Research Report

The time course of creativity: Multivariate classification of default and executive network contributions to creative cognition over time

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ABSTRACT

Research indicates that creative cognition depends on both associative and controlled processes, corresponding to the brain's default mode network (DMN) and executive control network (ECN) networks. However, outstanding questions include how the DMN and ECN operate over time during creative task performance, and whether creative cognition involves distinct generative and evaluative stages. To address these questions, we used multivariate pattern analysis (MVPA) to assess 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), we used classification accuracy 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 increased 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. We also computed correlations 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. Given the theorized roles of the DMN in generation and the ECN in evaluation, we interpret these results as tentative evidence for the existence of separate generative and evaluative stages in creative cognition that depend on distinct neural substrates.

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1.   The time course of creativity: multivariate classification of default and executive network contributions to creative cognition over time

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. Although creativity has traditionally been seen as a mysterious construct (Boden, 2007; Hennessey & Amabile, 2010), in recent decades considerable progress has been made in uncovering the neural and psychological bases of creative cognition. 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., 2014; Fugate, Zentall, & Gentry, 2013; Kenett, Levy, et al., 2018; Madore, Addis, & Schacter, 2016; Storm, Angello, & Bjork, 2011), attention (Frith, Kane, et al., 2021; Zabelina, 2018), personality (Kaufman et al., 2016; Oleynick et al., 2017), executive control (Beaty, Silvia, Nusbaum, Jauk, & Benedek, 2014; Benedek, Jauk, Sommer, Arendasy, & Neubauer, 2014; 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 and executive networks (Beaty, Benedek, Silvia, & Schacter, 2016; Beaty, Cortes, Zeitlen, Weinberger, & Green, 2021; Ellamil, Dobson, Beeman, & Christoff, 2012; Mayseless, Eran, & Shamay-Tsoory, 2015).

Despite this progress, however, cognitive science remains far from a precise understanding of how creative cognition arises from neurocognitive processes. A particularly striking gap in knowledge is how exactly different brain regions 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. Specific outstanding questions include whether the DMN underlies generation while the ECN underlies evaluation (Beaty et al., 2016, 2018; Kleinmintz, Ivancovsky, & Shamay-Tsoory, 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.

In the present study, we sought 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 reveal 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, we use MVPA on a large sample of participants ($N = 168$), training machine-learning classifiers to distinguish between two task conditions — a canonical task of divergent creative thinking and a semantic control task — with greater classification accuracy indicating a greater difference in brain activity between tasks, and indirectly, a greater amount of creative activity. We applied MVPA 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. We also computed correlations between classification accuracy and rated idea quality, 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, we aimed to test dual-process theories of creative cognition that posit separate stages of idea generation and evaluation.

1.1.   The cognitive basis of creativity

Most empirical research within cognitive psychology and neuroscience defines creative cognition as the production of ideas that are both novel (i.e., new, or original), and useful (i.e., context-appropriate, or helpful to a task or goal; Runco & Jaeger, 2012; Stein, 1953). A range of measures have been developed to assess creative cognition, perhaps the most common of which are "divergent thinking" tasks, such as the Alternate Uses Task (AUT; Guilford, 1967), and the Torrance test of verbal creative thinking (Torrance, 1966). These are open-ended problems which typically require participants to generate multiple ideas in response to a single stimulus. In the AUT, for example, participants are given an object name (e.g., "brick"), and asked to think of novel, original, and creative uses for the object (e.g., "use to grind up food").

As cognitive creativity research has grown in recent years, several theoretical frameworks have emerged to interpret its findings, perhaps the most popular of which are dual-process theories. These describe creative cognition as involving two broad sets of processes: associative memory processes that operate spontaneously, and deliberate control processes that guide and direct thought (Barr, 2018; Beaty et al., 2014; Benedek & Jauk, 2018; Mok, 2014; 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, Pringle, & Gabora, 2015). They also relate to the broader idea that creativity involves distinct generative and evaluative modes of thought (Ellamil et al., 2012; Finke, Ward, & Smith, 1992; Ward, Smith, & Vaid, 1997), which may operate in iterative phases (Kleinmintz et al., 2019), or simultaneously (Goldschmidt, 2016). Indeed, researchers have suggested that the generative mode may rely predominantly on associative processes, while the evaluative mode relies mainly on controlled processes (Bendetowicz et al., 2018; Mayseless et al., 2015; Sowden et al., 2015), though it is likely that both modes involve at least a small proportion of both kinds of process (Benedek & Jauk, 2018; Frith et al., 2021; Sowden et al., 2015; cf. Cortes, Weinberger, Daker, & Green, 2019).

