellect ($r = .22$, $p = .023$) scores, while no significant relationships were found between usefulness coefficients and any personality measures (*p*s > .344). By contrast, among Project ratings, participants' novelty coefficients were not significantly related to any personality measures (*p*s > .128), while usefulness coefficients were significantly and positively correlated with openness score ($r = .20$, $p = .033$), and positively but non-significantly related to intellect score ($r = .16$, $p = .085$). Together, results suggest that participants' openness and intellect scores may differently moderate the contributions of novelty and usefulness to evaluations of creativity depending on the context (see Figure 13). Specifically, when evaluating the creativity of AUT ideas, those higher in openness and intellect may place more weight on novelty, while when evaluating the creativity of urban planning projects, the same participants may place more weight on usefulness.

Notably, no measures of risk-taking were found to be significantly related to either novelty or usefulness coefficients, either among AUT ideas or Projects (*ps* > .159). Therefore, risk-taking measures were left out of subsequent LMEM analyses.

Figure 13

Scatterplots of the relationships between openness and novelty coefficients among AUT ratings (a) and between openness and usefulness coefficients among Project ratings (b)



Note. * $p < .05$.

6.3.3 Linear mixed-effects models

The first LMEM (Model 1) was primarily a sanity check to confirm the results of the SSMLE analyses, which had found significant differences between novelty and usefulness coefficients across idea context. As such, this model aimed to test whether idea context significantly moderated the relationships between creativity and novelty and usefulness. In addition, two further LMEMs were constructed to examine AUT ideas (Model 2) and Projects (Model 3) separately. These models were identical in structure and aimed to examine the relative contributions of novelty and usefulness to creativity, the significance of the interaction between novelty and usefulness, and the significance of interactions between openness and intellect and novelty and usefulness. Predictors for novelty, usefulness, openness and intellect (and their interactions) were added successively. Due to multicollinearity concerns, openness and intellect were added separately in the final step of both Model 2 and Model 3.

Model 1 (examining the effect of context) began with a null model containing only random intercepts across participants, with no fixed effects. Following this, main effects for novelty and usefulness were added (Model 1A) before random slopes for novelty and usefulness were added (Model 1B). Finally, the main effect for context was added together with interactions between context and novelty and usefulness (Model 1C).

Results are presented in Table 25. Comparing Model 1A to the null model, adding main effects for both novelty and usefulness improved model fit, as indicated by likelihood ratio testing and information criteria. Significant effects were found for both novelty ($\beta = 0.53$, $SE = 0.01$, $p < .001$), and usefulness ($\beta = -0.10$, $SE = 0.01$, $p < .001$). Adding random effects slopes for novelty and usefulness in Model 1B also improved model fit, confirming that novelty and usefulness contribute differently to creativity across participants. Finally, in Model 1C, adding effects for context again improved model fit significantly. The main effect of context was not significant ($p > .999$), while interactions between novelty and context ($\beta = 0.10$, $SE = 0.03$, $p < .001$), and usefulness and context ($\beta = -0.35$, $SE = 0.03$, $p < .001$), were highly significant. These results confirm that novelty and usefulness had different relationships with creativity across contexts. Indeed, since AUT ideas were coded as 1 and Projects as 0, the positive moderation effect of Novelty x Context reflects the fact that novelty was more related to creativity among AUT ideas than Projects. Conversely, the negative and larger moderation effect of Usefulness x Context reflects the fact that usefulness was far more related to creativity among Projects than AUT ideas. These results are completely consistent with the SSMLE results (see Table 23 above).

Table 25

Linear Mixed-Effects Model (LMEM) of Creativity Ratings for AUT ideas and Projects together, with Predictor Estimates for Novelty, Usefulness, and Context and Interactions

	Null Model		Model 1A		Model 1B		Model 1C	
Fixed effects	β	(SE_b)	β	(SE_b)	β	(SE_b)	β	(SE_b)
Intercept	0.00	(0.01)	0.00	(0.01)	0.00	(0.01)	0.00	(0.02)
N			0.53	(0.01)***	0.53	(0.03)***	0.40	(0.03)***
			-		-			
U			0.10	(0.01)***	0.05	(0.02)	0.23	(0.03)***
Context							0.00	(0.02)
N x Context							0.10	(0.03)***
							-	
U x Context							0.35	(0.03)***
Random Effects	s^2		s^2		s^2		s^2	
Intercept	0.00		0.00		0.00		0.00	
N					0.24		0.22	
U					0.23		0.23	
Model Comparison								
AIC	18185.55		15624.00		15624.00		14598.48	
BIC	18205.88		15657.89		15657.89		14686.58	
$R^2(m)$	.00		.33		.33		.46	
$\Delta\chi^2$ (*df*)			2565.55 (5) ***		2565.55 (10)***		172.61 (13)***	

Note. N = Novelty; U = Usefulness; Context = AUT ideas (coded as 1) vs Projects (coded as 0); Results for fixed effects are presented as standardized regression coefficients with standard error in parentheses; s^2 is the standard error estimate for random intercepts and slopes; Model 1A is compared to the null model, Model 1B is compared to Model 1A, Model 1C is compared to Model 1B; AIC = Akaike's Information Criterion; BIC = Bayesian Information Criterion; $R^2(m)$ = proportion of variation explained by fixed effects (Nakagawa & Schielzeth, 2013); $\Delta\chi^2$ = Likelihood ratio test statistic for comparison of models.
*** $p < .001$.

For Model 2 (examining AUT ideas), following the null model (which again contained only random intercepts across participants), main effects for novelty and usefulness were added (Model 2A) before random slopes for novelty and usefulness were added (Model 2B). Next, an interaction effect between novelty and usefulness was added (Model 2C) before main effects and interactions were added for openness (Model 2D.1) and intellect (Model 2D.2) separately.

