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Individual Differences in Creative Cognition

Sarah K. C. Dygert and Andrew F. Jarosz
Mississippi State University

Creativity is becoming an increasingly desirable characteristic across a number of domains, but the processes underlying various creative abilities remain ambiguous. The most frequently used assessments of creativity (i.e., divergent thinking tasks; creative problem-solving tasks) differ in surface features and are also rarely examined together. These inconsistencies, in addition to mixed findings in the literature, have caused considerable debate among creativity researchers concerning the particular roles of independent or dual processes that lead to success on different creativity tests. The present study expounded upon these mixed findings using a factor analytic method. The results indicated that individual differences in working memory and fluency ability impact performance on divergent thinking and creative problem-solving tasks, but to differing degrees. These results are discussed as supporting a dual-process view of creative thinking.

Keywords: creativity, divergent thinking, dual processes, problem solving, working memory

A study conducted by IBM (2010) found that 60% of CEOs rated creativity as the single most important characteristic to possess to be successful within the domain of business, especially for individuals in leadership positions. Although this investigation sheds light on the importance of creativity specifically in the workplace, the ability to think creatively is increasing in value in other domains as well. With the ever-increasing desire for creativity in modern culture, it is becoming increasingly necessary to better understand the specific processes that contribute to different creative behaviors, such as creative problem solving and creative idea generation.

The creativity literature overall tends to diverge in how creative thinking is defined and assessed. In 1956, Guilford developed his Structure-of-Intellect model that included creativity as an important factor. Later, he coined the terms *convergent thinking* and *divergent thinking* to refer to the two different types of mental processes that contribute to intelligence (Guilford, 1959, 1967). Convergent thinking refers to the processes that are active when deducing a single correct solution to a goal-directed problem. In contrast, divergent thinking refers to the mental processes that are active when an individual induces and generates multiple correct ideas or solutions to a problem. Although Guilford believed that both types of thinking contributed to intelligence, he primarily viewed convergent thinking as analytic and divergent thinking as creative.

Soon afterward, Wallach and Kogan (1965) began exploring divergent and convergent thinking in experimental paradigms, which led to the widespread use of different types of assessments to measure creativity. Convergent thinking is often assessed via creative problem-solving tasks because they have a single correct answer (Beaty, Nusbaum, & Silvia, 2014; Lee & Therriault, 2013; Nusbaum & Silvia, 2011; Zmigrod, Zmigrod, & Hommel, 2015). In addition to classical insight problems (e.g., Ash & Wiley, 2006; Duncker, 1945; Maier, 1931), other assessments of convergent thinking include the Remote Associates Test (Bowden & Jung-Beeman, 2003b; Mednick, 1962), Rebus puzzles (MacGregor & Cunningham, 2008, 2009), or matchstick arithmetic problems (Knoblich, Ohlsson, Haider, & Rhenius, 1999). For example, Rebus puzzles involve using verbal and spatial clues to describe a common idiom or phrase that must be uncovered by the solver. Generally, when problems like Rebus puzzles are first attempted, solvers often represent the problem such that the mental representation does not immediately yield the correct path to the solution (Wiley & Jarosz, 2012). This misrepresentation renders common analytic solution methods unreliable, and the solver must restructure the initial problem representation into a new one that actually includes the path to the correct solution. When the solution to the problem is uncovered, solvers often report feeling surprised (i.e., *Aha!*; Danek & Wiley, 2017), suggesting that the process of restructuring may lie below the threshold of awareness (Metcalfe & Wiebe, 1987). Because a single, correct solution to creative problems must be deduced, Wallach and Kogan (1965) suggested that convergent thinking (even in reference to creative problems) requires *attentional control* processes that guide the solver to the correct solution.

In contrast to convergent thinking, divergent thinking is often assessed with tests that allow individuals to make multiple correct responses according to a particular prompt. These tests are intended to reflect more closely the processes that would contribute to the generation of ideas in real-world situations. Indeed, performance on these tasks seems to predict creative achievements and

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Sarah K. C. Dygert and Andrew F. Jarosz, Department of Psychology, Mississippi State University.

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Correspondence concerning this article should be addressed to Sarah K. C. Dygert, Department of Psychology, Mississippi State University, P.O. Box 6161, Mississippi State, MS 39762. E-mail: skc195@msstate.edu

behaviors quite well (Beaty et al., 2013; Cramond, Matthews-Morgan, Bandalos, & Zuo, 2005; Nusbaum, Silvia, & Beaty, 2014; Plucker, 1999a, 1999b). The most widely used assessments of divergent thinking are included in the Torrance Tests of Creative Thinking (TTCT; Torrance, 1974, 2008). An example of a divergent thinking problem is the Alternate Uses Task (Wallach & Kogan, 1965), which prompts solvers to generate as many alternative or unusual uses for a common object, such as a brick or a newspaper, as they can within a limited time period (generally two to three minutes). Since Wallach and Kogan suggested that convergent thinking is guided by attentional control processes to arrive at a single solution, they made the opposite argument for divergent thinking, suggesting that these tasks instead draw upon *associative processes*. Thus, success on divergent thinking tasks would be driven by the ability to retrieve increasingly remote associates from memory.

Though some in the problem-solving literature have historically embraced Wallach and Kogan's (1965) attentional view of creative problem solving (Chuderski & Jastrzębski, 2018; Weisberg, 2006), followers of the associative theory of creativity (Bowden, Jung-Beeman, Fleck, & Kounios, 2005; Mednick, 1962) diverge from this distinction between convergent and divergent thinking. Rather, they explain the role of associative processes in creative problem solving as a spread of activation in memory, in which close associates related to a particular cue in the problem are accessed before more remote associates can be accessed. As problem solving continues, increasingly remote associates are accessed in an individual's semantic network through this spreading activation, allowing for creative ideas and solutions to be reached.

With the availability of these different assessments of creative thinking, two traditions of creativity research emerged from the literature: one such tradition was primarily pursued by cognitive psychologists and focused on creative problem solving as creativity, whereas the second tradition was primarily pursued by psychometricians and focused on divergent thinking as key to the creative process. This divergence in methodology has persisted to the present day, with only a few studies using creative problem solving and divergent thinking assessments together. Consequently, it is difficult to discern whether the processes that underlie these assessments of creative thinking are indeed isomorphic or task-specific. A brief consideration of each of these literatures follows.

Creative Problem Solving

Tasks traditionally used to measure convergent thinking, such as Rebus puzzles and classic insight problems, take the form of single-solution problems (Guilford, 1956) and have often been compared with analytic problem-solving tasks, such as mathematical word problems (e.g., Ash & Wiley, 2006) or algebra problems (e.g., Metcalfe & Wiebe, 1987). There is evidence that both types of problems can be solved using either creative or analytic problem-solving processes (Ash & Wiley, 2008; Danek, Williams, & Wiley, 2018; DeCaro, 2018; DeCaro, Van Stockum, & Wieth, 2016). However, the literature has historically classified a problem as *creative* (rather than *analytic*) if aspects of the problem make it difficult to solve via algorithms or general heuristics, or if aspects of the problem have strong tendencies to be solved via creative solution processes. In contrast, analytic problems are considered those that are amenable to algorithms and heuristics.

Research has largely focused on differences between these two problem types in their underlying processes and mechanisms. For example, when attempting to solve any kind of problem, a problem representation must first be developed, which includes past experience, information in the problem, and the possible paths to solution (Knoblich et al., 1999; Newell & Simon, 1972; Ohlsson, 1984). Algorithms or heuristics are then used to search the problem space in an attempt to reach a solution. Thus, people may initially approach analytic and creative problems in the same way, using similar strategies to search through any kind of problem space—correct or faulty (Ash & Wiley, 2006; DeCaro, 2018; DeCaro et al., 2016; Wiley & Jarosz, 2012; but see Kounios & Beeman, 2014[1]). However, the processes contributing to successful problem solving may diverge after these initial stages. Although the search through an initial problem representation reliably leads to success on analytic problems, this is often not the case for problems classified as creative. Instead, creative problem solving seems to involve other processes (e.g., restructuring; constraint relaxation; spreading activation) that are not required for solving analytic problems (see Figure 1). If the solver's initial problem representation is not appropriate for acquiring the solution, modifying the problem space or considering new alternatives allows creative solutions to surface (Knoblich et al., 1999; Ohlsson, 1984; see Wiley & Jarosz, 2012, for a review). Although the exact mechanisms underlying this representational shift remain unclear, researchers have offered several potential mechanisms that may contribute to the process, such as *opportunistic assimilation* (Seifert, Meyer, Davidson, Patalano, & Yaniv, 1995), *forgetting fixation* (Smith, 1995a, 1995b), or *spreading activation* in the semantic network to remote aspects of the problem (Mednick, 1962; Ohlsson, 1984, 1992). In light of these differences, the subsequent findings from various investigations seem to point to the involvement of both convergent *and* divergent processes in contributing to successful creative problem solving (Gilhooly, Ball, & Macchi, 2015; Gilhooly, Fioratou, Anthony, & Wynn, 2007; though see Weisberg, 2006, for an opposing perspective).

In support of the associative view of creative problem solving, it was found that participants differentially rate their progress toward solution throughout the problem-solving process depending on the type of problem at hand (Metcalfe, 1986; Metcalfe & Wiebe, 1987). Whereas participants were aware of their incremental progression toward solutions on analytic problems, they only became aware of how close they were to the solution on problems classified as creative immediately before solving them. Similarly, concurrent verbalization (i.e., *verbal overshadowing*) during prob-

[1] Work by Kounios et al. (2006; discussed further in Kounios & Beeman, 2014) demonstrated that brain state prior to the onset of problem solving relates to whether solvers eventually reach solution via insight. However, this does not preclude differences in initial solution strategy and only indicates that insight-related processes may achieve solution prior to analytic processes. For example, brain states may have a one-to-one relationship with a single strategy; they may bias individuals to make them more likely to use a certain approach; or they may simply make one of two concurrent approaches more likely to succeed. Without the addition of strategy measures concurrent to problem solving, it is impossible to differentiate which of these is the case. To that end, these data are actually compatible with initial differences in strategy.

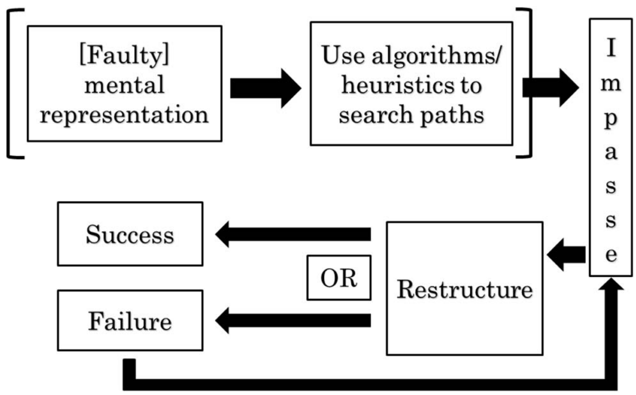

Figure 1. Model of creative problem solving (based on Ash & Wiley, 2006; Knoblich et al., 1999; Ohlsson, 1984; Wiley & Jarosz, 2012). Brackets indicate processes that lead to success in analytic problem solving.

lem solving impacts success rates differently on insight problems compared with analytic problems (Schooler, Ohlsson, & Brooks, 1993), with only performance on insight problems being harmed. Schooler and colleagues interpret these findings as evidence of unconscious activation of associates during creative problem solving, with concurrent verbalization disrupting the process of spreading activation to the correct remote associates. However, Fleck and Weisberg (2004) did not observe these same harmful effects of concurrent verbalization when using different protocol instructions, a single problem (Duncker's, 1945 candle problem), and without an analytic comparison condition, suggesting some ambiguity in these differences. Overall, these early investigations of creative problem solving still suggest that certain classes of creative problems benefit from different processes when compared with those that lead to success during traditional analytic problem-solving tasks.

Other work has explored the processes that lead to creative solutions. Ash and Wiley (2006) separately examined both the initial and restructuring phases of creative problem solving to address whether individuals use controlled-attention or associative processes during these phases of creative problem solving. A set of classic insight problems was manipulated to have either an expanded or restricted initial search space. Problems in the expanded search space condition included additional problem elements that solvers would be required to include in their initial, faulty representation of the problem. In the restricted search space condition, the restructuring phase was isolated from controlled-search processes by reducing the number of elements to be incorporated in the solver's problem representation, leading participants to essentially start the problem at impasse. When compared with measures of working memory (which is strongly linked to attentional control; Engle, 2002; Unsworth, 2016), working memory did not predict success on problems that isolated the restructuring phase, whereas it did predict success on problems that allowed for an initial search through an expanded problem space. Ultimately, these findings support a dual-process account of creativity, with the ability to control attention benefitting the initial search phase of problem solving, and associative processes benefitting the restructuring phase.

Additional evidence indicates that a lack of attentional control is sometimes beneficial for creative problem solving. For example, older adults, who are thought to have lower levels of attentional control, are better than younger adults at noticing external clues in the environment, enabling them to perform more successfully on a creative problem-solving task (Hasher, Zacks, & May, 1999). Congruently, the roles of both alcohol consumption and brain lesions in successful problem solving have also been explored as factors that induce a state of lowered attentional control. Studies have shown that intoxicated participants are better at solving creative problems than their sober counterparts (Benedek, Panzierer, Jauk, & Neubauer, 2017; Jarosz, Colflesh, & Wiley, 2012), and patients with lesions in the lateral prefrontal cortex (i.e., a brain region related to attention; Nagahama et al., 1996; Stuss et al., 2000) solve insight problems better than their healthy counterparts (Reverberi, Toraldo, D'Agostini, & Skrap, 2005). Finally, individuals who are awoken from REM sleep, and thus in a state of disorientation and diffuse attention, are also better at solving problems creatively than those who are awoken from non-REM sleep (Walker, Liston, Hobson, & Stickgold, 2002).