Considerable support for the role of associative processes in creative cognition comes from verbal fluency (Beaty et al., 2014) and free-association paradigms (Kenett, Anaki, & Faust, 2014; Kenett, Levy, et al., 2018; Marron et al., 2018), which suggest that creative cognition relates to memory structure (Kenett, 2019; Mednick, 1962), and to associative processes that spontaneously spread through memory (Volle, 2018). Support for the role of controlled processes in creative cognition is less conclusive. Some evidence suggests that

creativity benefits from reduced cognitive control, which may allow associative processes to operate more flexibly, such as during defocused idea incubation (Benedek & Jauk, 2018; Ritter & Dijksterhuis, 2014), jazz improvisation (Limb & Braun, 2008), and the reorganization of memory during sleep (Cai, Mednick, Harrison, Kanady, & Mednick, 2009; Lewis, Knoblich, & Poe, 2018). In other cases, however, controlled processes appear to play a key role in creative cognition, and performance in divergent thinking tasks has now been linked to intelligence (Beaty et al., 2014; Benedek, Jauk, Sommer, et al., 2014; Frith et al., 2021; Karwowski et al., 2016), and the executive functions of inhibition (Benedek, Jauk, Sommer, et al., 2014; Benedek, Franz, Heene, & Neubauer, 2012; Camarda et al., 2018), switching (Krumm et al., 2018; Pan & Yu, 2018; Zabelina & Ganis, 2018), and updating (Benedek, Jauk, Sommer, et al., 2014).

These findings suggest that creative cognition relies partly on associative processes, which operate spontaneously to reinterpret problems and connect distantly-related concepts (Beaty et al., 2014; Kenett, Levy, et al., 2018; Volle, 2018), and partly on controlled processes, which can guide thought in strategic directions, and inhibit distracting and unoriginal ideas (Beaty, Christensen, Benedek, Silvia, & Schacter, 2017; Camarda et al., 2018; Lloyd-Cox, Christensen, Silvia, & Beaty, 2021). 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), with divergent thinking tasks in particular comprising a significant executive control component (Beaty et al., 2014; Benedek, Jauk, Sommer, et al., 2014; Frith et al., 2021; Krumm et al., 2018; Nusbaum & Silvia, 2011).

Several outstanding questions remain, however. For example, it is 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 et al., 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. Answering these questions is central to understanding the cognitive basis of creativity.

1.2.   *The neural basis of creativity*

Neuroimaging studies also point to 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, groups of regions that are strongly implicated in associative and controlled cognition, respectively (Beaty et al., 2018; Chen et al., 2018; Christensen, Benedek, Silvia, & Beaty, 2021; Ellamil et al., 2012; Mayseless et al., 2015; Yeh, Hsu, & Rega, 2019; see Beaty, Seli, & Schacter, 2018, for a review).

The executive control network (ECN) is formed of lateral prefrontal and anterior inferior parietal regions, and typically activates during focused, goal-oriented cognition, such as working memory and switching tasks (Niendam et al., 2012; Seeley et al., 2007). The default mode network (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, Smallwood, & Spreng, 2014; Beaty and Lloyd-Cox, 2020). The two networks are typically anti-correlated, i.e., when one network activates, the other tends to deactivate (cf., Beaty et al., 2021), and they may compete for resources in many contexts (Anticevic et al., 2012). Interestingly, however, increased connectivity between default and executive control regions has been found in a large range of creative tasks, including verbal divergent thinking (Beaty, Benedek, Barry Kaufman, & Silvia, 2015; Green, Cohen, Raab, Yedibalian, & Gray, 2015; Kaufman, & Silvia, 2015; Mayseless et al., 2015), musical improvisation (Pinho, de Manzano, Fransson, Eriksson, & Ullén, 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, Benedek, Barry Kaufman, & Silvia, 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., 2018).