Results are presented in Table 26. As expected, adding main effects for novelty and usefulness improved the fit of Model 2A relative to the null model. Adding random effects slopes for novelty and usefulness in Model 1B also improved model fit. Significant main effects were found for both novelty (β = 0.50, *SE* = 0.03, $p < .001$), and usefulness (β = -0.11, *SE* = 0.03, $p < .001$). In Model 2C, a significant interaction was found between novelty and usefulness ($\beta = 0.08$, $SE = 0.01$, $p < .001$), and this added effect again improved model fit. This result is broadly comparable to previous research that has examined ratings for AUT ideas (Diedrich et al., 2015), which found that usefulness was less related to creativity among non-novel (i.e., common) ideas, and more related to creativity among novel ideas. However, in the present data, usefulness was found to be negatively related to creativity among non-novel AUT ideas, while being unrelated to creativity among novel AUT ideas (see Figure 14). Comparing Models 2D.1 and 2D.2 to Model 2C, neither openness nor intellect significantly improved model fit. Main effects for openness and intellect were non-significant (*p*s > .583), however significant interactions were found between both novelty and openness ($\beta = 0.07$, $SE = 0.03$, $p = .015$; see Figure 15a) and novelty and intellect ($\beta = 0.07$, $SE = 0.03$, $p = .014$), suggesting that both aspects of Openness/Intellect lead to a greater consideration of novelty when participants evaluated the creativity of AUT ideas. Neither openness nor intellect interacted significantly with usefulness (*p*s > .185).

Table 26

Linear Mixed-Effects Model (LMEM) of Creativity Ratings for AUT Ideas, with Predictor Estimates for Novelty, Usefulness, and Personality Factors and Interactions

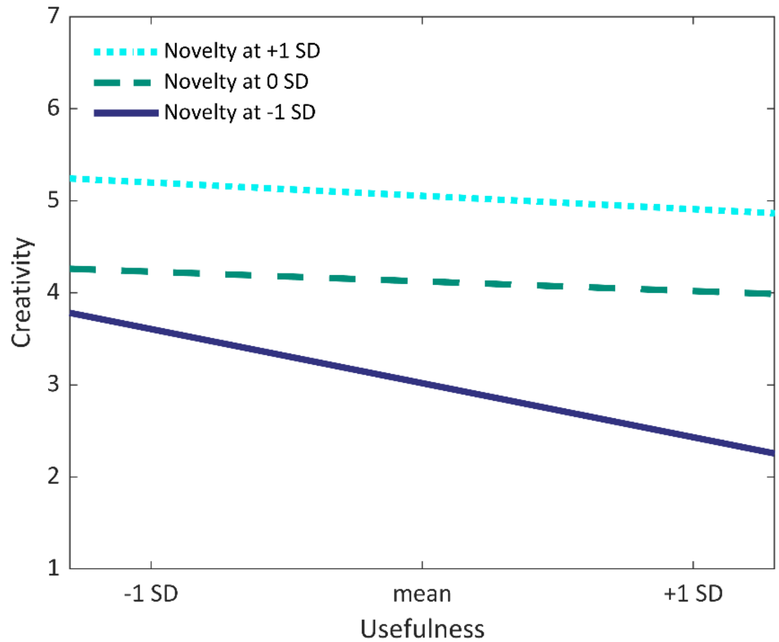
	Null Model		Model 2A		Model 2B		Model 2C		Model 2D.1		Model 2D.2	
Fixed effects	β	(SE_b)	β	(SE_b)	β	(SE_b)	β	(SE_b)	β	(SE_b)	β	(SE_b)
Intercept	0.00	(0.01)	0.00	(0.01)	0.00	(0.01)	0.04	(0.01)***	0.04	(0.01)***	0.04	(0.01)***
N			0.49	(0.01)***	0.50	(0.03)***	0.49	(0.03)***	0.49	(0.03)***	0.49	(0.03)***
			-		-		-		-		-	
U			0.17	(0.01)***	0.11	(0.03)***	0.10	(0.03)***	0.10	(0.03)***	0.10	(0.03)***
N x U							0.08	(0.01)***	0.08	(0.01)***	0.08	(0.01)***
O									0.00	(0.01)		
N x O									0.07	(0.03)*		
U x O									0.03	(0.03)		
I											0.01	(0.01)
N x I											0.07	(0.03)*
U x I											0.04	(0.03)
Random Effects	s^2		s^2		s^2		s^2		s^2		s^2	
Intercept	0.00		0.00		0.00		0.02		0.02		0.02	
N					0.27		0.27		0.26		0.26	
U					0.28		0.28		0.28		0.27	
Model Comparison												
AIC	15149.24		12752.45		11846.56		11793.32		11793.48		11792.93	
BIC	15169.01		12785.40		11912.45		11865.81		11885.74		11885.18	
$R^2(m)$	.00		.36		.50		.50		.50		.50	
$\Delta\chi^2$ (*df*)			2400.79 (5)***		915.90 (10)***		55.24 (11)***		5.84 (14)		6.39 (14)	

Note. N = Novelty; U = Usefulness; O = Openness; I = Intellect; Results for fixed effects are presented as standardized regression coefficients with standard error in parentheses; s^2 is the standard error estimate for random intercepts and slopes; Model 2A is compared to the null model, Model 2B is compared to Model 2A, Model 2C is compared to Model 2B, and Model 2D.1 and 2D.2 are each compared to Model 2C; AIC = Akaike's Information Criterion; BIC = Bayesian Information Criterion; $R^2(m)$ = proportion of variation explained by fixed effects (Nakagawa & Schielzeth, 2013). $\Delta\chi^2$ = Likelihood ratio test statistic for comparison of models.