Taken together, these findings support the associative view of creative problem solving because a lack of controlled attention appears to promote solution rates on creative problems, but not on analytic problems. However, it is also important to recognize that controlled attention is likely necessary during the initial search through the problem space. Some aspects of problem solving that may lead to representational change, such as reaching impasse, may only occur after the solver has acknowledged that they have exhaustively searched through the available pathways in the current problem space. In this case, attentional resources necessarily play a role during this search phase. Even after restructuring, solvers may still require attentional resources to search the pathways in the new problem representation that will lead to solution. Finally, some problems may be amenable to both analytic and creative processes right from the start of problem solving (Kounios & Beeman, 2014). In this way, the evidence points toward a combined, dual-process account of creative problem solving (Benedek & Jauk, 2017; Gilhooly et al., 2007; Lee & Therriault, 2013). Whereas controlled attention may assist the problem solver throughout the initial search phase, associative processes may ultimately allow the problem solver to modify their problem space after an unsuccessful search, potentially opening an avenue for representational change.

Divergent Thinking

A separate perspective of creative thinking is the *controlled-attention theory* (Beaty & Silvia, 2012, 2013; Beaty, Silvia, et al., 2014; Benedek & Jauk, 2017; Nusbaum & Silvia, 2011). This theory proposes that when individuals produce novel ideas or solutions to problems, they draw upon executive processes (specifically controlled attention) to systematically map and search through various goal states that lead to some end goal. Contrary to Wallach and Kogan's (1965) argument that only associative processes underlie success on divergent thinking tests, recent evidence within the divergent thinking literature seems to support an interactive role between controlled-attention processes and associative processes in contributing to successful creative idea generation.

Divergent thinking tests are most often scored according to some variation of the following: the total number of items produced (*fluency*), the number of categories produced (*flexibility* or *switching*), the number of items produced within a category (*clustering*), and the number of unique or original items produced (*originality*). Although these are all frequently-used measures of divergent thinking, it has been noted that many of these scores confound with each other (Clark & Mirels, 1970; Hocevar & Michael, 1979; Silvia, 2008). Thus, the likelihood that someone will frequently switch between categories or provide many unique responses is dependent upon the total number of responses that the individual provides. Scores on divergent thinking tests therefore become similar to tests of *verbal fluency*, which are traditionally used as measures of memory retrieval. Although divergent thinking and verbal fluency tasks have been treated very differently in the literature, the surface similarities between them lend a starting point for acquiring a better understanding of the underlying processes that drive performance on each type of test.

Verbal fluency tasks prompt participants to provide as many responses related to a particular cue (e.g., animals; letter F) as possible in two to three minutes (Rosen & Engle, 1997; Troyer & Moscovitch, 2006). The cue in a verbal fluency test acts as the start of an effortful and strategic search through the problem space, allowing for the retrieval of relevant concepts (Moscovitch, 1995). Within the individual-differences literature, investigations with working memory have contributed to a better understanding of the processes and mechanisms that underlie verbal fluency performance. For example, it has been shown that retrieval of information from memory on a verbal fluency task can occur either strategically or automatically (Craik, Govoni, Naveh-Benjamin, & Anderson, 1996), hinting toward an interaction between executive and associative processes in verbal fluency performance.

Rosen and Engle (1997) have expanded upon Craik and colleagues' (1996) findings by exploring the contributing role of working memory in the strategic retrieval of concepts from memory. Across four experiments, they found that individuals with higher working memory consistently produced more responses on a verbal fluency task than did individuals with lower working memory, suggesting that working memory indeed plays a role in successful verbal fluency performance. However, when participants were required to complete a verbal fluency task, monitor for repetitions, and also perform a concurrent attention-demanding task (i.e., digit tracking), only individuals with high working memory spans decreased in fluency scores as compared with a control condition. In contrast, individuals with low working memory spans produced the same number of responses, regardless of whether they were also required to attend to a concurrent attention-demanding task, suggesting that individuals with lower working memory use automatic retrieval processes because of their insufficient attentional resources. On the other hand, individuals with higher working memory show decreases in performance when under concurrent attentional load because they no longer have the additional attentional resources to allocate to a strategic search through memory. Ultimately, evidence in the verbal fluency literature indicates that verbal fluency tasks draw upon controlled and associative processes, suggesting that convergent and divergent processes both play a role in successful verbal fluency performance.

Similar patterns of results have also been demonstrated in the divergent thinking literature. For example, it has repeatedly been found that the rate of unique responses increases as the amount of time spent on a divergent thinking task increases (Beaty & Silvia, 2012; Christensen, Guilford, & Wilson, 1957; Parnes, 1961; Ward, 1969). Similarly, low-frequency words become more frequent as time passes on a verbal fluency task (Bousfield & Barclay, 1950; Bousfield & Sedgewick, 1944). Mednick (1962), an associative theorist, suggests that this phenomenon is likely to occur because common associates to the cue will be activated before the activation spreads to more remote associates available within the problem space. However, evidence from several investigations again appears to support an interactive role of both associative and controlled-attention processes in successful divergent thinking performance. A recent study challenged Mednick's associative view by investigating the contributions of associative and controlled-attention processes in a 10-min divergent thinking task (i.e., unusual uses; Beaty & Silvia, 2012). Because fluid intelligence is driven by executive, attention-demanding processes (Kane et al., 2004), fluid intelligence was used as the measure of attentional control (Beaty & Silvia, 2012). The results indicated that fluid intelligence significantly moderates the serial increase of unique responses in divergent thinking tasks—the higher an individual's fluid reasoning skills, the lower the serial effect will be. More generally, individuals with high levels of fluid intelligence produced more creative ideas from the beginning to the end of the 10 min. Because this investigation found a moderating effect of an executive ability that correlates highly with controlled-attention processes, the results also promote a dual-process account of divergent thinking in contributing to this serial effect. Whereas spreading activation may play a role in the activation of remote associates that contribute to creative idea generation, it would seem as though controlled attention also plays a substantial role in performance on divergent thinking tests. Drawing from the findings in the verbal fluency literature, controlled-attention processes may also be particularly important for implementing strategies and managing interference from old responses during idea generation (Rosen & Engle, 1997).

Contrasting evidence, however, brings ambiguity to the role of controlled attention in divergent thinking performance. Recent factor analytic work exploring the impact of mind wandering and working memory on divergent thinking failed to find a relationship between working memory, a construct highly related to attention (Engle, 2002; Unsworth, 2016), and divergent thinking performance (Smeekens & Kane, 2016). Whereas some work has found low or absent zero-order correlations between divergent thinking tasks and working memory (Lee & Therriault, 2013; Lin & Lien, 2013), others have found small positive relationships (Benedek, Jauk, Sommer, Arendasy, & Neubauer, 2014; De Dreu, Nijstad, Baas, Wolsink, & Roskes, 2012). Thus, further work is required to truly understand the role of controlled-attention processes in divergent thinking.

Although verbal fluency and divergent thinking tasks have traditionally been used for different purposes in the literature, the surface similarities between these tasks may actually reflect a larger proportion of shared processes than has traditionally been considered. This idea is reinforced by the research discussed above. The findings among these investigations suggest that divergent thinking and verbal fluency may draw upon both divergent and convergent processes in the development and generation of ideas. Recently, researchers have begun investigating the underlying processes involved in divergent thinking, verbal fluency, and creative problem solving to expand upon the growing evidence suggesting that dual-processes are involved in creative thinking (Gilhooly et al., 2007; Lee & Therriault, 2013; Nusbaum & Silvia, 2011).

Dual-Processes in Creative Thinking

Dual-process theories (Benedek & Jauk, 2017; Gilhooly et al., 2007; Lee & Therriault, 2013) propose that individuals draw upon both associative and controlled-attention processes to actively engage in creative thinking. Despite creativity researchers' increasing support for dual-process theories of creativity, the lack of communication between the divergent thinking and creative problem-solving literatures has stymied recent attempts to adequately explore these processes together. Most studies still rely upon solely creative problem-solving tasks or divergent thinking tasks, rarely considering both at once. There are, however, a few exceptions to this rule.

Nusbaum and Silvia (2011)

A meta-analysis of 21 studies on the topic of intelligence and divergent thinking indicated a small, positive relationship between the two (Kim, 2005). Nusbaum and Silvia (2011) proposed that these relationships could be attributable to the inappropriate usage of the traditional scoring method (i.e., fluency) for divergent thinking tasks. Thus, they conducted a latent variable analysis to explore the role of fluid intelligence in divergent thinking, using a revised scoring system (the snapshot method), and found that fluid intelligence predicted divergent thinking both directly and indirectly through *category switching* as a mediator. These findings appear to support a controlled-attention view of divergent thinking. However, the factor models used by Nusbaum and Silvia require some additional consideration. For example, their fluid intelligence factor (*Gf* in the model) extracts variance from three lower-order factors: fluid intelligence (*fluid IQ* in the model), strategy use (i.e., for verbal fluency tasks), and verbal fluency. Because the lower-order fluid IQ factor extracts shared variance from commonly used assessments of Gf, it is unclear as to why strategy-use and verbal fluency would also be modeled to contribute shared variance to a higher-order Gf factor. Without a convincing theoretical basis for including these measures in the model, the Gf factor may be biased toward aspects of verbal fluency, rather than traditional measures of Gf. It is not surprising, then, that a fluency-biased factor would also predict divergent thinking, making it difficult to clearly interpret the implications of this model.

Lee and Therriault (2013)

Much like Nusbaum and Silvia (2011); Lee and Therriault (2013) were also concerned with the similarities between divergent thinking and verbal fluency but were more interested in understanding how fluid intelligence and working memory contributed to success on divergent thinking, convergent thinking (i.e., insight problem solving), and verbal fluency tasks. As such, they first examined the contribution of verbal fluency to success on divergent and convergent thinking tasks, using a confirmatory factor analytic approach. Divergent thinking was measured by an unusual uses task and the Abbreviated Torrance Test for Adults (ATTA; Goff, 2002), which consisted of three subtests from the full version of the Torrance inventory. Convergent thinking was measured by a 30-problem Remote Associates Test (RAT), one classic insight problem, and an eight-letter anagram problem. The results demonstrated that verbal fluency significantly predicted both types of creative thinking, but it predicted convergent thinking more strongly than divergent thinking. A second analysis replicated these findings and also showed that both working memory and fluid intelligence significantly contributed indirectly and directly (respectively) to verbal fluency.

Lee and Therriault's (2013) findings suggest a dual-process account of creative thinking. Verbal fluency, which is known to be related to working memory (Rosen & Engle, 1997), predicted both divergent and convergent thinking, albeit to different extents. However, Lee and Therriault (2013) did not provide factor loadings in their confirmatory models, so the descriptive statistics must be considered more closely to understand how well the factors predicted success on individual tasks. For example, descriptive statistics indicated that the three convergent thinking tasks included in the models only weakly correlated with each other. Because the convergent thinking factor was modeled to extract shared variance from three relatively uncorrelated tasks, it seems unlikely that the shared variance being extracted into this factor represents the underlying processes that contribute to creative problem solving. In addition, two of the three convergent thinking tasks consisted of only a single problem, which essentially eliminates performance variability across the convergent thinking tasks. Thus, the results of this investigation should be interpreted with some caution.

DeYoung, Flanders, and Peterson (2008)

DeYoung et al. (2008) expanded upon Gilhooly and colleagues' (2007) theory that creative problem solving may require both divergent and convergent thinking properties. Verbal creative problem solving performance was regressed onto three measures of divergent thinking: fluency, flexibility, and originality.[2] In another regression predicting creative problem solving performance, it was found that convergent thinking (verbal intelligence and working memory), divergent thinking (flexibility), and breaking frame (the ability to identify a black four of hearts in the anomalous card task; Bruner & Postman, 1949) all predicted unique variance in creative problem solving. Together, these findings suggest that dual-processes are likely involved in both creative problem-solving and in divergent thinking. This is particularly evident because working memory, which is related to attentional control, predicted creative problem solving, divergent thinking, and breaking frame independently from verbal intelligence. However, it is still unclear as to the extent to which creative problem solving and divergent thinking each draw upon executive and/or associative processes in contributing to creative thought.

[2] Upon discovering that only flexibility independently predicted performance on insight problem solving, DeYoung et al. (2008) used only flexibility scores as the index of divergent thinking in all subsequent analyses.

Chuderski and Jastrzębski (2018)

Evidence against a dual-process view of creativity has also been presented, in which latent variable modeling was used to explore the individual and combined impact that different components of working memory (e.g., updating, binding, etc.) have on creative problem solving (Chuderski & Jastrzębski, 2018). Results demonstrated that each component of working memory contributes independently to creative problem solving, and when combined into a single factor, explain half of the variance in creative problem solving. Subjective insight ratings were also obtained and analyzed. When problems solved with insight were separated from those solved by analysis, working memory predicted both solution strategies relatively equally. The authors interpret these findings as supporting a controlled-attention perspective of creative thinking.

Here again, there are considerations to be taken into account when interpreting these results. For example, in most studies participants are given between 3 and 5 min to solve a single classic insight problem (Ash & Wiley, 2006; Cunningham, MacGregor, Gibb, & Haar, 2009; Cushen & Wiley, 2012; DeCaro et al., 2016; Knoblich, Ohlsson, & Raney, 2001). Chuderski and Jastrzębski (2018), however, gave less than 90 s per item. This is problematic, as it has been demonstrated that problems solved in a short amount of time may draw upon different processes than those with longer solving times (Cranford & Moss, 2012). Thus, the shortened time limit may have artificially biased their measures toward analytic, rather than creative, solution methods. Likewise, subjective ratings of insight are multidimensional (Danek & Wiley, 2017), and Chuderski and Jastrzębski's (2018) limited instructions may have failed to adequately represent the more detailed instructions typically used (Bowden & Jung-Beeman, 2003a). This may have, in turn, impacted their parsing of insightful versus analytic problems. Finally, Chuderski and Jastrębski's finding of a relationship between working memory and creative problem solving does not provide evidence against the dual-process theory, which also suggests that such a relationship should exist for some aspects of creative problem solving. Indeed, their finding of a stronger relationship between working memory and analytic problem-solving success, compared with creative problem-solving success, lends support to the idea that creative problem-solving recruits independent processes not required during analytic problem solving. Further work is therefore required to fully understand the role of working memory in creative problem solving.