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., 2018) 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., 2021). 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., 2016). 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., 2016; Ellamil et al., 2012; Jung, Mead, Carrasco, & Flores, 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., 2017) 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., 2021; Dixon et al., 2018), and may underly different creative tasks (Peña, Sampedro, Ibarretxe-Bilbao, Zubiaurre-Elorza, & Ojeda, 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).

1.3. 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; Wang, Hao, Ku, Grabner, & Fink, 2017).

Studies using electroencephalography (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, Zanon, Mastria, Avenanti, & Corazza, 2020; Camarda et al., 2018; 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, Boyle, Foulser, Mellin, & Fröhlich, 2015).

Focusing on the production of a single creative idea, Schwab, Benedek, Papousek, Weiss, and Fink (2014) gave participants 10 sec 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 et al. (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-sec time windows from the 12-sec 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.

1.4. 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., 2016; 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, we used MVPA 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), we divided the idea generation periods for both tasks 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, we also computed correlations 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, we 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, we 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, we 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. Methods

We report how we determined our sample size, all data exclusions, all inclusion/exclusion criteria, whether inclusion/exclusion criteria were established prior to data analysis, all manipulations, and all measures in the study.

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., 2018; Frith et al., 2021). Sample size was determined by a prior study (Beaty et al., 2018). 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 > .5 mm, $n = 4$; 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. Materials

To assess creativity, the AUT was used. This task involves generating creative uses for common objects (e.g., using a "sock" as a "filtration device"). 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 work (Beaty et al., 2015; Fink et al., 2009). These stimuli are available via OSF (see Open Practises Statement).

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., 2021).

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 Fig. 1). Following a fixation cross jittered between 4 and 6 sec, 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 sec. A 12-sec thinking period then began, with
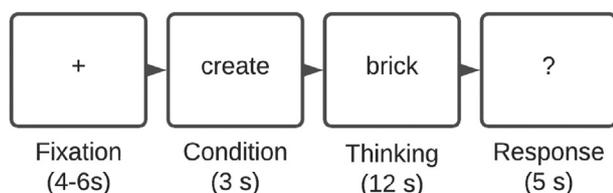
the object name stimulus (e.g., "brick") presented for the entire duration. Participants were instructed to use the thinking period to either generate the most creative use they could think of ("create"; creative condition), or the most prototypical physical characteristic they could recall ("object"; 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-sec 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.

2.4. fMRI data acquisition and preprocessing

In-scanner tasks were completed in a single MRI run, and programmed using E-Prime software. The E-Prime experiment files are available via OSF (see Open Practises Statement). Stimuli were viewed through a mirror attached to the head coil. Imaging was performed with a 3 T 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] = 2000 ms, echo time = 30 ms, flip angle = 78°, 32 axial slices, $3.5 \times 3.5 \times 4.0$ mm, distance factor 0%, field of view = 192×192 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 128 sec 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 .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.

Fig. 1 − Trial procedure, from fixation (left) to response (right). Duration in seconds is presented below each frame.

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-sec thinking period (see Fig. 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, we did not average across trials. 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 sec, and formed of two volumes. For each participant, a GLM was fitted with 138 regressors of interest, corresponding to three time periods × 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.

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). We extracted masks for three networks: the default mode network (DMN), the executive control network (ECN), and a combined network formed of both the default and control networks (Both). We included the combined mask 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.

2.7. Multivariate pattern analysis

Next, we conducted MVPA classification of trials as creative (AUT) or non-creative (OCT), for all networks of interest. Classifiers were trained on labelled creative and non-creative trials, and then tested to classify unlabeled trials. We 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). The custom script is available via OSF (see Open Practises Statement). Linear Discriminant Analysis (LDA) was used for classification, which was conducted separately for each network of interest (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, we used permutation testing, 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 is .001.