* $p < .05$; *** $p < .001$.

Figure 14

Simple slopes plot of the interaction between novelty and usefulness as predictors of creativity among AUT ratings



Model 3 was constructed in exactly the same way as Model 2 but now applied in the context of Projects rather than AUT ideas. Results are presented in Table 27. Relative to the null model, adding main effects for novelty and usefulness again improved the fit of Model 3A. Adding random effects slopes for novelty and usefulness in Model 3B also improved model fit. Significant main effects were found for both novelty (β = 0.41, *SE* = 0.03, *p* < .001), and usefulness (β = 0.22, *SE* = 0.03, *p* < .001). In Model 3C, an interaction between novelty and usefulness was added, but this was non-significant (β = -0.04, *SE* = 0.03, *p* = .116), and did not improve model fit. Comparing Models 3D.1 and 3D.2 to Model 3C, neither openness nor intellect significantly improved model fit. Main effects for openness and intellect were non-significant (*p*s > .964). A significant interaction was found between usefulness and openness (β = 0.08, *SE* = 0.03, *p* = .020), while an interaction between usefulness and intellect did not reach significance (β = 0.06, *SE* = 0.03, *p* = .063). These results suggest that participants who are higher in openness may place greater importance on usefulness when evaluating the creativity of Projects (see Figure 15b). Neither openness nor intellect interacted significantly with novelty (*p*s > .155).

Table 27

Linear Mixed-Effects Model (LMEM) of Creativity Ratings for Projects, with Predictor Estimates for Novelty, Usefulness, and Personality Factors and Interactions

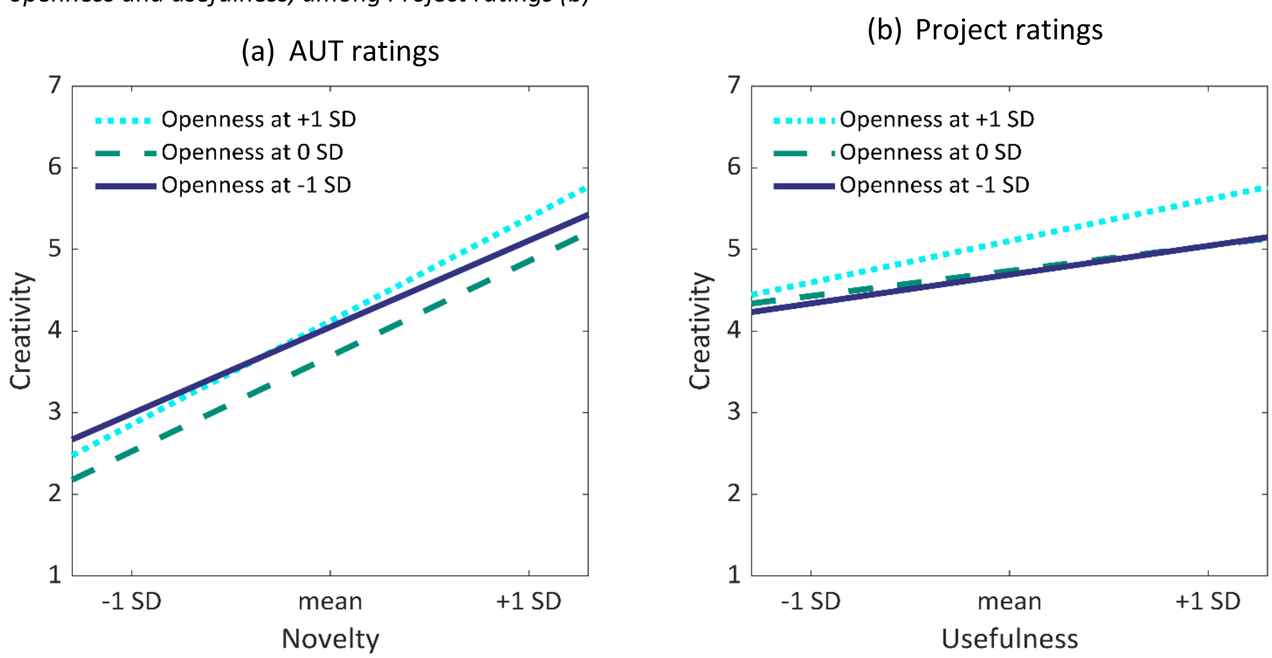
	Null Model		Model 3A		Model 3B		Model 3C		Model 3D.1		Model 3D.2	
Fixed effects	β	(SE_b)	β	(SE_b)	β	(SE_b)	β	(SE_b)	β	(SE_b)	β	(SE_b)
Intercept	0.00	(0.03)	0.00	(0.02)	0.00	(0.02)	0.01	(0.02)	0.01	(0.02)	0.01	(0.02)
N			0.41	(0.03)***	0.40	(0.03)***	0.39	(0.03)***	0.39	(0.03)***	0.39	(0.03)***
U			0.22	(0.03)***	0.23	(0.03)***	0.23	(0.03)***	0.23	(0.03)***	0.23	(0.03)***
N x U							-0.04	(0.03)	-0.04	(0.03)	-0.04	(0.03)
O									0.00	(0.02)		
N x O									-0.01	(0.03)		
U x O									0.08	(0.03)*		
I											0.00	(0.02)
N x I											-0.05	(0.03)
U x I											0.06	(0.03)
Random Effects	s^2		s^2		s^2		s^2		s^2		s^2	
Intercept	0.00		0.00		0.00		0.00		0.00		0.00	
N					0.22		0.22		0.22		0.21	
U					0.24		0.24		0.23		0.23	
Model Comparison												
AIC	3056.37		2712.51		2680.53		2680.06		2680.25		2682.07	
BIC	3071.44		2737.62		2730.74		2735.29		2750.54		2752.37	
$R^2(m)$	.00		.27		.35		.35		.35		.35	
$\Delta\chi^2$ (*df*)			347.86 (5)***		41.99 (10)***		2.47 (11)		5.81 (14)		3.99 (14)	