The Present Study

Although there is a substantial literature exploring the nature of individual differences in creative thinking, a number of gaps remain. First, there is a lack of factor analytic studies directly comparing theoretical models of creative cognition, with most studies only showing the fits of single models and refraining from model comparisons. Furthermore, few investigations have jointly studied both divergent thinking tasks and creative problem-solving tasks, making it unclear not only how performances on these tasks are related, but also whether they measure the same construct, as they claim to do. Understanding the interrelationships between these tasks will ultimately allow for a more global understanding of creative cognition by highlighting the shared and unique aspects of these seemingly different creative abilities. Indeed, factor analytic work can provide a stronger understanding of the exact contributions of controlled and associative processes to both forms of creative thinking, providing insight into their common and unique roles. Finally, when considering existing experimental and neuroscientific data, a factor analytic approach provides an alternative assessment of current theories of creative thinking by highlighting individual differences in these abilities, a perspective that is congruent with the spirit of Underwood's (1975) call for using individual differences as a crucible for theory testing. Thus, the purpose of the proposed study is to better understand the mechanisms and processes that underlie different forms of creative thinking. More specifically, the proposed study will use confirmatory factor analysis and structural equation modeling to address various questions that remain uncertain. First, models were developed to test the question of whether fluency and divergent thinking tasks measure a single unitary construct, or two independent constructs (as they are treated in the literature). Next, models were formed and compared with each other to test whether divergent thinking tasks also rely on shared processes with creative problem-solving tasks, and/or whether creative problem solving also requires processes involved during divergent thinking. Dependent upon these findings, the third question to be addressed is whether working memory capacity predicts divergent thinking and creative problem solving differently.

Method

Participants and Data Screening

We report how we determined our sample size, all data exclusions (if any), all manipulations, and all measures in these studies (Simmons, Nelson, & Simonsohn, 2012). Data from 236 participants enrolled in general psychology at Mississippi State University and recruited through the Psychology Research Program were obtained across a 2-day experiment for course credit. Thirty-four participants were not included in the sample because they did not come back for the second session. Five additional participants were excluded because they did not complete two or more of the 16 tasks administered, and one participant was excluded for providing nonsensical responses on the computer tasks (e.g., random number or letter strings) and scribbles on the paper tasks. Of the remaining participants ($N = 196$; 65 males, 131 females), less than 0.01% of the dataset was missing because of technical difficulties related to the working memory tasks. Missing data points were imputed in a single data set using bootstrapped linear regression in R. These imputed values were then inserted into the data set, and manifest variables were standardized prior to analyses. As a check, data were also tested without the imputations and demonstrated the same pattern of results. A Mahalanobis distance analysis tested for multivariate outliers among each of the four factors of interest (i.e., fluency, divergent thinking, creative problem solving, working memory). There were no multivariate outliers in the sample.

It is recommended that a minimum of five participants be included per each proposed model parameter (Hancock & Mueller, 2013). Thus, the goal was to obtain a total of 200 participants to maintain sufficient power for analyzing models with up to 20 parameters. Data collection extended past 200 participants to accommodate the expected effects of attrition, so data collection ended once 200 participants had completed *both* sessions (note that, because more than one participant could sign up for a session, this resulted in a total of 202 participants). After the exclusion procedure, the obtained sample size of 196 participants was sufficient for appropriately conducting analyses on the most complex proposed model, which totaled 14 proposed parameters. Because several of the tasks used in this study require an extensive knowledge of the English language, only native English-speaking individuals were included as participants in this investigation.

Materials

Divergent thinking tasks. All of the divergent thinking tasks were conducted using paper and pencil. Participants completed two verbal divergent thinking tasks (unusual uses; consequences) and two figural divergent thinking tasks (circles; incomplete pictures). For these tasks, written instructions emphasized that creative or unique responses are desired (Silvia, Martin, & Nusbaum, 2009). The divergent thinking tasks were scored for originality using the *snapshot scoring method* (Silvia et al., 2008), which aims to reduce the risk of confounding the quality of responses with the quantity of responses (i.e., fluency). Two subjective judges were recruited to provide a single rating representing the creative quality of a participant's entire set of responses on a scale from 1 to 5, with 1 being *not creative at all* and 5 being *very creative*. The judges' ratings were then averaged into a single creativity score for each individual, representing a holistic view of each person's level of creativity across the entire set of responses that they provided. Interrater reliabilities were calculated using Cronbach's alpha (Cronbach, 1951) and are shown in Table 1.

Unusual uses task. The unusual uses task used adapted materials and procedures from Guilford, Merrifield, and Wilson (1958). The unusual uses task prompted participants to list as many unusual or creative uses for a newspaper as they could in three minutes.

Consequences task. The consequences task used materials and procedures adapted from DeYoung et al. (2008) and Torrance (1974). Participants were prompted to list as many potential consequences or implications (positive or negative) of all humans having the ability to flap their arms and fly. It was emphasized that creative or unique responses were desired, and participants had three minutes to list as many ideas as possible.

Circles task. The circles task adapted materials and procedures from Torrance (2008). Participants were provided with a sheet of 24 blank circles, and they used the circles to draw as many creative or unique objects or pictures as possible within five minutes. The task instructions also specified that the participants' drawings must represent actual objects or parts derived from such objects, and the circles were required to be instrumental to the formation of the drawings.

Incomplete pictures task. The incomplete pictures task used materials and procedures adapted from Torrance (2008). This task provided participants with a sheet of nine individual squares, with each square consisting of differently formed lines and shapes. Participants used the incomplete shapes to draw as many unique or creative objects or pictures as possible within five minutes. Similar to the circles task, participants were instructed to use the abstract shapes and lines as the foundation for their sketches, and their drawings were also required to be complete and identifiable, such that the object(s) within the picture could be named.

Fluency tasks. All of the fluency tasks were conducted using paper and pencil. Participants completed two verbal fluency tasks (letter fluency; category fluency) and two figural fluency tasks (design fluency; Ruff figural fluency). Following typical instructions for these tasks (i.e., because fluency tasks are not intended to be creative), the instructions emphasized the quantity of responses over the quality, or uniqueness, of responses. These tasks were scored only for fluency by summing the total number of responses provided for each task.

Letter fluency task. The letter fluency task used materials and procedures adapted from Borkowski, Benton, and Spreen (1967); Lee and Therriault (2013), and Nusbaum and Silvia (2011). The letter fluency task requires participants to generate as many words as possible that start with the letter F within three minutes.

Category fluency task. The category fluency task used materials and procedures adapted from Benton and Hamsher (1978); Lee and Therriault (2013); Nusbaum and Silvia (2011), and Rosen and Engle (1997). The category fluency task requires participants to generate as many animal names as possible within three minutes.

Design fluency task. The design fluency task adapted materials and procedures from Jones-Gotman and Milner (1977) and Demakis and Harrison (1997). This task requires participants to generate as many abstract, unnamable designs as possible using exactly four lines (i.e., geometric shapes are not acceptable because they can be named). Scribbling was prohibited, and specifications of a line were also included in the instructions. Participants had five minutes to complete the task.

Ruff figural fluency task. The Ruff figural fluency task adapted materials and procedures from Ruff (1996). Participants were presented with a sheet of 35 dot matrices that were arranged in a five by seven array. Participants connected the dots within each unit in as many different ways as possible within a 3-min time period. It was emphasized that the quantity of responses was important for the task but that repetitions in responses were to be avoided.

Creative problem-solving tasks. The creative problem-solving tasks were conducted via desktop computers or paper and pencil. Participants completed two verbal creative problem-solving

Table 1
Descriptive Statistics

Task	*M*	*SD*	Min	Max	Skew	Kurtosis	α
Insight	.32	0.23	0.00	1.00	0.52	−0.55	.58
Figural Rebus	.38	0.19	0.04	0.88	0.19	−0.75	.80
Verbal Rebus	.47	0.17	0.00	0.83	−0.56	0.07	.75
Anagrams	.51	0.18	0.10	0.87	−0.22	−0.58	.83
Design fluency	18.16	9.46	1.00	48.00	0.76	0.43	—
Ruff fluency	8.06	3.23	.67	23.33	0.97	2.08	—
Letter F	27.14	7.34	9.00	53.00	0.50	0.61	—
Animals	30.18	9.29	.00	61.00	−0.07	1.53	—
Circles	1.93	0.97	1.00	5.00	1.01	0.16	.82
Incomplete pics	2.24	0.90	1.00	5.00	0.29	−0.76	.73
Newspaper	2.46	0.86	1.00	5.00	0.25	−0.57	.46
Flying	2.28	0.91	1.00	5.00	0.33	−0.62	.59
Operation span	54.36	14.04	8.00	75.00	−0.97	0.62	.84
Running span	48.53	15.55	2.00	87.00	−0.23	−0.13	.82
Symmetry span	26.08	8.59	1.00	41.00	−0.57	−0.11	.82
Rotation span	23.88	9.29	0.00	42.00	−0.39	−0.44	.70

Note. $N = 196$ for all tasks; α = Cronbach's alpha. Descriptive statistics were calculated based on raw, unstandardized scores.

tasks (anagrams; verbal Rebus puzzles) and two figural creative problem-solving tasks (figural Rebus puzzles; classic insight). Accuracy and response times were recorded for all items within each computerized task.

Anagram task. The anagram task used materials and procedures adapted from Gilhooly (1978) and was presented via computer. Anagrams require participants to unscramble a series of letters into the correct word or phrase. The anagram task included 30 five-letter, one-solution anagrams as experimental items and three anagrams as practice items. Items varied across a range of difficulty. Participants first completed the practice items to become accustomed to the procedure before completing the experimental items. Participants had a maximum of 30 s to solve each problem but were instructed to press the spacebar if they solved the problem before the allotted 30 s. Participants then entered their answer into a response box on another slide and pressed *Enter* to continue to the next problem.

Verbal Rebus puzzle task. This task used materials and procedures adapted from MacGregor and Cunningham (2008, 2009) and was presented via computer. Rebus puzzles require participants to use visual and spatial clues of verbal information to uncover a common idiom or phrase. The verbal Rebus puzzle task included 24 experimental problems and 3 practice problems. Participants had a maximum of 30 s to solve each problem. If they solved the problem before it timed out, they pressed the spacebar. They then entered the answer into a free-response box and pressed *Enter* to move on to the next problem.

Figural Rebus puzzle task. The figural Rebus puzzle task, presented via computer, required participants to use visually and spatially represented figures within an image to uncover a common idiom or phrase. This task included 25 experimental items and three example items, and it followed the same procedure as the verbal Rebus puzzle task. Participants had 30 s to solve each problem, and they pressed the spacebar if they solved a problem before it timed out. Participants entered their answer into a free-response box before moving on to the next problem.

The materials for the figural Rebus puzzle task were designed and normed for use in the current study. A large set of idioms and phrases were retrieved and compiled into a list. A team of trained researchers drew 75 sketches of the items in that list. Much like verbal Rebus puzzles, these sketches avoid directly interpretable depictions of the idioms, leading solvers to initially misrepresent the problems and forcing them to restructure their original misrepresentation to reach solution. Twenty-eight of these items were selected on the basis of covering a range of difficulty in pilot studies. Two examples of problems used in the task are displayed in Figure 2.

Classic insight task. The classic insight task was presented via paper and pencil and used materials and procedures from Ash and Wiley (2006). This task included various figural versions of classic insight problems, such as matchstick arithmetic problems (Knoblich et al., 1999), Katona squares problems (Katona, 1940), and coin problems (Ormerod, MacGregor, & Chronicle, 2002). This task included seven total problems, six of which were derived from the *Few Moves Available* condition in Ash and Wiley (2006). The seventh problem was the triangle of coins problem (Cunningham et al., 2009). Participants had three minutes to solve each problem, and responses for each problem were scored for accuracy. Afterward, these scores were averaged into a composite accuracy score, reflecting the proportion of correctly answered problems out of seven.

Working memory capacity tasks. The working memory tasks were conducted via desktop computers. Participants completed two standard verbal working memory tasks (operation span; running span) and two standard visual working memory tasks (symmetry span; rotation span). All of the tasks are untimed, but the processing component of each task depends on a person's pacing during the practice trials to minimize the opportunity for rehearsal. It generally takes 15 min for participants to complete each task. Accuracy and response times were recorded for all items within each task. Accuracy was assessed as the number of units (e.g., letters, words, numbers) that were correctly recalled in the appropriate serial position for each trial.

Operation span task. The operation span task used materials and procedures from Unsworth, Heitz, Schrock, and Engle (2005). This task required participants to remember a series of letters, while also mentally solving math equations. Within an individual trial, participants were shown an equation that they must solve mentally. The next screen displayed a number, and participants indicated whether the displayed number is the correct or incorrect answer to the equation previously presented. After making a response, a letter was shown that the participant was instructed to

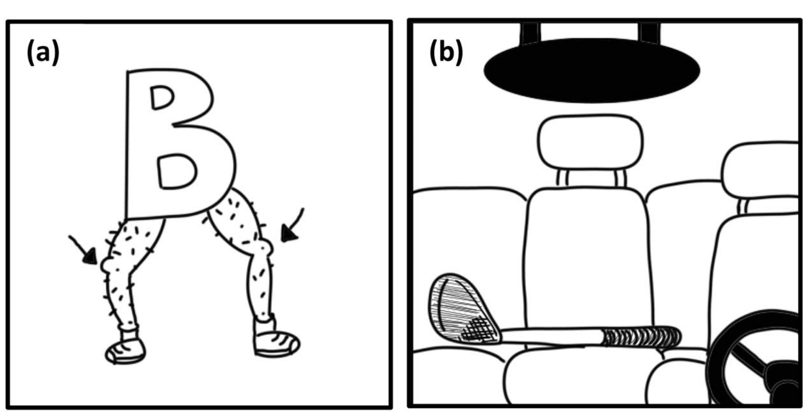

Figure 2. Examples of (a) an easier figural Rebus puzzle (*bee's knees*; solution rate = 57.1%), and (b) a more difficult figural Rebus puzzle (*backseat driver*; solution rate = 28.8%).

remember. At the end of each trial, participants were asked to recall all of the letters shown to them in correct serial order. Trial length ranged from two to seven items, and the whole task included three iterations of each trial length.