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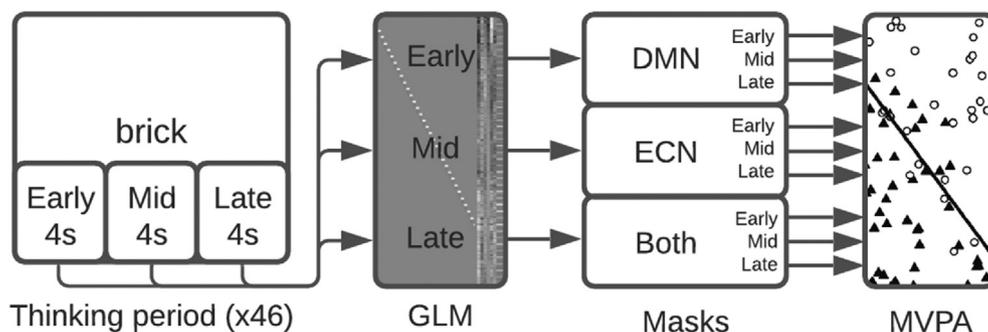

Fig. 2 — Analysis process (left to right). Thinking periods in each of the 46 trials were split into three equal time periods (early, mid, late). For each time period, 46 parameter-estimate images were extracted from the GLM (one for each trial). Three different network masks were then applied to each of these three sets of images, before they were fed into MVPA classifiers.

2.8. Correlation analysis

As discussed, classification accuracy in our 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, we computed Pearson correlations between participants' classification accuracies (for all networks and time phases) and their rated creativity scores (see Coutanche et al., 2011; Kim et al., 2015).

3. Results

3.1. Descriptive statistics

Processed, participant-level data is available via OSF (see Open Practises Statement). 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.

3.2. Classification accuracy and comparisons

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 ($ps = .001$). Specifically, all accuracies were greater than all 1000 randomly relabeled permutations. Classification accuracy reached the

Fig. 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.**

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 = .01) and time phase (F [2,168] = 90.54, p < .001, η_p^2 = .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, we report Cohen's d_{av} 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 during the early time phase (see Fig. 3), with accuracy in the ECN (M = .73, SD = .11) significantly greater than in the DMN (M = .70, SD = .10; t [167] = 2.80, p = .005, d_{av} = .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).

We 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 = .72, SD = .11) was significantly greater than in the DMN (M = .70, SD = .10; t [167] = 2.15, p = .032, d_{av} = .23), but did not differ significantly from accuracy in the ECN (p = .485). No

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	.00	.79
AUT creativity	1.85	.30
Early DMN	.70	.10
Early ECN	.73	.11
Early Both	.72	.11
Mid DMN	.60	.10
Mid ECN	.61	.10
Mid Both	.61	.10
Late DMN	.64	.10
Late ECN	.65	.10
Late Both	.65	.10

Note. Gf = fluid intelligence; AUT = alternate uses task; DMN = default mode network; ECN = executive control network; Both = DMN + ECN.
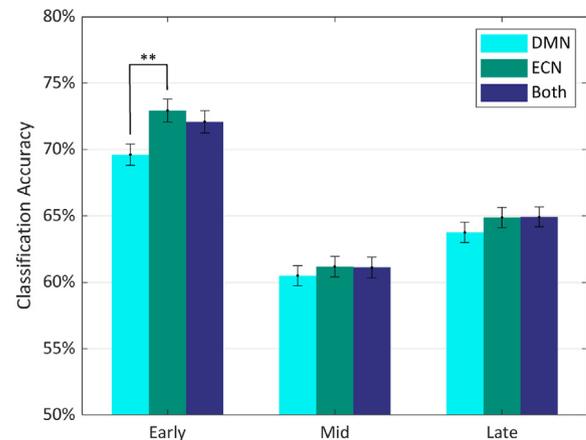
Table 2 – Results of *t*-tests contrasting classification accuracy between networks in each time phase, and between time phases in each network.

(A) Across networks (DMN vs ECN)			
DMN vs ECN	t	p	Cohen's D*av*
Early	−2.80	.005	.31
Mid	−.64	.524	.07
Late	−1.04	.299	.11
(B) Across time (within DMN)			
DMN	t	p	Cohen's D*av*
Early vs Mid	8.22	.000	.90
Early vs Late	5.27	.000	.57
Mid vs Late	−3.03	.003	.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	.76
Mid vs Late	−3.42	.001	.37

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

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.