Note. N = Novelty; U = Usefulness; O = Openness; I = Intellect; Results for fixed effects are presented as standardized regression coefficients with standard error in parentheses; s^2 is the standard error estimate for random intercepts and slopes; Model 3A is compared to the null model, Model 3B is compared to Model 3A, Model 3C is compared to Model 3B, and Model 3D.1 and 3D.2 are both compared to Model 3C; AIC = Akaike's Information Criterion; BIC = Bayesian Information Criterion; $R^2(m)$ = proportion of variation explained by fixed effects (Nakagawa & Schielzeth, 2013); $\Delta\chi^2$ = Likelihood ratio test statistic for comparison of models.

* $p < .05$; *** $p < .001$.

Figure 15

Simple slopes plot of the interaction between openness and novelty, among AUT ratings (a), and between openness and usefulness, among Project ratings (b)



6.4 Discussion

If creative ideas are both novel and useful (Runco & Jaeger, 2012; Stein, 1953), individuals should weigh up these two components when evaluating the creativity of ideas. The present study focused on the evaluation of exogenous (i.e., non-self-generated) ideas, and examined how the weightings applied to novelty and usefulness vary according to the context of the idea and the personality of the rater. Both SSMLE and LMEM analyses indicated that the relative importance of novelty and usefulness to evaluations of creativity can vary widely over different contexts, and that those with different personalities may consider novelty and usefulness to different extents. Specifically, while novelty was more important to evaluations of creativity than usefulness among both AUT ideas and Projects, I found that usefulness was far more important in the context of Projects than in the context of AUT ideas. Moreover, I found that individuals higher in openness (and to a lesser extent, intellect) placed a greater emphasis on novelty when evaluating AUT ideas, while placing a greater emphasis on usefulness when evaluating Projects.

The finding that raters generally consider novelty more than usefulness when evaluating creativity was in line with predictions and with prior research (Acar et al., 2017; Caroff & Besançon, 2008; Diedrich et al., 2015; Han et al., 2021; Runco & Charles, 1993). Among both AUT ideas and Projects, novelty coefficients were significantly greater than usefulness coefficients in SSMLE analyses, while LMEMs found larger coefficients for novelty than usefulness in both contexts.

However, I also found clear differences between contexts. In line with predictions, raters considered novelty more in the context of AUT ideas, and usefulness more in the context of Projects. Specifically, LMEMs revealed significant interactions between idea context and both novelty and usefulness, while SSMLE analyses revealed greater novelty coefficients among AUT ideas than Projects, and greater usefulness coefficients among Projects than AUT ideas. Indeed, separate LMEMs for AUT ideas and Projects suggested that while usefulness was negatively related to creativity among AUT ideas, it was positively related to creativity among Projects. These findings are consistent with the notion that different contexts can lead to different considerations of novelty and usefulness (Long, 2014; Runco et al., 2005). In contexts such as the AUT, where ideas are unlikely to be used in the real world, usefulness may not contribute to evaluations of creativity, or may even contribute negatively. By contrast, in contexts where ideas are clearly applicable to the real-world, usefulness may play a far greater role in evaluations of creativity. These results extend previous research by highlighting how the context in which an idea was generated can impact evaluations of creativity.

Considering the role of rater personality in evaluations of creativity, findings were more nuanced than expected. While it was predicted that higher openness would be related to a greater consideration of novelty, this was only the case in the context of AUT ideas. In the context of Projects, higher openness was related to a greater consideration of usefulness. In addition, while it was suggested that intellect might relate to a greater consideration of usefulness in both contexts, intellect actually followed the same context-dependent pattern as openness. Specifically, among AUT ideas, both openness and intellect were positively correlated with SSMLE novelty coefficients, while significant interactions between these traits and novelty were found in an LMEM. By contrast, among Projects, openness and intellect were positively correlated with SSMLE usefulness coefficients (though for intellect this correlation was non-significant), while significant interactions between openness and usefulness were found in an LMEM. Indeed, there was no evidence to suggest that openness and intellect were differently related to considerations of novelty and usefulness, as might be expected based on the different relationships between these traits and achievements in the arts and sciences (Kaufman et al., 2016). Overall, this suggests that the twin aspects of openness and intellect may be better considered as a single trait in the context of creativity evaluations.

Also contrary to predictions, no significant relationships were found between risk-taking and novelty and usefulness coefficients, suggesting that an individual's preference for risk-taking does not relate to different considerations of these components when evaluating creativity. However, it is important to consider that the present study examined the evaluation of exogenous ideas. If participants had instead evaluated the creativity of their own ideas, it is plausible that their risk-taking preference, and indeed their openness/intellect score, might have a more profound impact on their consideration of novelty and usefulness (see Rodriguez et al., 2020; Silvia, 2008).

Considering other findings, in line with previous research (Diedrich et al., 2015) an interaction was found between novelty and usefulness among AUT ideas. Examination of a simple slopes plot of this interaction (see Figure 14) indicates that, in the present study, usefulness was negatively related to creativity among non-novel ideas and unrelated to creativity among novel ideas. By contrast, no such interaction was found among Projects. It was also notable that openness and intellect did not show significant main effects as predictors of creativity in the LMEMs, either among AUT ideas or among Projects. Indeed, no significant correlations were found between any personality measures and participant mean ratings for creativity, novelty, or usefulness in either context. This suggests that while the trait openness/intellect plays a role in how raters weigh novelty and usefulness, it may not impact overall creativity judgements, at least in the case of exogenous ideas.