Running span task. The running span task used materials and procedures from Jarosz and Jaeger (2019), based on work by Broadway and Engle (2010). This task required participants to recall the last few letters from a series of individually presented letters on the computer screen without knowing the exact number of letters that would be shown. The number of letters presented in one string ranged between four and nine letters, and the number of letters that participants recalled ranged between three to six letters. The whole task included three iterations of each number of letters presented and those to be recalled.

Symmetry span task. The symmetry span task used materials and procedures from Unsworth, Redick, Heitz, Broadway, and Engle (2009). This task required participants to first decide whether an image consisting of shaded squares in an eight-by-eight array was symmetrical. Next, they were shown a four by four array that consisted of a single filled square, and participants had to remember the location of the filled squares across the varying number of items (between two and five) within a trial. At the end of a trial, participants clicked the to-be-remembered squares in the correct serial order that they were presented in a blank four-by-four array. The whole task included three iterations of each trial length.

Rotation span task. The rotation span task used materials and procedures from Unsworth et al. (2005). Within an individual trial, participants first determined whether a rotated letter (G, F, or R) is either normal or mirror-reversed. These letters were rotated at 0°, 45°, 90°, 135°, 180°, 225°, 270°, or 315°. After making a judgment, participants were shown an arrow that was positioned at one of the previously listed degree rotations. The arrows themselves could be either short or long, and participants had to remember both the size and degree of rotation of the arrow. The number of items in each trial ranged from two to five, and the whole task consisted of 12 total trials. At the end of a trial, an array of arrows (both long and short) in each degree of rotation were displayed. Participants then clicked the to-be-remembered arrows in the correct serial order as they were presented.

General Procedure

Participants entered the testing room and sat at a computer. They first provided written informed consent, and then the testing began. The experimenter loaded and started all computerized tasks for participants. For the paper and pencil tasks, pre-prepared packets with randomized items were provided.

Tasks were split across two sessions on two separate days. Task order was largely determined by the need to present divergent thinking tasks after the completion of all of the fluency tasks, to prevent the divergent thinking instructions from contaminating performance on the fluency tasks (see Nusbaum et al., 2014). On the first day, participants completed the fluency tasks and the working memory tasks. The fluency tasks were presented first and took approximately 15 min to complete all four. The ordering of the tasks was in a fixed random order: letter fluency, Ruff fluency, category fluency, and design fluency. The working memory tasks were presented next and took approximately one hour to complete. Operation span was presented first, followed by symmetry span, running span, and rotation span. The entire session lasted between an hour and an hour and a half.

During the second session, which was exactly one week later, participants completed the creative problem-solving tasks and the divergent thinking tasks in a session lasting up to an hour and a half. The divergent thinking tasks (presented first) took approximately 20 min to complete, and the creative problem-solving tasks took approximately an hour. The divergent thinking tasks presented the unusual uses task first, followed by the circles task, the consequences task, and the incomplete pictures task. The creative problem-solving tasks were presented as follows: classic insight, figural Rebus puzzles, anagrams, and verbal Rebus puzzles.

Planned Analyses

Three separate sets of analyses were proposed a priori. Each analysis set consists of theoretically driven models that address specific questions regarding the underlying constructs or processes involved in creative thinking. Analysis Set I investigates whether the surface features of divergent thinking and fluency tasks are indeed surface-level similarities or representative of the same construct; Analysis Set II addresses whether divergent thinking and creative problem-solving are also representative of the same construct. Because Analysis Sets I and II aim to address the psychometric similarities between tests of creativity and fluency, a reviewer requested that a bifactor model (unplanned by the authors) be added to these first two analysis sets as a robust test of shared versus independent variance. All models except the bifactor models were planned a priori in these sets. Analysis Set III investigates the role of controlled processes (i.e., working memory) on divergent thinking and creative problem solving. Although the bifactor component was retained in Set III (because later analyses built upon prior analyses), the overall predictions and structures of the models to be compared in Set III were the same as in the originally planned, a priori models. Additionally, a final analysis set consisting entirely of unplanned models was conducted post hoc to further explore and supplement the findings that resulted from Analysis Set III. Further details about each analysis set and its respective models are provided in the results section below.

Results

Four separate sets of analyses (Analysis Sets I–IV) were conducted to address various questions about the underlying mechanisms and processes contributing to individual differences in performance on common assessments of creativity. Each set of analyses builds upon the question(s) and findings from the prior set(s). Within each analysis set (with the exception of the bifactor models in Analysis Sets I and II, the general factor in Set III, and all models in Set IV), models and predictions were developed a priori and were compared against each other to obtain a better understanding of the relationships to be addressed by each question. All models are displayed in figures, where circles represent unmeasured latent constructs, and rectangles represent observed task performance (i.e., manifest/observed variables). Single-headed arrows from one variable to another indicate regressions, whereas double-headed arrows indicate correlations. Factor loadings are displayed next to each manifest variable, and correlations are displayed on top of double-headed arrows.

Chi-square difference tests are inappropriate for comparing the fit of non-nested models (Lin & Dayton, 1997; Vuong, 1989), which make up a considerable portion of the models being tested. Thus, Akaike information criterion (AIC; Akaike, 1974) and Bayesian information criterion (BIC; Schwarz, 1978) were used as the model selection indices for appropriately making comparisons across nested and non-nested models. AIC and BIC are parsimony fit indices, meaning that they value parsimonious (i.e., simpler) models over more complex ones. AIC and BIC values are not scaled from 0–1, so the only criterion for accepting one model over another is that smaller values are more desirable, indicating that the estimated model is close to the true model. If the change in AIC or BIC values between two competing models is less than two (ΔAIC or ΔBIC < 2), then both models can be interpreted as fitting the data equally well (Burnham & Anderson, 2004). Although AIC and BIC are both parsimony fit indices, they are calculated differently, and thus, penalize model complexity differently. For example, AIC rewards models for having fewer parameters, regardless of sample size; BIC, on the other hand, rewards parsimony by handicapping increasingly large sample sizes in complex models. Consequentially, AIC and BIC can favor different models as best-fitting. Notably, BIC's penalty for large sample sizes is also not well-calibrated for small sample sizes, and overly penalizes models with small samples (e.g., fewer than 500 participants; Yang, 2006). As such, the sample-size adjusted BIC (SABIC), which penalizes smaller sample sizes less heavily, is reported and used instead of BIC as the model selection criteria.[3] If neither metric preferred one model over another (and/or if AIC and BIC conflicted), then the more parsimonious model was accepted as the better-fitting model. Although it rarely occurred, if a model did not appropriately converge, it was not considered as a candidate for model selection (see the Appendix).

Although AIC and SABIC indices were used to compare, accept, and reject models throughout the analysis, the following statistics are also reported as supplemental goodness-of-fit indices: chi-square,[4] root mean square error of approximation (RMSEA), standardized root-mean-square residual (SRMR), and comparative fit index (CFI). Chi-square, RMSEA, and SRMR indices are absolute fit indices, which indicate how closely any given model fits the observed data (McDonald & Ho, 2002). The chi-square statistic tests for differences between the model's covariance matrix and the sample data (Hooper, Coughlan, & Mullen, 2008; Hu & Bentler, 1999; Schermelleh-Engel, Moosbrugger, & Müller, 2003). The RMSEA statistic compares the sample covariance matrix to an unknown population covariance matrix (Byrne, 1998; Hooper et al., 2008). An accepted rule-of-thumb for interpreting RMSEA values is as follows: values ≤ 0.01 indicate excellent fit; values ≤ 0.05 indicate good fit; values ≤ 0.08 indicate acceptable fit; values ≥ 0.10 indicate poor fit (MacCallum, Browne, & Sugawara, 1996). Finally, SRMR compares the square root of the sample covariance matrix to an unknown population covariance matrix and can be interpreted in a similar fashion as RMSEA: SRMR values ≤ 0.08 indicate good fit. CFI, on the other hand, is an incremental fit index, which indicates how closely a model fits the observed data when compared with a restrictive baseline model (Bentler, 1990; Bentler & Bonett, 1980). CFI values ≥ 0.95 indicate good fit (Hu & Bentler, 1999).

Confirmatory factor analysis was used to conduct Analysis Sets I and II, and structural equation modeling was used to conduct Analysis Sets III and IV. All analyses were conducted using the *lavaan* package in R 3.6.0 (R Core Team, 2018). See Table 1 for descriptive statistics and Table 2 for task correlations. Fit statistics for models across all four analysis sets are displayed in Table 3.

Analysis Set I

Models and predictions. The first analysis addresses the question of whether divergent thinking and verbal fluency are unidimensional or independent constructs. Model 1A in Figure 3 specifies divergent thinking and fluency as two independent, but covarying, constructs—representing the way in which these variables have traditionally been treated in the literature. In contrast, Model 1B loads all of the divergent thinking and fluency tasks onto a single construct, suggesting that it is not only the surface features of these tasks that are similar. Rather, they are both driven by the same underlying processes, which explain variance in both types of tasks. Models 1A and 1B were proposed a priori, and it was predicted that both types of tasks would be driven by the same underlying processes; thus, Model 1B was expected to be the better-fitting model. Finally, Model 1C is a bifactor model (Holzinger & Swineford, 1939) that serves as a robust test of shared versus independent variance between the two constructs: a domain-general factor ("gCr" in the model) extracts shared variance across all eight tasks in the model, in addition to the domain-specific divergent thinking and fluency factors that load onto their respective sets of tasks. Thus, Model 1C reflects a case where fluency and divergent thinking tasks require both shared and distinct processes and provides an explanation for the relationship between the two sets of tasks.

Because Model 1C was not proposed a priori, the sample size obtained for the study may be underpowered for detecting effects in such a large model, even though the model demonstrates structural identification (i.e., the number of free parameters exceeds the number of known parameters). Indeed, Model 1C did not appropriately calculate the domain-specific path coefficient for the Letter F task or the residual estimate for the Ruff task, suggesting that these specific parameters are empirically underidentified. This empirical underidentification is likely attributable to multicollinearity between the residual variances of the two fluency tasks and can be resolved by constraining similarly loading paths to be equal in the model. Thus, to increase the likelihood that models correctly converged in this set and in future sets, paths with factor loadings within .05 of each other on a shared factor in Model 1A were constrained to be equal in Models 1A and 1C. Because each analysis set builds on the prior sets, the same constraining procedure was repeated across the remaining analysis sets to maintain consistency. In the figures below, constrained paths are indicated

[3] BIC values are reported in the Appendix, in addition to the SABIC values.

[4] Chi-square tests are used to compare model fit across nested models only, and they assume that the non-standardized covariance matrix is used (Hu & Bentler, 1999). Because it was necessary to impute raw values for missing data before standardizing them, our data do not meet this assumption. AIC and SABIC were used instead of chi-square tests to compare across models, but chi-square values are reported in the Appendix as a *goodness-of-fit index* nonetheless (not as a model comparison index).

Table 2
Pearson's Correlations for All Tasks

Task	Insight	FigReb	VerbReb	Ana	DesFlu	Ruff	LetterF	Animals	Circles	IncomPic	News	Fly	Oper	Run	Symm	Rot
Insight	**1**	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
Figural Rebus	**.45**	**1**	—	—	—	—	—	—	—	—	—	—	—	—	—	—
Verbal Rebus	**.40**	**.66**	**1**	—	—	—	—	—	—	—	—	—	—	—	—	—
Anagrams	**.36**	**.43**	**.53**	**1**	—	—	—	—	—	—	—	—	—	—	—	—
Design fluency	.30	.34	.29	.25	**1**	—	—	—	—	—	—	—	—	—	—	—
Ruff fluency	.12	.08	−.01	−.01	**.52**	**1**	—	—	—	—	—	—	—	—	—	—
Letter F	.17	.39	.33	.45	**.38**	**.22**	**1**	—	—	—	—	—	—	—	—	—
Animals	.20	.31	.31	.28	**.41**	**.30**	**.36**	**1**	—	—	—	—	—	—	—	—
Circles	.29	.35	.32	.14	.24	.12	.13	.20	**1**	—	—	—	—	—	—	—
Incomplete pics	.29	.30	.26	.20	.36	.27	.29	.25	**.37**	**1**	—	—	—	—	—	—
Newspaper	.10	.18	.24	.15	.21	.05	.12	.19	**.21**	**.27**	**1**	—	—	—	—	—
Flying	.25	.22	.10	.13	.24	.14	.22	.27	**.20**	**.33**	**.35**	**1**	—	—	—	—
Operation span	.22	.21	.22	.28	.13	.05	.21	.21	.09	.09	.09	.05	**1**	—	—	—
Running span	.28	.39	.40	.36	.25	.10	.27	.18	.18	.16	.08	.18	**.45**	**1**	—	—
Symmetry span	.34	.19	.21	.27	.20	.13	.08	.13	.06	.11	−.04	.04	**.56**	**.29**	**1**	—
Rotation span	.35	.23	.24	.25	.17	.07	.03	.19	.11	.08	−.05	.00	**.51**	**.37**	**.67**	**1**

Note. $N = 196$. Factor correlations are highlighted in bold font. Correlations were calculated based on raw, unstandardized scores.

by dotted arrows: the circles and newspaper tasks are constrained to be equal for the divergent thinking factor, and the Ruff fluency task and the animals task are constrained to be equal for the fluency factor. Because the constrained models in Analysis Set I demonstrated comparable or better fits than the unconstrained equivalent versions of these models, only the constrained models are reported in the results. The Table in the Appendix reports model fit and model comparison statistics for all models (constrained and unconstrained) across all analysis sets.