3.3. Correlations

To assess how the creative brain activity within each network and time phase related to behavioral measures, we computed Pearson correlations 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	.24**	-
Early DMN	.01	.25**
Early ECN	.00	.19*
Mid DMN	.07	.17*
Mid ECN	.06	.23**
Late DMN	-.06	.16*
Late ECN	-.07	.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. Fig. 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.

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 Fig. 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 ($z = −.86$, $p = .391$). 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.

4. Discussion

The present study examined how two brain networks, the DMN and ECN, contribute to creative cognition over time
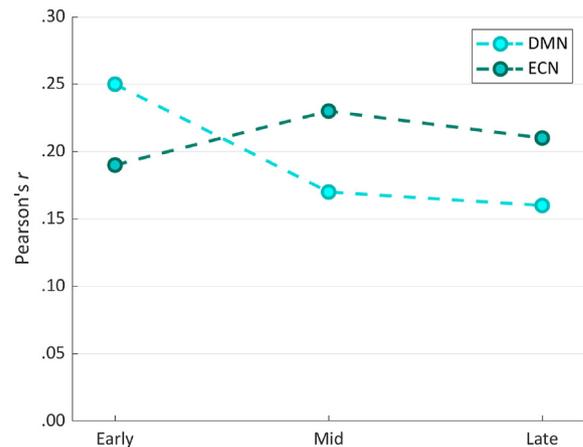

Fig. 4 – Strength of correlation between AUT creativity and classification accuracy in the DMN and ECN, across all time phases. *Note.* DMN = default mode network; ECN = executive control network.

during the production of a single creative idea. We 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, we used MVPA 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. We also computed correlations 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 predictions assumed that generative and evaluative stages involve different combinations of associative and controlled processes, and so different proportions of DMN and ECN activity. Specifically, we 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, we 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. Our 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, our findings provide tentative evidence for distinct stages in creative cognition, potentially corresponding to generation and evaluation.

4.1. Neurocognitive mechanisms of creative cognition

These findings offer new insight into the dynamics of neuro-cognitive 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., 2017; 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., 2016; 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., 2017), it seems

likely that generation relies *mostly* on the DMN, while evaluation relies *mostly* on the ECN (Beaty et al., 2016; 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.

4.2. The time-course of brain network contributions to creative cognition

Overall, we found very similar time patterns of classification accuracy in the DMN and ECN: 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., 2016). 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-sec 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 our 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., 2018; 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. We found markedly different time-patterns of correlations between the two networks. 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, our 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., 2018; 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., 2016; 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., 2016; 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, our 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, we found a small correlation between fluid intelligence and creative performance ($r = .24$), as expected from previous findings regarding the relationship between intelligence and creativity (Benedek, Jauk, Sommer, et al., 2014; Benedek, Jung, & Vartanian, 2018; Nusbaum & Silvia, 2011).

4.3. Limitations and directions for future research

To our 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. We believe our 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, our 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 our 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, 2021; 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., 2016), 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 our 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.

5. 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). However, the field remains far from possessing a complete, process-level understanding of creativity. We believe that further progress toward this goal will depend greatly on an increased focus on how neural activity changes over time during creative cognition. Together with modern analytic tools such as MVPA, connectivity analysis, EEG, and trans-cranial brain stimulation, research into the time course of creative cognition could reveal much about the details of cognitive operations during creativity, and how these operations vary across tasks and individuals.

Funding

Open practices statement

Processed data, analysis code and materials for the creative (AUT) and non-creative (OCT) tasks are available via OSF (https://osf.io/4wr9g/). Raw data cannot be made available as this is prevented by the study's Institutional Review Board. However, raw data can be made available to requestors following completion of a data sharing agreement. Legal copyright restrictions prevent public archiving of the letter sets task, number series task, and the series completion task of the CFIT, which can be obtained from the copyright holders in the cited references (see Section 2.2). The study was not preregistered.

CRediT author statement

James Lloyd-Cox: Conceptualization, Data Curation, Methodology, Formal Analysis, Software, Writing – Original Draft, Writing – Review & Editing, Visualization.

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Roger E. Beaty: Conceptualization, Investigation, Funding Acquisition, Project Administration, Resources, Supervision, Writing – Review & Editing.

Data availability

A link to the processed data and code for this study is included in the manuscript.

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