6.4.1 Impact and implications

To my knowledge, the present study is the first to investigate how differences in idea context and rater personality can lead to different considerations of novelty and usefulness during evaluations of creativity. These findings help extend a growing body of work that has examined how individuals consider novelty and usefulness when evaluating creativity (Acar et al., 2017; Caroff & Besançon, 2008; Diedrich et al., 2015; Runco & Charles, 1993; Storme & Lubart, 2012), and how variations in the evaluation of creativity relate to individual differences (Herman & Reiter-Palmon, 2011; Karwowski et al., 2020; Lee et al., 2017; Mastria et al., 2019; Mueller et al., 2012). Overall, these findings highlight the importance of considering contextual and interpersonal factors when researchers examine how creativity is evaluated, defined, and perceived, strengthening recent calls for creativity assessments that can account for variation across raters (Barbot et al., 2019; Myszkowski & Storme, 2019). Indeed, it seems likely that both the generation and evaluation of creative ideas may involve markedly different processes depending on both the individual in question and the context of the problem. Different individuals may consider different criteria more important than others when performing creative tasks and may use a different balance of cognitive processes to produce ideas that meet these criteria. Similarly, different creative contexts may call for different levels of novelty and usefulness (or other components), leading individuals to weigh these aspects differently when they evaluate ideas depending on the specific requirements of the problem.

6.4.2 Limitations and future directions

One limitation of the present research is that it did not assess the intelligence or creativity of the raters. Intelligence has been linked to a greater consideration of novelty when raters evaluate creativity (Storme & Lubart, 2012), and it would be interesting to examine how intelligence interacts with the consideration of novelty and usefulness in different contexts. For example, intelligence might follow a similar pattern to openness, relating to a greater consideration of novelty among AUT ideas and greater consideration of usefulness among real-world projects. Meanwhile, assessing creativity would allow researchers to better examine links between how individuals generate their ideas and how they evaluate the ideas of others. For example, do individuals who tend to generate highly novel but non-useful ideas themselves also consider novelty more than usefulness when evaluating the ideas of others? These questions should be examined by future research.

Indeed, assessing the creativity of raters (e.g., by having them complete the AUT) would also provide an opportunity for them to evaluate their own ideas. The present study focused on the evaluation of exogenous ideas which, while more relevant to creativity assessment methodologies, has been found to differ from the evaluation of self-generated ideas (Karwowski et al., 2020; Rodriguez et al., 2020; Runco & Smith, 1992). It is possible that individuals consider novelty and usefulness differently when evaluating the creativity of their own ideas as opposed to others' ideas. It is also possible that personality traits play a different role depending on whether participants evaluate their own ideas or others' ideas. For example, research has found that individuals with higher general personality scores provide higher-quality evaluations of exogenous ideas, but lower-quality evaluations of their own ideas (Rodriguez et al., 2020). As such, future studies could examine and compare evaluations of both self-generated and exogenous ideas.

Moreover, the present study focused on only the two most widely discussed components of creativity: novelty and usefulness. However, research suggests that additional factors, such as surprise (Acar et al., 2017; Simonton, 2018), may also be considered by individuals when they evaluate creativity. Indeed, the best-fitting LMEMs in the present study only explained around 50% of the variance in creativity ratings, indicating considerable room for other explanatory factors. Future studies could therefore collect additional ratings for other components of creativity.

A further option for future studies is to examine relationships between mood and uncertainty and the weightings placed on novelty and usefulness. Indeed, prior research has indicated that more positive moods (Mastria et al., 2019), and more certainty among raters (Lee et al., 2017), relate to higher creativity ratings of exogenous ideas, while greater promotion focus is related to more accuracy when evaluating the novelty of one's own ideas (Herman & Reiter-Palmon, 2011). Together, this research implies that some individuals may show a greater affinity for creative and novel ideas, and led us to expect that those with higher openness and risk-taking scores might place a greater emphasis on novelty when evaluating creativity. However, the relationships between openness and considerations of novelty and usefulness were found to depend on the context, while no relationships were found for risk-taking. Future research could assess or manipulate the promotion vs. prevention focus of raters, as well as their current mood and level of certainty, to examine how these factors specifically influence considerations of novelty and usefulness. For example, does greater uncertainty lead to a greater consideration of usefulness when participants evaluate creative ideas?

6.4.3 Conclusion

Relatively few existing studies have examined differences in how individuals evaluate creativity, and the factors they consider during their evaluations. The present study found that both the context of ideas and the personality of raters play important and interacting roles in how novelty and usefulness are considered in evaluations of creativity. There is enormous potential for further research to investigate the factors (including mood, personality, intelligence, and cultural background) that can influence how individuals weigh up different aspects of an idea when assessing its creativity. After all, evaluation is a critical part of creative cognition. Understanding how creativity is perceived and defined in different contexts and across different raters is highly important not just to our understanding of subjective assessments, but to our understanding of creativity itself.

CHAPTER 7: TOWARDS A MECHANISTIC UNDERSTANDING OF CREATIVE COGNITION

7.1 Review of research questions

Creativity is a hugely important yet mysterious ability that enables humans to craft innovative solutions, adopt original perspectives, to invent, imagine, and entertain. However, defining precisely what creativity is and what constitutes a creative idea has proven difficult and controversial (Plucker et al., 2004; Simonton, 2018; Taylor, 1988; Treffinger, 1992), with considerable variation in the working definition of creativity across fields of research (Hennessey & Amabile, 2010; Puryear & Lamb, 2020).