Table 3
Model Fit Statistics Across Analysis Sets I–IV

Set	Model	*Df*	AIC	SABIC	CFI	RMSEA [CI]	SRMR
Set I	**1A**	**21**	**4214.95**	**4216.60**	**.98**	**.04 [.00, .08]**	**.05**
	1B	20	4245.98	4247.74	.86	.10 [.07, .13]	.07
	1C	14	4225.86	4228.28	.96	.06 [.01, .10]	.04
Set II	2A	21	4127.13	4128.79	.95	.07 [.04, .10]	.05
	2B	20	4166.21	4167.97	.84	.12 [.09, .15]	.08
	2C	18	4128.09	4130.07	.95	.07 [.04, .11]	.05
	2D	18	4127.60	4129.58	.95	.07 [.03, .10]	.05
	2E	14	4129.73	4132.15	.96	.08 [.04, .11]	.04
	2F	**14**	**4124.58**	**4127.01**	**.97**	**.06 [.01, .10]**	**.04**
Set III	3A*	45	6081.20	6084.84	.95	.06 [.04, .08]	.06
	3B	**44**	**6079.70**	**6083.45**	**.96**	**.06 [.03, .08]**	**.06**
	3C	44	6082.17	6085.92	.95	.06 [.04, .08]	.05
	3D	44	6085.16	6088.91	.95	.06 [.04, .09]	.07
	3E	43	6081.70	6085.55	.95	.06 [.04, .08]	.06
Set IV	4A	91	8125.69	8130.65	.92	.07 [.05, .08]	.07
	4B	90	8104.40	8109.47	.94	.06 [.04, .07]	.06
	4C	89	8101.65	8106.83	.94	.05 [.04, .07]	.06
	4D	89	8104.63	8109.81	.94	.06 [.04, .07]	.06
	4E	**89**	**8094.48**	**8099.66**	**.95**	**.05 [.03, .07]**	**.06**
	4F	88	8095.81	8101.10	.95	.05 [.03, .07]	.06

Note. For each analysis set listed, models are organized from the most parsimonious model to the most complex model (as indicated by the decreasing degrees of freedom). Model names highlighted in bold font indicate the best-fitting model within its respective set. Ninety percent confidence intervals are displayed in brackets next to the RMSEA value.
* Model did not appropriately converge.

Set I results. Model fit statistics were computed for each model separately and then compared. Model 1B demonstrated poor fit: the CFI and RMSEA criteria were not met (see Table 3). For Models 1A and 1C, CFI, RMSEA, and SRMR exceeded the criteria for good fit. The AIC and SABIC values also unanimously favored Model 1A, as indicated by the lower values compared with those for Models 1B or 1C. The independence model performed better than either the homogenous or the bifactor model in terms of both absolute and relative fits, so Models 1B and 1C are rejected, leaving Model 1A to be accepted as the best-fitting model.

Set I discussion. Because AIC and SABIC favored Model 1A, this suggests that fluency and divergent thinking are distinct, but related, constructs. Despite the initial prediction that one construct would account for performance on both types of tests, the direct evaluation of their relationship revealed that these tests do indeed assess different cognitive abilities. Still, it is important to note that the fluency and divergent thinking factors are correlated (r = .63), sharing almost 40% of their variance, though the failure of Model 1C suggests that this correlation does not imply a common underlying construct.

Analysis Set II

Models and predictions. The second set of analyses explores how the processes underlying divergent thinking and creative problem solving interact and contribute to performance on each type of task. Model 2A in Figure 4 depicts divergent thinking as an independent construct from creative problem solving, representing the standard view of how these tasks are considered in the literature. The theoretical underpinnings of this model would suggest that divergent thinking and creative problem solving only predict unique variance in the tasks that purport to measure these different creative constructs. Model 2B, however, would suggest that variance across all creative thinking tasks can be explained by a single creativity construct, indicating that both divergent thinking and creative problem-solving tasks are inseparable forms of creative thinking.

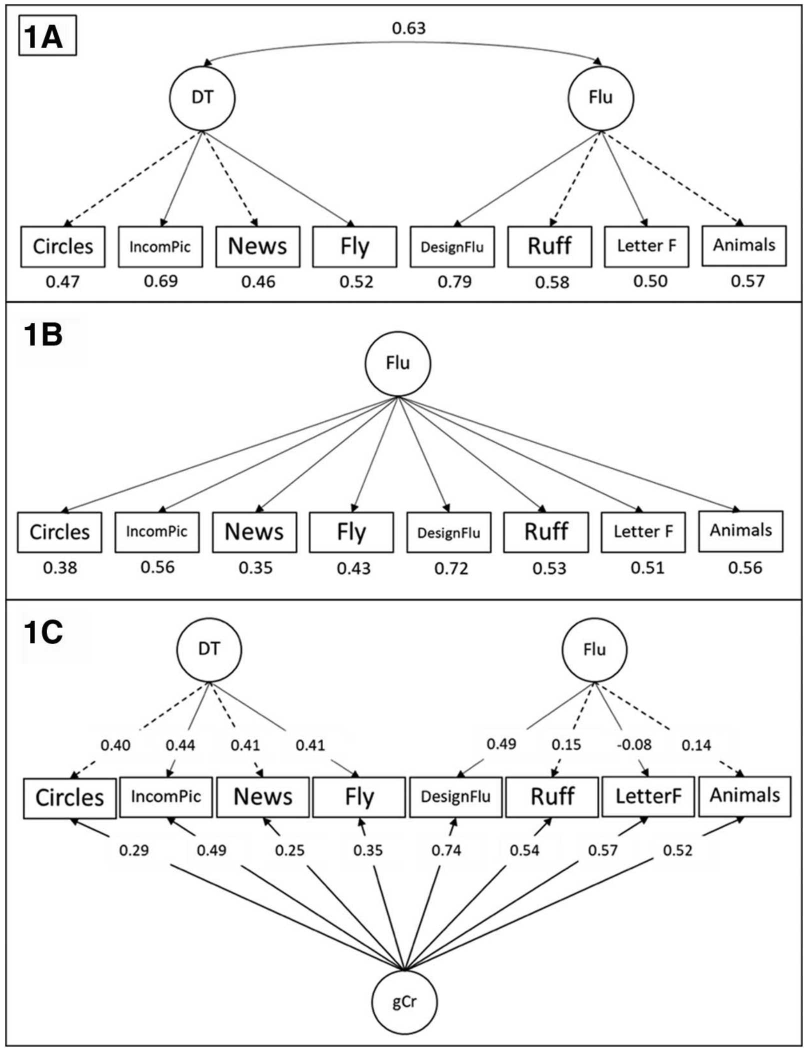

Figure 3. Path diagrams for Analysis Set I representing competing hypotheses of the dimensionality of divergent thinking and fluency. Dotted arrows indicate constrained paths. Model 1A in box indicates the best-fitting model within its respective set. DT = divergent thinking ability; Flu = fluency ability; gCr = domain-general creativity; Circles = Torrance Test of Creativity—circles task; IncomPic = Torrance Test of Creativity—incomplete pictures; News = unusual uses task—newspaper; Fly = consequences task—humans flying; DesignFlu = design fluency; Ruff = Ruff figural fluency; Letter F = letter fluency; Animals = category fluency.

Because there is mixed, yet increasing, evidence that shared processes are involved in creative problem solving and divergent thinking tasks, the remaining models represent valid potential representations of the underlying processes involved in these types of tasks. Model 2C depicts the divergent thinking factor as explaining *unique* variance in the divergent thinking tasks, as well as *shared* variance in the creative problem-solving tasks. This model suggests that performance on the creative problem-solving tasks requires the usage of both types of creative-thinking processes, whereas performance on the divergent thinking tasks only requires the usage of processes unique to those tasks. Model 2D depicts the opposite, with the creative problem-solving factor explaining shared variance across all tasks. This model suggests that performance on the divergent thinking tasks, but not the creative problem-solving tasks, requires both types of creative thinking. In each of these cases, the results would suggest that one construct directly impacts performance on two different types of creative thinking tasks, whereas the other construct only impacts performance on its respective task set.

Model 2E depicts a saturated model in which variance across all creative thinking tasks is explained by *only* shared processes. This model suggests that each factor drives performance on both kinds of tasks, indicating that all creative thinking tasks require a combination of both divergent thinking and creative problem-solving processes to be successful on either set of tasks. Consequentially, neither factor has a truly unique influence on either set of manifest variables. As outlined previously, accumulating evidence suggests that associative and controlled processes play a role in both types

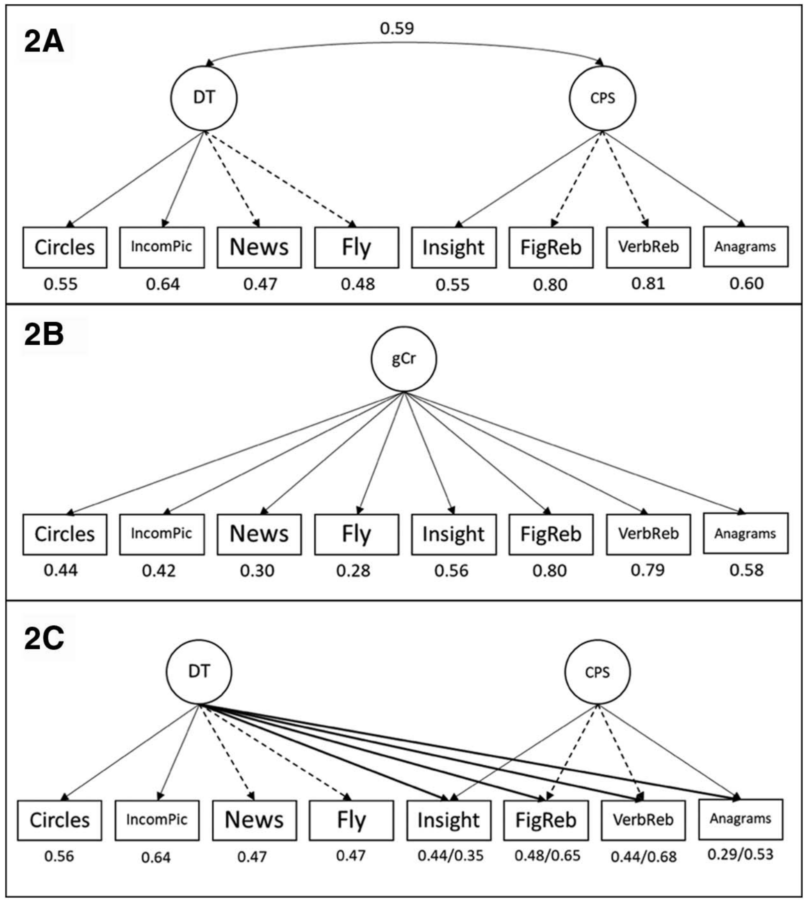

Figure 4. Path diagrams for Analysis Set II representing the differing hypotheses about the relationships between divergent thinking and creative problem solving. Bolded lines emphasize cross-loadings between factors, and dotted arrows indicate constrained paths. For cases in which two factor loadings are provided beneath a manifest variable, the first value represents the loading from the factor on the left, and the second value represents the loading from the factor on the right. Model 2F in box indicates the best-fitting model within its respective set. CPS = creative problem-solving ability; Insight = classic insight task; FigReb = figural Rebus puzzle task; VerbReb = verbal Rebus puzzle task. (*Figure continues on next page.*)

of creative thinking. Thus, it was predicted that Model 2E would provide the best fit to the data because it should account for the shared processes across both task types.

Finally, Model 2F is a bifactor model and was included post hoc per a reviewer's request. This model represents a combination of Models 2A and 2B, because it suggests that there is both a domain-general mechanism that can explain shared variance across all eight creativity tasks, and also that divergent thinking and creative problem solving represent unique abilities that require domain-specific processes to successfully be completed. Thus, if Model 2F is accepted over 2A, then this would suggest that a domain-general factor can adequately explain the correlation between creative problem solving and divergent thinking depicted in Model 2A.

Set II results. Model fit statistics were computed for each model separately and then compared. As the model fit statistics in Table 3 demonstrate, the AIC values across all models were similar (with the exception of Model 2B), but Model 2F was favored over Model 2A ($\Delta AIC_{2A\text{-}2F} = 2.55$). However, SABIC indicated that Model 2F fit equally as well as Model 2A ($\Delta SABIC_{2A\text{-}2F} = 1.78$). CFI, RMSEA, and SRMR indicated good fit for both models, but these values indicated a stronger overall fit for Model 2F. Because AIC and SABIC did not favor conflicting models and AIC favored Model 2F, Model 2F is accepted as the best-fitting model.

Set II discussion. In contrast to Analysis Set I, the bifactor model was the best-fitting model in this analysis set. The bifactor model indicates that divergent thinking and creative problem-solving tasks involve both domain-specific and domain-general processes that are unique or common (respectively) to the tasks that aim to measure these abilities. That Model 2F was accepted over Model 2A indicates that the correlation between divergent thinking and creative problem-solving tasks can best be explained by domain-general creative processes. The domain-specific factors therefore represent processes specific to those types of tasks. For example, the creative problem-solving factor may represent individuals' ability to apply general problem-solving heuristics or

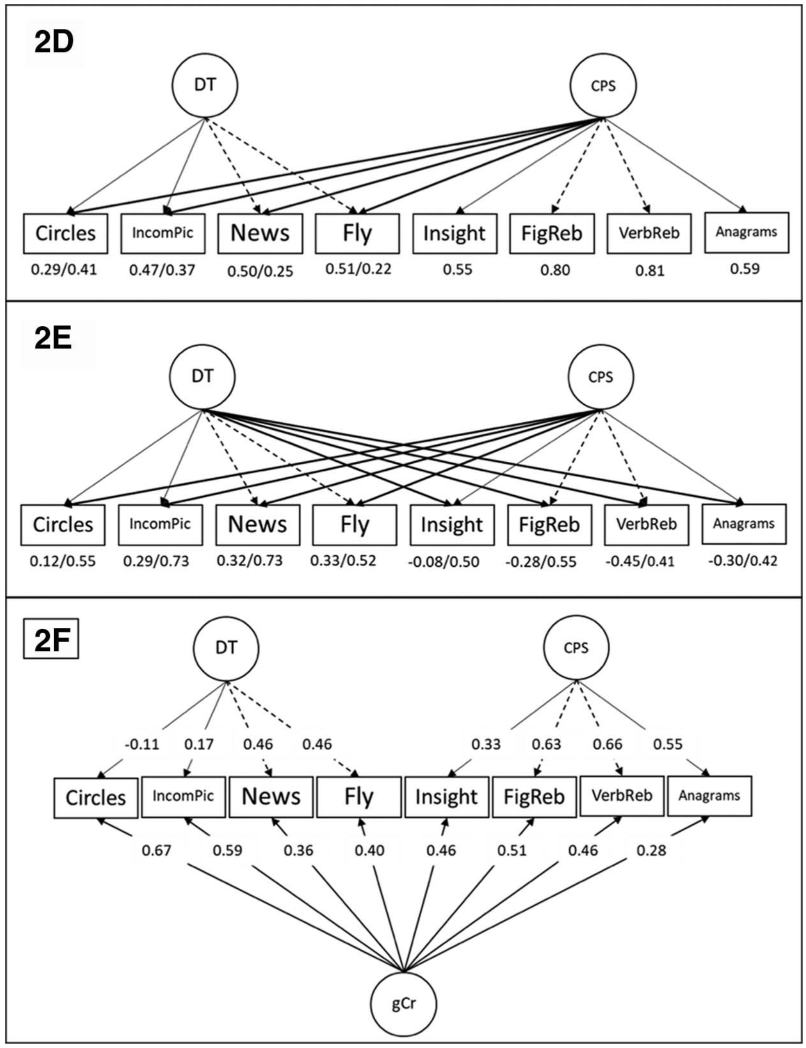

Figure 4. (*continued*)

strategies. Similarly, it is possible that the remaining variance in the divergent thinking factor, which shared almost 40% of its variance with fluency in Model 1A, may represent fluency ability. The next set of analyses attempts to explore this shared variance further by examining the relationship of working memory to each of these constructs.

Analysis Set III

Models and predictions. In this analysis set, a working memory factor predicts the best-fitting model from the prior set of analyses. Five models were developed to explore the relationships between working memory and the bifactor model of creativity, with each proposed model representing a different prediction regarding the underlying mechanisms involved in creative thinking (see Figure 5). Although the bifactor structure was inherited from Analysis Set II to all models in Set III, the overall structures and predictions of Models 3B, 3C, and 3D were planned a priori. Models 3A and 3E are only meaningful based on the bifactor structure, and are thus post hoc models. In the first model, working memory only predicts the domain-general creativity factor, suggesting that only the domain-general aspects of creative thinking require working memory resources. Models 3B and 3C build upon this framework: in Model 3B, working memory predicts the general and creative problem-solving factors only, suggesting that working memory is involved in both the domain-general aspects of creative thinking, as well as the domain-specific processes unique to creative problem-solving tasks; in Model 3C, working memory predicts the general and divergent thinking factors only, suggesting that working memory is involved in both the domain-general aspects of creative thinking, as well as the domain-specific processes unique to divergent thinking tasks. Model 3D depicts working memory as predicting only the divergent thinking and creative problem-solving factors but not the domain-general factor. This model would suggest that only the domain-specific processes involved in divergent thinking and creative problem-solving tasks draw upon working memory resources, leaving the domain-general aspects of creative thinking unexplained by working memory. Finally, the fifth model depicts working memory as a predictor of

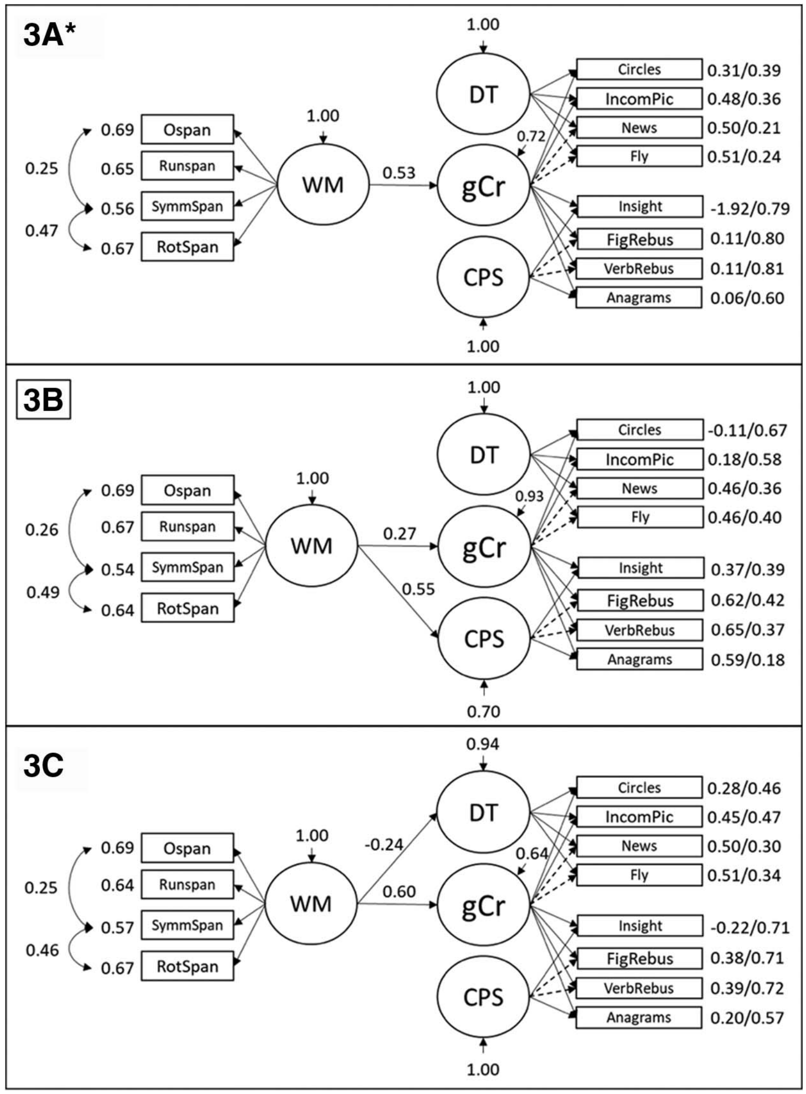

Figure 5. Path diagrams for Analysis Set III representing differing hypotheses about individual differences in divergent thinking and creative problem solving. Single-headed arrows originating from outside of the model and pointing to a factor indicate the residual variance of that factor. Double-headed arrows between observed variables indicate an oblique relationship between the residual variances and were added as post hoc modification indices. For cases in which two factor loadings are provided next to a manifest variable, the first value represents the domain-specific factor loading, and the second value represents the domain-general factor loading. Model 3B in box indicates the best-fitting model within its respective set. WM = working memory capacity; Ospan = operation span task; Runspan = running span task; SymmSpan = symmetry span task; RotSpan = rotation span task. * Model did not appropriately converge. (*Figure continues on next page.*)

all three factors, representing a strong test of the executive theory. Model 3E suggests that both the domain-general and the domain-specific processes involved in creative problem-solving and divergent thinking tasks require working memory resources to be successful.

Set III results. Initial model fits for all models in Analysis Set III were on the lower end of the cutoff range for good fit as recommended by Hu and Bentler (1999; CFI ≥ 0.95). Indeed, the CFIs for all five models in the set were around 0.92. As such, modification indices (MI) were used to help improve the overall fits of the models in this (and following) set(s). MIs were calculated based on the largest model in the set (i.e., Model 3E) and were used conservatively: only theoretically meaningful recommendations for correlated error variances were considered, starting with the highest MI value. The first modification was to allow the residuals of the symmetry span task and the rotation span task to correlate (MI = 15.98). Model fit improved with the addition of the modification (CFI = 0.94), but it still did not cross the threshold for good fit as recommended by Hu and Bentler (1999). Thus, with the first modification included in the model, MIs were

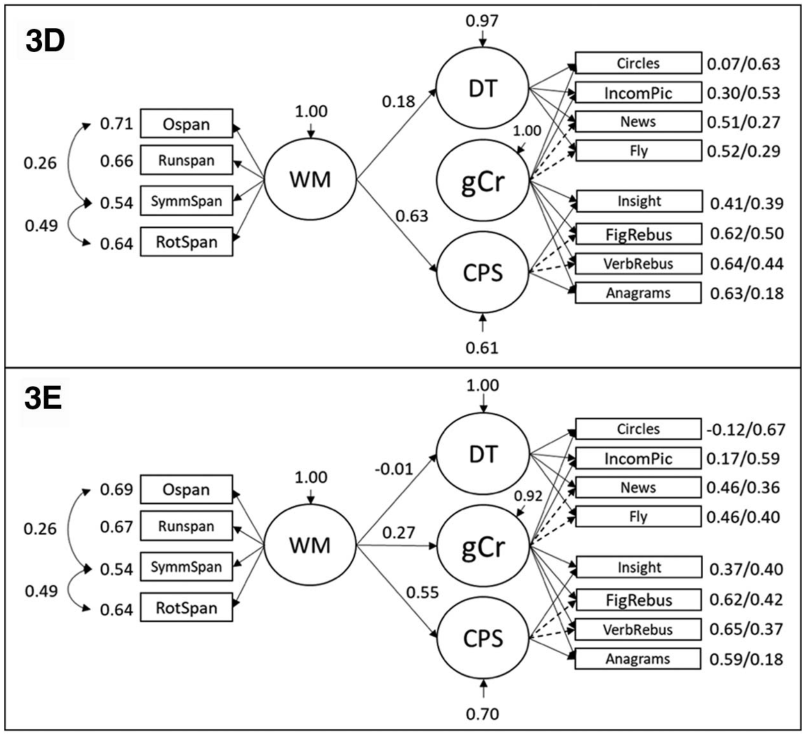

Figure 5. (*continued*)

recalculated, and the highest meaningful MI recommendation was again accepted. The second and final modification was to allow the error variances of the symmetry span and operation span tasks to correlate (MI = 10.05). These modifications effectively improved model fits, with the CFI of all models in the set reaching at least 0.95 from 0.92. Even with these model enhancements, however, Model 3A did not correctly converge and produce accurate estimates. Model 3A is marked in tables and figures with an asterisk to indicate that it did not produce accurate estimates and should be interpreted with caution.

Both AIC and SABIC preferred Models 3A and 3B equally (see Table 3; $\Delta AIC_{3A-3B} = 1.50$; $\Delta SABIC_{3A-3B} = 1.39$). Although AIC and SABIC did not favor one model over another, Model 3A did not produce correct estimates and, therefore, should not be accepted over another model that did, despite Model 3A being more parsimonious. Still, AIC and SABIC both trended toward accepting Model 3B, and the CFI and chi-square indices mimic this trend as well. These results indicate that working memory impacts performance on both domain-general creative processes (0.27) and domain-specific creative problem-solving processes (0.55), but not domain-specific divergent thinking processes.

Set III discussion. That Model 3B was accepted as the best-fitting model suggests that working memory plays a role in the domain-general aspects of both types of creative thinking tasks, as well as the domain-specific processes unique to creative problem-solving tasks. Prior evidence has suggested that working memory may impact only certain portions of the creative problem-solving process (e.g., the search phase; Ash & Wiley, 2006), which may explain the domain-specific working memory relationship in this model. This would also explain why the domain-general factor, which may represent processes specific to creative cognition, has a much weaker relationship with working memory. Opposing evidence suggests that fluid intelligence is isomorphic with creative problem-solving ability, and working memory is a primary predictor of successful creative problem-solving (Chuderski & Jastrzębski, 2018). Considering the strong relationship that remains between working memory and the creative problem-solving factor (0.55), the results of the current analysis set may appear to lend support for the business-as-usual perspective, which suggests that systematic and incremental methods or heuristics can be used to solve any kind of problem (Weisberg, 2006). Indeed, working memory accounted for both domain-general and domain-specific variance involved in successful creative problem-solving, suggesting that executive processes may play more of a complex role in creative problem-solving than originally considered. However, it is important to note that the explained variance in these factors was far from complete. The variance explained in the general creativity factor by working memory was only 7.29%, suggesting working memory had only a minimal influence on general creative task performance. Likewise, considerable variance in creative problem solving was left unexplained, with working memory only explaining 30.25% of its variance. Thus, the business-as-usual perspective cannot adequately explain these findings, and it is likely that multiple processes are involved in these tasks.

In addition, once domain-general processes were accounted for, working memory did not predict divergent thinking performance. This finding is consistent with prior work showing that working memory does not predict uniqueness scores of diver-

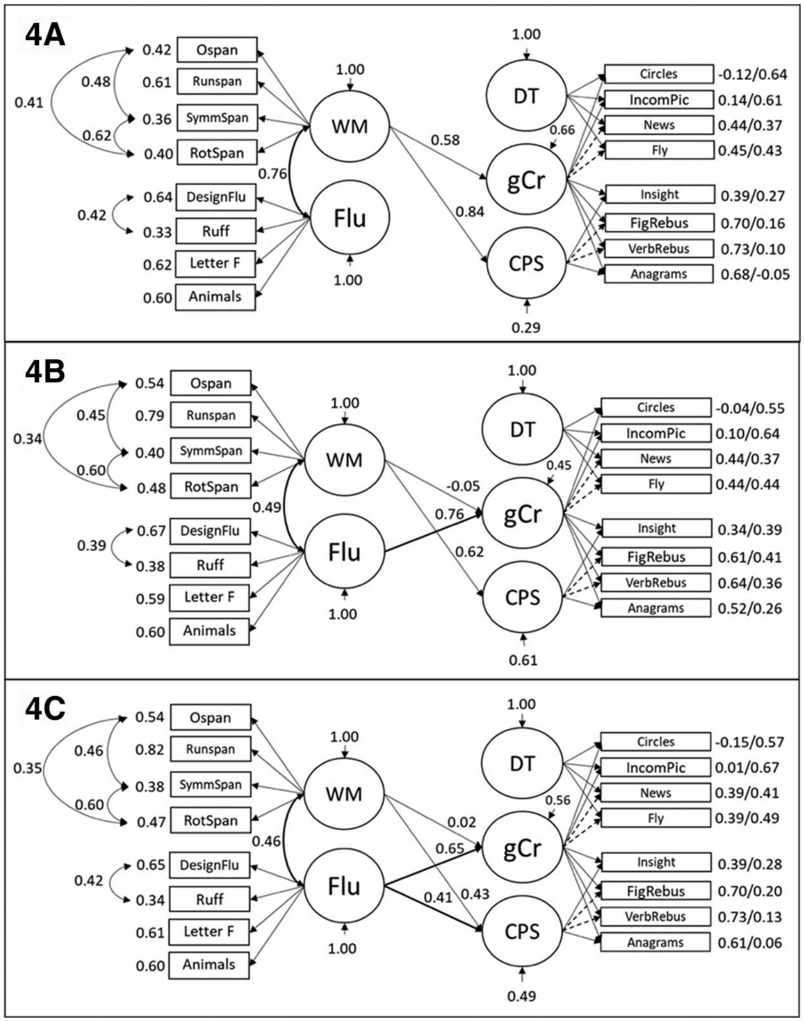

Figure 6. Path diagrams for Analysis Set IV representing differing hypotheses about individual differences in divergent thinking and creative problem solving. Single-headed arrows originating from outside of the model and pointing to a factor indicate the residual variance of that factor. Double-headed arrows between observed variables indicate an oblique relationship between the residual variances and were added as post hoc modification indices. For cases in which two factor loadings are provided next to a manifest variable, the first value represents the domain-specific factor loading, and the second value represents the domain-general factor loading. Model 4E in box indicates the best-fitting model within its respective set. (*Figure continues on next page.*)

gent thinking tasks (Smeekens & Kane, 2016) and implies that other constructs are driving divergent thinking task performance.