Indeed, despite considerable growth in NCR in recent years, our understanding of the mechanisms underlying creative cognition, and the processes by which creative ideas are produced, remains in its infancy. Guided by theoretical accounts such as dual process theories (Barr, 2018; Benedek & Jauk, 2018; Sowden et al., 2015; Volle, 2018), NCR has examined how creative performance, both in the real world and in the lab, relates to cognitive and psychological factors including attention (Frith et al., 2021b; Zabelina, 2018), memory (Benedek et al., 2014b; Fugate et al., 2013; Kenett et al., 2018a; Madore et al., 2016; Storm et al., 2011), personality (Beaty et al., 2018a; Kaufman et al., 2016; Oleynick et al., 2017), and executive control (Beaty et al., 2014; Benedek et al., 2014c; Krumm et al., 2018). Meanwhile, neuroimaging studies have consistently found evidence that creative performance relates to interactions between the DMN and ECN (among other networks; Beaty et al., 2016a, 2021a; Ellamil et al., 2012; Mayseless et al., 2015).

However, considerable outstanding questions remain regarding the processes that produce creative ideas, and how these vary in different creative contexts. In addition, verbal theories seem increasingly ill-equipped to manage the size and complexity of creative cognition as a construct. For example, it remains unclear how exactly the DMN and ECN contribute to creative cognition, and what processes underlie their interactions. Meanwhile, though researchers have suggested that inhibitory control is important for creative performance in some contexts, but not others (Chrysikou, 2018; Benedek & Jauk, 2018), it is unclear exactly which forms of creative cognition benefit from which forms of inhibitory control. Likewise, while researchers have argued that creative cognition involves several cognitive abilities likely to depend on control over WM, such as switching between categories of idea (Nijstad et al., 2010; Zhang et al., 2020), generative and evaluative states (Ellamil et al., 2012; Ward et al.,1997), and narrow-and broad forms of attention (Gabora, 2010; Zabelina & Robinson, 2010), it is unclear which forms of WM control benefit which aspects of creative cognition.

Indeed, our understanding of the mechanisms underlying creative thought is currently mostly verbal in nature. As a high-level construct, creative cognition likely involves complex interactions between numerous cognitive and psychological factors. The interactions of these factors are difficult to conceptualize and make concrete predictions about using verbal theorizing alone, but could be made far clearer through the increased use of computational models. Finally, the evaluation of creative ideas is an important but relatively neglected part of the creative process. Differences in how individuals evaluate the creativity of ideas likely affects how they generate their own ideas, and can indicate how working definitions of creativity vary across persons. Indeed, the twin criteria for creativity are novelty and usefulness, but how and why individuals differ in their considerations of these factors when evaluating the creativity of ideas has not previously been explored.

7.2 Review of chapters and findings

This thesis sought to investigate these various outstanding questions for NCR, to push the field further towards a more mechanistic understanding of creative cognition.

A first study, discussed in Chapter 2, examined how two large-scale brain networks, the DMN and ECN, contribute to creative cognition over time. Given that these networks have been associated with spontaneous, generative thought (Andrews-Hanna et al., 2014; Beaty et al., 2018d), and controlled, evaluative thought (Niendam, 2012; Seeley et al., 2007), respectively, understanding how their contribution to creative thinking varies over time during the course of a single creative trial could reveal the existence of distinct generative and evaluative stages. For example, an initial generative phase might involve more creative activity in the DMN, and less in the ECN, while a later evaluative phase might involve the opposite. Indeed, generative and evaluative phases in creative cognition have often been suggested (e.g., Ellamil et al., 2012; Kleinmintz et al., 2019), but until now have remained largely speculative.

Using multivariate pattern analysis (MVPA), the study assessed how the DMN and ECN contribute to creative cognition over three successive time phases during the production of a single creative idea. Training classifiers to predict trial condition (creative vs non-creative), classification accuracy was used as a measure of the extent of creative activity in each brain network and time phase. Across both networks, classification accuracy was highest in early phases, decreased in mid phases, and rose again in later phases, following a U-shaped curve. Notably, classification accuracy was significantly greater in the ECN than the DMN during early phases, while differences between networks at later time phases were non-significant. Correlations were also computed between classification accuracy and human-rated creative performance, to assess how relevant the creative activity in each network was to the creative quality of ideas. In line with expectations, classification accuracy in the DMN was most related to creative quality in early phases, decreasing in later phases, while classification accuracy in the ECN was least related to creative quality in early phases, increasing in later phases. These results could be interpreted as tentative evidence for the existence of separate generative and evaluative stages in creative cognition, dependent on distinct neural substrates. Future research could expand on these findings by examining creativity activity in sub-networks of the DMN and ECN, across narrower slices of time, to get a more fine-grained sense of how creative cognition unfolds in these brain regions.

A second study (see Chapter 3) sought to unpack the details of the relationship between creative cognition and inhibitory control. Researchers have noted how creative cognition sometimes appears to be aided by inhibitory control (Benedek et al., 2012, 2014c; Camarda at al., 2018), and sometimes appears to be impeded by it (Carson, et al., 2003; Dorfman et al., 2008; Radel et al., 2015). It has been suggested that the relationship between creative cognition and inhibitory control might depend on the nature of the creative task, with real-world creative tasks benefiting from reduced inhibitory control and in-lab creative performance benefiting from greater inhibitory control (Benedek & Jauk, 2018; Chrysikou, 2018). Meanwhile, a less frequently discussed possibility is that the relationship also depends on the nature of the inhibitory control in question. After all, inhibitory control is a multi-faceted construct consisting of response inhibition, cognitive inhibition, and latent inhibition (among other forms; Cipolotti et al., 2016; Diamond, 2013; Engelhardt et al., 2008).