Because working memory does not fully account for the unique or shared variance in creative problem-solving tasks, the business-as-usual view cannot account for these results, supporting the dual-process view. Still, it remains unclear what best explains this remaining variance. Given that the results from Analysis Set I indicated that fluency and divergent thinking are strongly related (r = .63), but independent, factors, and that Lee and Therriault (2013) found that fluency predicted both divergent and convergent thinking in their study, it could be that fluency is necessary for reaching remote ideas or solutions. Working memory, then, would allow for a controlled search through the activated ideas and/or solution paths. As such, a fourth set of analyses was conducted to explore this relationship. Analysis Set IV continues to build on the findings described so far by reintroducing fluency into the proposed models.

Analysis Set IV

Models and predictions. In this last analysis set, a fluency factor predicted the best-fitting model from the prior set of analyses (see Figure 6). Six models were developed for the current set post hoc, in which working memory always predicts both domain-general creative thinking and domain-specific creative problem-solving abilities. All six proposed models allow the fluency and working memory factors to correlate. Model 4A suggests that fluency directly relates to working memory and only indirectly relates to domain-general and

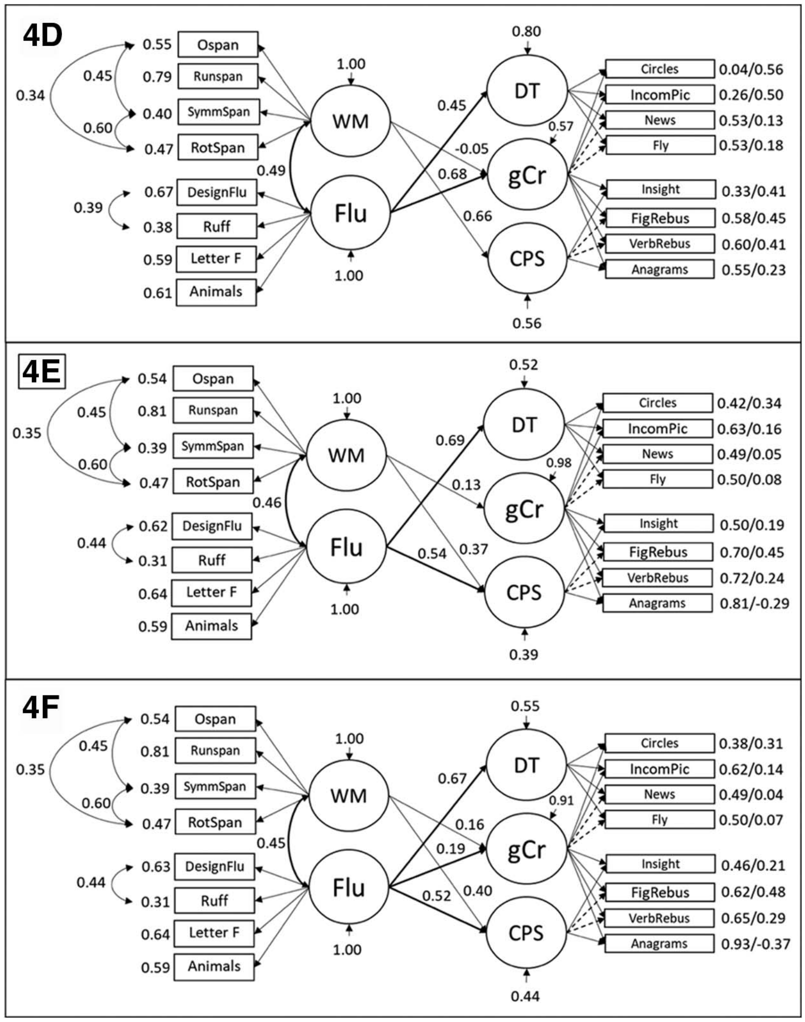

Figure 6. (*continued*)

domain-specific creative problem-solving abilities, through working memory. Model 4B suggests that fluency impacts performance on domain-general creative thinking tasks, both directly and indirectly through its relationship with working memory. Model 4C suggests that fluency impacts domain-general and domain-specific creative problem-solving ability. Model 4D depicts the opposite of Model 4C, suggesting that fluency impacts domain-general and domain-specific divergent thinking. Model 4E suggests that fluency directly impacts domain-specific success on creative problem-solving and divergent thinking tasks, while indirectly impacting domain-general creative thinking ability through its relationship with working memory. Finally, Model 4F depicts fluency as directly impacting domain-general and domain-specific creative thinking. This model would suggest that fluency is important not just for creative task performance in general, but also plays specific roles in both divergent thinking and creative problem solving.

Set IV results. MIs from the prior set were embedded into the models for the current analysis set. Even with these embedded modifications, however, all six models in the current set fell below the threshold for good fit as recommended by Hu and Bentler (1999). As such, MIs were again calculated based on the largest model (Model 4F) in the set and were used to improve overall fits. The additional modifications made in this set were to correlate the error variances of the figural fluency tasks (MI = 24.97) and two more of the working memory tasks (operation span & rotation span, MI = 14.45).[5] These modifications effectively improved the fits of all models in the set, with the poorest-fitting model (Model 4A) improving its CFI from 0.87 to 0.92. However, even with the added modification indices, Models 4E and 4F were the only ones in this set to meet the criteria for good fit across all indices—the remaining models demonstrated moderate fits across all indices.

AIC and SABIC both favored Models 4E and 4F equally (see Table 3; $\Delta AIC_{4F\text{-}4D} = 1.33$; $\Delta SABIC_{4F\text{-}4D} = 1.44$). Because Models 4E and 4F both demonstrated satisfactory fits and neither model selection metric preferred one over another, the simplest of these competing models is accepted. Thus, Model 4E is accepted as the

[5] Models from Analysis Set III were rerun with the final set of MIs in Analysis Set IV, and their inclusion did not change the model selection results; it only improved model fits.

best-fitting model in this final analysis set, suggesting that fluency ability plays a larger role in both types of creative thinking than was originally considered.

Set IV discussion. Introducing fluency back into the models from Analysis Set III provides insight into the processes that play a role in each of these types of creative thinking tasks. Specifically, fluency impacts performance on both types of task, above and beyond the effects of working memory. Indeed, the direct paths from fluency to the domain-specific creative thinking factors are both significant in Model 4E, explaining 47.6% of variance in divergent thinking and 29.2% of variance in creative problem solving. Although working memory significantly impacted the domain-general creative thinking factor in Set III, this direct path is no longer significant in Model 4E.[6] Likewise, the unique creative problem-solving variance explained by working memory is reduced from 30.25% in Set III to 16% in Set IV, suggesting that some of working memory's impact on performance can be accounted for by fluency. Despite not having a direct impact on domain-specific divergent thinking, working memory still has a moderate relationship with fluency ability, which implies that though working memory may play a role in divergent thinking performance, fluency mediates any impact of working memory on divergent thinking success.

Fluency's impact on domain-specific divergent thinking and creative problem-solving helped to understand considerable unexplained variance in these constructs in Model 3B, reducing the residual variance in these factors from 1.00 and 0.70 to 0.52 and 0.39, respectively. Together, these findings lend support for the dual-process theory and indicate a role for fluency in both divergent thinking and creative problem-solving tasks. Though working memory plays a substantially more direct and impactful role in domain-specific creative problem-solving processes, working memory's indirect contributions to divergent thinking processes still suggest that the tasks commonly used to assess creative thinking are multifaceted and draw upon shared and unique processes to different extents.

Discussion

When Guilford (1959, 1967) coined the terms *divergent thinking* and *convergent thinking*, he referred to the processes that are active when generating multiple solutions or a single solution, respectively. In addition, he suggested that divergent thinking tapped into creative processes, whereas convergent thinking tapped into more analytic, deductive processes. Drawing upon Guilford's ideas, Wallach and Kogan (1965) suggested potential cognitive mechanisms involved in these tasks. They suggested that attentional control processes are involved in deducing single solutions and that associative processes are involved in idea generation, spurring the creation of the creative problem-solving and divergent thinking traditions of creativity research, led by cognitive psychologists and psychometricians, respectively.

More recent evidence has suggested that creative problem-solving and divergent thinking tests may require both divergent and convergent processes to perform successfully on either type of task (Benedek & Jauk, 2017; Gilhooly et al., 2007; Lee & Therriault, 2013). For example, on the unusual uses for a newspaper task, dual-process theorists would propose that spreading activation is necessary for individuals to access remote associates in memory (Mednick, 1962) and that controlled-attention processes are necessary for choosing the most creative ideas that become active (Beaty & Silvia, 2012).

Four sets of analyses explored whether divergent thinking and creative problem-solving tasks draw upon dual processes using a large-scale, structural equation modeling approach. The results of Analysis Set I indicate that fluency and divergent thinking tasks do not stem from a single construct, but represent two independent sets of measures, as they are treated in the literature. Although the results of Analysis Set II indicate that divergent thinking and creative problem-solving tasks also represent two independent sets of measures, these tasks also share a common explanatory construct that explains domain-general variance across both types of tasks. The results of Analysis Sets III and IV indicated that dual processes best explain performance on the creative thinking tasks because working memory and fluency are both key mechanisms that influence performance on these tasks above and beyond that explained by task-specific constructs.

In Analysis Set I, the relationship between fluency and divergent thinking measures was investigated. Fluency tasks are often used as a measure of memory retrieval, whereas divergent thinking tasks are used as a measure of creativity. Both require individuals to produce many correct responses. The surface similarities between these two tasks have concerned researchers in the past (Lee & Therriault, 2013; Nusbaum & Silvia, 2011). Thus, the first analysis investigated whether they were isomorphic or distinct. The results of this analysis indicated that the cognitive processes involved in performing successfully on these two types of tasks are indeed independent from, but related to, each other.

Similarly, Analysis Set II investigated whether divergent thinking and creative problem-solving tasks represent a single, unified construct or two distinct constructs. This stage of analysis was motivated by the ideas put forth by dual-process theorists (Benedek & Jauk, 2017; Gilhooly et al., 2007; Lee & Therriault, 2013), who suggest that divergent and convergent thinking skills may contribute to performance on either or both types of creative thinking tasks, while still retaining some unique qualities. The results of this analysis indicated that the different types of assessments indeed represent distinct constructs because neither type of creative thinking was better explained by cross-loading onto the opposite set of creative assessments. Importantly, however, the bifactor model was a better fit than the two-factor, independence model, indicating that these tasks require the use of processes unique *and* shared across these tasks.

Creativity research has seemed to diverge between two traditions in which the tendency has been to centralize research on only one type of assessment, with the Remote Associates Test and the Torrance tests as prime examples. In turn, this has driven a large number of studies using these specific tasks. Although there are valid logistical reasons to conduct research in this way, this type of research can also run the risk of turning the study of creativity into the study of a specific task or task set. In analyzing multiple types of tasks together, the present work provides evidence that divergent thinking and creative problem-solving tasks measure both shared and separable processes. As such, future work should take

[6] After accepting model 4E, a version of model 4E was rerun without the nonsignificant path between working memory and domain-general creative thinking, and it demonstrated poorer fits than model 4E.

these complexities into consideration when exploring the many facets of creative thinking.

It has been suggested that attentional control mechanisms play a role in performance on either divergent thinking or creative problem-solving tasks (or both; Beaty & Silvia, 2012; Benedek & Jauk, 2017; Gilhooly et al., 2007; Guilford, 1959, 1967; Lee & Therriault, 2013; Mednick, 1962; Wallach & Kogan, 1965), so Analysis Set III explored working memory's effect on both types of creative thinking. This analysis indicated that working memory explains unique variance in creative problem-solving tasks and shared variance across all creative thinking tasks. This finding indicates that working memory is involved to different extents when generating creative ideas or solving problems creatively, with creative problem solving requiring more working memory resources than divergent thinking. Prior research has suggested that working memory may be necessary for implementing a controlled search through the problem space when first attempting to solve an insight problem (Ash & Wiley, 2006). Perhaps controlled attention is not necessary during the restructuring phase of creative problem-solving because associative processes may be responsible for initiating spreading activation to remote ideas or solutions (Mednick, 1962), explaining why individuals report feeling surprised when they realize that they have obtained the solution (or at least, an accurate path to solution). Similarly, the controlled-attention theory (Beaty & Silvia, 2012, 2013; Beaty, Silvia, et al., 2014; Benedek & Jauk, 2017; Gilhooly et al., 2007; Nusbaum & Silvia, 2011) suggests that controlled attention is necessary for idea generation because it allows individuals to systematically search through memory and appropriately choose ideas relevant to the goal, an idea that may be reflected in working memory's influence on the general creativity factor. Likewise, the lack of a relationship between working memory and the domain-specific divergent thinking factor replicates prior failures to find such a relationship (Smeekens & Kane, 2016), and suggests other processes are in play. Thus, it appears as though the results of Model 3B are congruent with the findings in the creative problem-solving literature, though further work is necessary to understand working memory's role in divergent thinking.

Adding fluency back into the model in Set IV shed considerable light on the processes required for creative performance. Though fluency did not explain the general creativity factor, it uniquely impacted both types of creative thinking, replicating previous effects (Lee & Therriault, 2013). More importantly, fluency's presence as a direct predictor of domain-specific creative problem solving accounted for a substantial amount of previously unexplained variance from Model 3B. Likewise, fluency mediated effects of working memory on divergent thinking performance. Together, these results provide evidence that fluency ability impacts performance on creative thinking, above and beyond that of working memory.

The results of the current study provide support for the dual-process theory in creative thinking (Benedek & Jauk, 2017; Gilhooly et al., 2007; Lee & Therriault, 2013). It is evident that creative problem-solving requires the use of at least two mechanisms (working memory and fluency), with each predicting substantial unique variance in the creative problem-solving factor in Model 4E—these factors also line up nicely with prior work suggesting roles for both divergent (fluency) and convergent (working memory) processes (Guilford, 1956). The impact of dual processes in divergent thinking are more subtle. Based on Model 4E, one could argue that divergent thinking only requires a single mechanism instead of two because working memory did not have a direct effect on the divergent thinking factor. However, this ignores the indirect effects of working memory through fluency, as seen in the correlation between the two factors. Prior experimental research also supports this, showing that working memory impacts verbal fluency ability (Rosen & Engle, 1997) and the selection of different strategies on verbal fluency tasks (e.g., automatic vs. strategic memory retrieval; Craik et al., 1996). Thus, both processes may still be involved, with working memory having its influence through fluency itself. This may be because working memory plays a similar role in divergent thinking tasks as it does in fluency tasks.

The different emphases of working memory and fluency on task performance highlight some of the differences between divergent thinking and creative problem-solving tasks themselves. Whereas fluency predicted both forms of creative thinking, working memory seemed to play a different role depending on the task being completed. For example, as an individual is thinking of words that start with the letter ‘F’ (a verbal fluency task), they may start by constructing a network in memory that accesses smaller words first (e.g., fin, fat, for, fun) before accessing larger, more remote words (e.g., function, favorite, favorable). They may even develop strategies to help them produce more responses (Craik et al., 1996). As more options for solution paths are accessed in memory, working memory can allow the individual to maintain memory of responses already provided, rejected, or considered, while inhibiting access to those responses previously deemed irrelevant to the task's goal (Moscovitch, 1995). If attention is diverted, remote associates or ideas may become automatically active, making remote ideas more accessible. It is likely that a similar process is used for approaching divergent thinking tasks, although these tasks also require that individuals break away from typical responses to provide creative ones. Because divergent thinking tasks emphasize quality over quantity of responses, controlled processes, such as response maintenance and goal-directed strategies, may play a lesser role in success; associative processes, on the other hand, will necessarily play more of a role in allowing remote solutions to be accessed and retrieved. This distinction between divergent thinking and fluency tasks also sheds light on why they represent different constructs, even though people may initially approach and solve them using similar methods. Finally, on creative problem-solving tasks, such as a Rebus puzzle, associative processes will allow them to construct a network of potentially relevant idioms using the particular images or verbal clues provided in the problem as a starting guide. Working memory will play a large role at this stage, allowing the solver to conduct a controlled search through the problem space and to determine whether accessed idioms are consistent with the problem goals. After completing the search of all the potential paths to solution from the problem representation, associative processes will again be necessary to allow the solver to access additional, goal-relevant solutions. Thus, all three types of tasks (fluency, divergent thinking, and creative problem-solving) require the use of associative and controlled processes (or divergent and convergent thinking, respectively), but to different extents, in different stages, and perhaps for different purposes.

Several limitations should be considered when interpreting the present work. For example, one might question the appropriateness of a psychometric approach because strategy usage cannot be directly assessed for each participant on any given trial. However, it is notable that a common factor was found across all eight creative tasks, demonstrating that there are commonalities among them—something long assumed yet not demonstrated in the field. It is difficult to attribute these findings to *shared strategies* or approaches because this would imply that a highly similar strategy is used across all eight tasks from which the common factor is drawn. However, this conclusion seems untenable when considering tasks as diverse as anagrams or the complications due to people being able to fly. Likewise, the fact that the domain-general creativity construct is weakly predicted by working memory in the final model, and not at all by fluency ability, quickly rules out a few of the common explanations of what that shared variance might represent (i.e., WMC; attention; fluency). The parsimonious explanation, then, becomes a *shared process* across tasks. If so, these findings become even more interesting, as that process bears only weak relationships to those individuals' working memory and fluency ability. Future work might build on these findings, integrating strategy measures to better assess how these factors change when accounting for different strategies and approaches to problem solving.

Another concern is the low interrater reliability for the newspaper task ($\alpha = .46$), which was quite low compared with reliability on the other divergent thinking tasks in this study, as well as those reported in other work. It is possible that this poor reliability could stem from using only two raters when completing snapshot scoring. However, this explanation seems unlikely, considering that the coefficients for the other divergent thinking tasks are substantially higher, for which the same two raters were recruited. A more plausible explanation is that there was simply an extensive range of responses that participants provided on these tasks, making it more difficult for raters' scores to reliably agree.

It is also not ideal that tasks measuring the same construct were grouped together, with the fluency and working memory tasks presented on the first day and the creative problem-solving and divergent thinking tasks presented on the second day. This grouping of tasks may inflate some relationships between factors, while masking others as a result of state-based differences. For example, the relationship between working memory and fluency may have been overestimated when compared with the relationship between working memory and divergent thinking, because of differences in fatigue, mood, or other factors between sessions. Task grouping and order was selected to minimize the potential contamination of instructions to be creative on other tasks in the experiment, pertaining especially to the fluency tasks (see Nusbaum et al., 2014), making a perfect balancing of tasks across sessions impossible. However, participants completed the second session exactly one week after the first session, at the same time of day, minimizing some of these concerns and making it likely that many state-based factors would be the same. Additionally, any state-based factors impacting working memory should impact fluency performance equivalently, as both sets of tasks were presented on the same day. Because both of these served as predictors in the SEM models, this lowers the risk of one predictor's influence on the creativity measures being underestimated compared with the other. Even so, interpretations of models should take task order into account.

A final concern is that the creative problem-solving tasks did not instruct participants to type their responses before verifying whether the response was correct or incorrect. As a consequence, participants who solved problems insightfully may have used an analytic strategy to verify the correctness of their solution, biasing the creative problem-solving factor to rely more on working memory. This in turn could have inflated the working memory and creative problem-solving relationship, based only on a change of strategy at the end of the problem. However, verifying a response via analysis would not eliminate the contribution of insightful processes that would remain present in the latent factor. Furthermore, as a verification process, it would be more likely to impact reaction time, rather than the accuracy measures used in this study, further reducing the risk of overestimating the relationship between creative problem solving and working memory.

One area that would be interesting to explore in future work is how analytic problem solving interacts with each of these constructs. If fluency truly plays a special role in creative thinking abilities, then it should not play a role in analytic problem-solving performance. Recent work (Chuderski & Jastrzębski, 2018) has used factor analysis to explore these two types of problem solving, though in the absence of divergent thinking and fluency measures. Future studies should implement both groups of tasks to further explore these relationships. Likewise, factor analysis is an effective method of extracting shared variance from a set of tasks to represent a process-pure construct but does not allow for strong causal arguments. Future work should expand upon these findings by using experimental methods to closely monitor and analyze which aspects of problem solving or divergent thinking are impacted by fluency and working memory.

Prior to the current investigation, only a small number of studies have investigated divergent thinking and creative problem-solving tasks simultaneously. The present study is among the first to build and test multiple sets of confirmatory models of creative thinking against each other, each representing a different theory about the underlying mechanisms involved. This method allowed for previously unanswered questions to be tested directly, such as whether verbal fluency and divergent thinking tasks represent the same construct or how cognitive mechanisms interact in the context of multiple creative tasks. In addition, care was taken to ensure that an adequate number of tasks from a variety of modalities were employed. Thus, each factor was as representative as possible of the tasks used commonly in the literature and the abilities that they aim to measure. By assessing multiple forms of creativity with other, more process-oriented measures, the present work provides a clear picture of multiple processes working together to promote creativity. Not only does this support the dual-process perspective of creative thinking, but it also suggests that creativity is anything but business-as-usual.

Context Paragraph

The present work was completed as part of Sarah K. C. Dygert's master's thesis. The idea for this project stemmed from multiple conversations between Sarah K. C. Dygert and Andrew F. Jarosz regarding possible shared or unshared mechanisms underlying different tests of creative thinking. Both authors have research interests in individual differences in creative cognition, so asking and testing a variety of theoretically driven questions about this topic, as well as using a factor analytic approach to do so, was a particularly intriguing and exciting collaboration for both parties.

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(*Appendix follows*)

Appendix

Fit Statistics for All Constrained and Unconstrained Models

Set	Model	*df*	AIC	BIC	SABIC	CFI	RMSEA [CI]	SRMR	χ^2	χ^2 *p*
Set I	**1A**	**21**	**4214.95**	**4264.12**	**4216.60**	**.98**	**.04 [.00, .08]**	**.05**	**27.37**	**.159**
	1A.2	19	4218.72	4274.45	4220.60	.97	.05 [.00, .08]	.05	27.15	.101
	1B	20	4245.98	4298.43	4247.74	.86	.10 [.07, .13]	.07	56.40	.000
	1C	14	4225.86	4297.98	4228.28	.96	.06 [.01, .10]	.04	24.28	.042
	1C.2*	12	4221.31	4299.98	4223.95	.99	.04 [.00, .09]	.03	15.73	.204
Set II	2A	21	4127.13	4176.30	4128.79	.95	.07 [.04, .10]	.05	40.81	.006
	2A.2	19	4131.08	4186.80	4132.95	.94	.08 [.04, .11]	.05	40.76	.003
	2B	20	4166.21	4218.66	4167.97	.84	.12 [.09, .15]	.08	77.89	.000
	2C	18	4128.09	4187.10	4130.07	.95	.07 [.04, .11]	.05	35.77	.008
	2C.2	16	4129.53	4195.09	4131.73	.95	.07 [.04, .11]	.05	33.21	.007
	2D	18	4127.60	4186.61	4129.58	.95	.07 [.03, .10]	.05	35.28	.009
	2D.2	16	4131.13	4196.69	4133.33	.95	.08 [.04, .11]	.05	34.81	.004
	2E	14	4129.73	4201.84	4132.15	.96	.08 [.04, .11]	.04	29.41	.009
	2E.2*	12	4130.42	4209.10	4133.07	.96	.08 [.04, .12]	.04	26.10	.010
	2F	**14**	**4124.58**	**4196.70**	**4127.01**	**.97**	**.06 [.01, .10]**	**.04**	**24.26**	**.043**
	2F.2	12	4125.58	4204.26	4128.23	.97	.06 [.01, .11]	.03	21.27	.047
Set III	3A*	45	6081.20	6189.38	6084.84	.95	.06 [.04, .08]	.06	76.87	.002
	3B	**44**	**6079.70**	**6191.16**	**6083.45**	**.96**	**.06 [.03, .08]**	**.06**	**73.38**	**.004**
	3C	44	6082.17	6193.62	6085.92	.95	.06 [.04, .08]	.05	75.84	.002
	3D	44	6085.16	6196.62	6088.91	.95	.06 [.04, .09]	.07	78.84	.001
	3E	43	6081.70	6196.43	6085.55	.95	.06 [.04, .08]	.06	73.37	.003
Set IV	4A	91	8125.69	8273.20	8130.65	.92	.07 [.05, .08]	.07	167.44	.000
	4B	90	8104.40	8255.20	8109.47	.94	.06 [.04, .07]	.06	144.16	.000
	4B.2	92	8158.19	8302.43	8163.04	.88	.08 [.06, .09]	.09	201.94	.000
	4B.3	92	8145.06	8289.29	8149.91	.89	.07 [.06, .09]	.08	188.81	.000
	4C	89	8101.65	8255.72	8106.83	.94	.05 [.04, .07]	.06	139.40	.001
	4D	89	8104.63	8258.70	8109.81	.94	.06 [.04, .07]	.06	142.38	.000
	4E	**89**	**8094.48**	**8248.56**	**8099.66**	**.95**	**.05 [.03, .07]**	**.06**	**132.24**	**.002**
	4F	88	8095.81	8253.16	8101.10	.95	.05 [.03, .07]	.06	131.57	.002

Note. For each analysis set listed, models are organized from the most parsimonious model to the most complex model (as indicated by the decreasing degrees of freedom), with constrained and unconstrained versions of the same models reported next to each other. Model names highlighted in bold font indicate the best-fitting model within its respective set. χ^2 values represent model fit, not model comparison statistics. Ninety percent confidence intervals are displayed in brackets next to the RMSEA value. Model key: 1A – constrained independence model; 1A.2 – unconstrained independence model; 1B – unconstrained one-factor model; 1C – constrained bifactor model; 1C.2* – unconstrained bifactor model; 2A – constrained independence model; 2A.2 – unconstrained independence model; 2B – unconstrained one-factor model; 2C – constrained cross1 model (DT onto CPS); 2C.2 – unconstrained cross1 model (DT onto CPS); 2D – constrained cross2 model (CPS onto DT); 2D.2 – unconstrained cross2 model (CPS onto DT); 2E – constrained fully cross-loaded model; 2E.2* – unconstrained fully cross-loaded model; 2F – constrained bifactor model; 2F.2 – unconstrained bifactor model; 3A* – constrained bifactor model, with WM predicting gCr only (doesn't calculate estimates correctly); 3B – constrained bifactor model, with WM predicting gCr and CPS only; 3C – constrained bifactor model, with WM predicting gCr and DT only; 3D – constrained bifactor model, with WM predicting DT and CPS only; 3E – constrained bifactor model, with WM predicting gCr, DT, and CPS; 4A – base model, in which fluency doesn't predict any factors (only correlates with WM); 4B – fluency predicts gCr only; 4B.2 – fluency predicts CPS only; 4B.3 – fluency predicts DT only; 4C – fluency predicts gCr and CPS only; 4D – fluency predicts gCr and DT only; 4E – fluency predicts DT and CPS only; 4F – fluency predicts all factors.

* Model did not appropriately converge.

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