The relationship between creative cognition and inhibitory control was examined using a large battery of measures including verbal and visual measures of divergent and convergent thinking, self-report measures of creative achievement and engagement in creative activities, two measures of response inhibition, a measure of cognitive inhibition (RIF), a measure of latent inhibition, and a self-report measure of self-monitoring, together with measures of openness, intellect, risk-taking, and fluid intelligence. Using correlations and regressions, it was found that both visual and verbal measures of divergent thinking related to cognitive inhibition (the suppression of distracting concepts), and were not related to response or latent inhibition. Moreover, it was found that verbal convergent thinking, as assessed by the RAT, was not significantly related to any form of inhibition, suggesting that this measure may be better described as a measure of associative processes and insight (e.g., Kounios & Beeman, 2014), and not as a measure of the executive processes that are commonly linked to convergent thinking (see also Cortes et al., 2019). Finally, the study did not replicate previous findings regarding a link between weaker latent inhibition and greater real-world creative achievement (Carson et al., 2003), and indeed did not find real-world creative achievement to be significantly related to any form of inhibitory control. Overall, the results suggest that cognitive inhibition may be the most relevant form of inhibitory control for creative cognition, but only as measured by lab-based tasks with limited time constraints.

A third study, described in Chapter 4, examined whether control over WM is linked to creative cognition, and if so, which aspects of creative performance benefit from WM control. While WM control might enable individuals to adjust their attention in creative tasks, and to switch between generative and evaluative states, effective control over WM might also allow individuals to switch between a greater number of semantic categories, or to cover a larger area of semantic memory when generating ideas. I examined how WM control, as measured by the executive functions of cognitive inhibition, WM updating, and shifting, impacts performance on both verbal measures of convergent and divergent thinking, and measures of chain association and verbal fluency. I also collected data on WMC (which is often linked to WM updating; Schmiedek et al., 2014), real-world creative achievement, intelligence, openness, intellect, and self-report measures of attention control. Notably, in addition to typical measures of creative performance such as RAT score and human-rated creativity in the AUT, I used automated measures of semantic distance (Beaty & Johnson, 2021; Devlin et al., 2019) to probe how often participants switch semantic categories, and the semantic breadth covered by their responses.

In this exploratory, observational study, I found significant correlations among measures of creative cognition and association-making, both between tasks (RAT, AUT, and VF performance), and within the various AUT measures (fluency, creativity, and automated measures of creativity and semantic breadth). By contrast, few significant relationships were found between measures of executive functions (besides a moderate correlation between WM updating and WMC). Executive functions were also only slightly related to self-report measures of attention control. Critically, I found few relationships between executive functions and creative and associative abilities. Significant correlations were only found between updating and WMC and RAT and VF performance, suggesting that the associative processes involved in the RAT and VF tasks benefit from greater WM updating. The study was unable to replicate the finding from Chapter 3 where cognitive inhibition was found to relate to verbal divergent thinking. Though issues with data quality may have arisen from the online nature of the study (see Bianco et al., 2021), these results suggest that if creative cognition does in fact involve control over WM, executive functions may not be the best way to assess this, and there may be other forms of WM control that are more relevant to creative idea generation. Future, in-person studies should use multiple measures of each construct and examine relationships with structural equation modeling.

Indeed, while observational studies examining correlations can highlight interesting relationships among variables, they are unable to test causal pathways by which a cognitive factor can influence creative outcomes. Creative cognition likely depends on a large number of cognitive processes, which may interact very differently in different tasks and individuals. Computational modeling can provide a much more effective means to examine the interactions of these processes than verbal theories alone (as discussed in Chapter 5). For example, models could be constructed to reflect competing hypotheses regarding the causal relationships between inhibitory control, control over WM, and creative performance. These models could then be trained and tested on data such as that collected in Chapter 4. Comparing how closely the models can simulate human creative performance could then indicate which hypothesis is most accurate. Further, more fine-tuned empirical research might then be developed on the basis of these modeling results.

A final study outlined in Chapter 6 examined the contextual and interpersonal factors that affect how people consider novelty and usefulness when evaluating creativity. Novelty and usefulness are the critical requisites for a creative idea, as defined in the standard definition of creativity (Runco & Jaeger, 2012), and yet how considerations of novelty and usefulness vary across individuals or across creative tasks during creative evaluations is unclear. Individual participant regressions and mixed-effects modeling were used to examine how the contributions of novelty and usefulness to ratings of creativity vary according to the context of the idea (i.e., how relevant it is to the real world) and the personality of the rater. Participants rated the novelty, usefulness, and creativity of ideas from two contexts: AUT responses and genuine suggestions for urban planning projects. The study also assessed three personality traits of participants: openness, intellect, and risk-taking.

The study found that novelty contributed more to evaluations of creativity among AUT ideas than projects, while usefulness contributed more among projects than AUT ideas. Further, participants with higher openness and higher intellect placed a greater emphasis on novelty when evaluating AUT ideas, but a greater emphasis on usefulness when evaluating projects. These results indicate that both the context in which ideas are generated and the personality of raters play important and interacting roles in how novelty and usefulness are considered in evaluations of creativity. However, neither openness nor intellect affected the creativity rating itself. These findings underline the importance of considering interpersonal and contextual factors when examining evaluations of creativity, and future studies should examine if the same results emerge when participants evaluate their own ideas, and indeed if they show the same preferences for novelty vs usefulness when generating their own ideas. It would also be interesting to see how considerations of novelty and usefulness vary when greater uncertainty or reward-seeking behavior is induced in the participant.

7.3 Next steps for Neurocognitive Creativity Research

This thesis found tentative evidence for the existence of distinct generative and evaluative phases in creative cognition, in a study highlighting the impressive potential of MVPA for examining the nuances of neural activity underlying creative thinking. In addition, two online studies comprising a large battery of tasks probed how creative cognition relates to executive functions including inhibitory control, WM updating, and shifting. While results were mixed overall, some evidence was found that divergent thinking benefits from cognitive inhibition, while convergent thinking and verbal fluency benefit from greater WM updating abilities. Finally, it was found that an individual's openness to experience can affect how they consider novelty and usefulness when assessing the creativity of ideas in different contexts.

Taking these studies as a whole, one can make several conclusions. The field of NCR has a great wealth of research findings, and while some are reliable, such as that creative ability is positively related to openness to experience (Oleynick et al., 2017), and that creative cognition involves the cooperation of the DMN and ECN (Beaty et al., 2016a, 2018b), many findings are not so reliable. As discussed, some studies have found that creative cognition benefits from increased inhibitory control, while others have found it benefits from reduced inhibitory control (Benedek & Jauk, 2018; Camarda et al., 2018a; Radel et al., 2015). Similarly conflicting findings have been found for WM updating (de Vink et al., 2021; e.g., Lunke & Meier, 2016; Smeekens & Kane, 2016; Stolte et al., 2020), and executive shifting (e.g., Benedek et al., 2014c; Krumm et al., 2018; Pan & Yu, 2018; Zabelina et al., 2019), with some studies even reporting opposite results to others. Indeed, the present findings were similarly conflicting, with one study finding a relationship between cognitive inhibition and creative cognition (Chapter 3), and another finding no relationship between these factors (Chapter 4).

There are various possible reasons for the present conflicting findings, and indeed those in the wider literature. First, it has been found that participant engagement can be reduced in online studies, particularly for demanding tasks (Bianco et al., 2021). The Stroop tasks administered in Chapter 3 used feedback for incorrect trials throughout, and the time penalty this incurred likely discouraged participants from responding randomly. However, similar tasks used in Chapter 4, such as the executive shifting task, followed prior studies by not including any feedback for nonpractice trials, which may have led to lower participant engagement. Moreover, such conflicting results may simply be a sign that the relationships between creative cognition and executive functions like inhibitory control are nuanced and can vary greatly across persons. While sample sizes were relatively large in the studies in both chapters (N=151 and N=200, respectively), individual differences in the engagement of executive processes during creative cognition may be sufficient to produce markedly different results in different samples.

An additional factor affecting the reliability of findings is variation in measures of creativity. In Chapter 3 both visual and verbal measures of divergent thinking were used, whereas Chapter 4 used only verbal measures. Indeed, studies by different research groups often use quite different measures of divergent thinking ability (e.g., Benedek et al., 2014c; Camarda et al., 2018a; Menashe et al., 2020; Radel et al., 2015; Stolte et al., 2020), which may explain some of the variation in findings regarding the relationship between creative cognition and executive functions. Even just focusing on the AUT, research has found that the instructions given to participants (Acar et al., 2019), and the object cues themselves (Beaty, Kenett, Hass, & Schacter, 2023), can lead to considerable variation in creative performance. Finally, as noted in Chapter 3, researchers often use only one measure of a given executive function, despite the existence of multiple sub-types of, for example, inhibitory control (Cipolotti et al., 2016; Diamond, 2013), and despite correlations between measures of the same executive function often being only small to moderate in strength (Schmiedek et al., 2014).

Future studies examining the mechanisms of creative cognition should use multiple measures of each construct under investigation, and focus on relationships between latent factors, to minimize measurement error (e.g., Benedek et al., 2014c; Frith et al., 2021a). Researchers should also continue to work towards more standardized assessments, to minimize variance in how creative performance is operationalized across studies (Barbot et al., 2019). Moreover, researchers should focus on developing causal hypotheses regarding the relationships between creative cognition and factors such as inhibitory control, testing these using experimental intervention (e.g., Camarda et al., 2018a; Radel et al., 2015). Finally, greater computational modeling, especially in tandem with experimental intervention, could greatly help to increase our understanding of the mechanisms underlying creative thought and the effects that variation in a specific cognitive factor has on creative performance.

In addition to these points, research should continue to investigate the dynamics of neural activity supporting creative cognition. For example, future research using MVPA could compare less creative to more creative trials, removing the need for control tasks by providing a more direct measure of brain activity relevant to creative quality. Research could also focus on more tightly defined neural regions, and narrower time slices of fMRI data, to better unpack how creative activity unfolds over time across different networks and regions within networks. Use of a button press to indicate the precise point of idea generation could also help researchers to better identify the neural activity that produces creative ideas. Finally, research should continue to investigate the evaluation of creativity, and the factors that can affect how individuals judge the creativity of ideas in different contexts.

7.3.1 Closing remarks

Creativity is a large and complex construct, but it need not be mysterious. Vague and poorly defined theoretical accounts of creativity can be exchanged for more formal theories supported by computational models. Such models can aid the development and testing of causal hypotheses regarding the processes underlying creative cognition, and can highlight promising avenues for future research. Moreover, our understanding of the constructs involved in creativity can also be improved by taking a more fine-grained approach when examining the neural activity supporting creative cognition, and the relationships between creative cognition and more fundamental cognitive processes. Researchers should use multiple measures of each construct being examined, embody their hypotheses in formal computational models, and work towards standardized assessment techniques, to create a clearer and more reliable picture of the mechanisms underlying creative cognition.

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