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1 **Towards Greater Computational Modeling**
2 **in Neurocognitive Creativity Research**

3

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10

11 **ABSTRACT:**

12 Creative cognition is the driving force behind all cultural and scientific progress. In recent
13 years, the field of neurocognitive creativity research (NCR) has made considerable
14 progress in revealing the neural and psychological correlates of creative cognition.
15 However, a detailed understanding of how cognitive processes produce creative ideas,
16 and how these processes interact differently across tasks and individuals, remains elusive.
17 In this article, we argue that the increased adoption of computational modeling can help
18 greatly in achieving this goal. While the verbal theories guiding NCR have evolved from
19 broader accounts into more specific descriptions of neurocognitive processes, they remain
20 more open to interpretation and harder to falsify than formal models. Translating theories
21 into computational models can make them more concrete, accessible, and easier to
22 compare, and helps researchers to develop causal hypotheses for how variation in
23 cognitive factors leads to variation in creative outcomes. Currently, however,
24 computational modeling of creativity is conducted almost entirely separately from NCR,
25 and few attempts have been made to embody the cognitive theories of NCR in models
26 that can simulate performance on common lab-based tasks. In this paper, we discuss
27 theories of creative cognition and how they might benefit from the wider adoption of
28 formal modeling. We also examine recent computational models of creativity and how
29 these might be improved and better integrated with NCR. Finally, we describe a pathway
30 toward a mechanistic understanding of creative cognition through the integration of
31 computational modeling, psychological theory, and empirical research, outlining an
32 example model based on dual-process accounts.

33

34 **KEYWORDS:** Creativity; theory; psychology; neuroscience; computational modeling

35 **PUBLIC SIGNIFICANCE STATEMENT:** This review argues that creativity research would
36 benefit greatly from the wider adoption of computational modeling. We discuss how
37 translating verbal theories of creative cognition into formal computational models can
38 make them more rigorous, accessible, and communicable, and can highlight questions for
39 future research. We examine previous models of creativity and explain how these can be
40 improved to benefit our understanding of human creative cognition and the development
41 of artificial creative systems.

42

43

44 **Towards Greater Computational Modeling in Neurocognitive Creativity Research**

45 Creativity, a hallmark of human cognition, has traditionally been considered an elusive
46 target for scientific investigation (Hennessey & Amabile, 2010; Iger, 2019), and even
47 today, there exists considerable variation in how creativity is conceived, operationalized,
48 and assessed across fields (Hennessey & Amabile, 2010; Plucker, 2022; Plucker, Beghetto,
49 & Dow, 2004; Puryear & Lamb, 2020). However, recent decades have witnessed
50 tremendous growth in neurocognitive creativity research (NCR) – research that aims to
51 uncover the neural and cognitive basis of creative thought. While definitions of creativity
52 vary (e.g., Acar, Burnett, & Cabra, 2017; Simonton, 2018), most NCR defines creative
53 cognition as the production of novel and useful ideas (Diedrich, Benedek, Jauk, &
54 Neubauer, 2015; Runco & Jaeger, 2012; Stein, 1953).

55 Presently, NCR covers a diverse range of research areas, and has begun to uncover how
56 creative cognition relates to cognitive and psychological factors including attention (Frith
57 et al., 2021b; Liu & Peng, 2020; Zabelina, 2018), memory (Benedek, Beaty, Schacter, &
58 Kenett, 2023; Kenett et al., 2018; Madore, Addis, & Schacter, 2016; Storm, Angello, &
59 Bjork, 2011), executive control (Benedek, Jauk, Sommer, Arendasy, & Neubauer, 2014b;
60 Camarda et al., 2018a; Chrysikou, 2019; Lebuda & Benedek, 2023), personality (Bonetto,
61 Pichot, Pavani, & Adam-Troïan, 2021; Kaufman et al., 2016; Oleynick et al., 2017), and
62 reward processing (Beverdors, 2019; Boot, Baas, van Gaal, Cools, & de Dreu, 2017; Lin &
63 Vartanian, 2018). NCR has also made considerable progress in identifying the neural
64 correlates of creative cognition, for example finding that greater creative performance
65 relates to enhanced EEG alpha waves (Agnoli, Zanon, MASTRIA, Avenanti, & Corazza, 2020;
66 Fink et al., 2018; Rominger et al., 2019; Stevens & Zabelina, 2020), and greater fMRI
67 connectivity between large-scale brain networks (Beaty, Cortes, Zeitlen, Weinberger, &
68 Green, 2021; Chen, Beaty, & Qiu, 2020; Mayseless, Eran, & Shamay-Tsoory, 2015;
69 Sunavsky & Poppenk, 2020).

70 However, it remains unclear how exactly these neural and psychological correlates lead to
71 the production of creative ideas (see Beaty, Seli, & Schacter, 2018b for an overview of
72 cognitive processes that may relate to the neural connectivity patterns observed during
73 creative cognition). Despite the remarkable progress of NCR, our theoretical
74 understanding of creative cognition is still in its infancy. Over recent decades, the
75 cognitive theories that guide NCR have evolved from more abstract accounts, such as the
76 distinction between convergent and divergent thinking (Guilford, 1959, 1967), to more
77 specific accounts that describe how creative ideas can emerge from, for example,
78 spontaneous and controlled processes (Benedek et al., 2023; Benedek & Jauk, 2018; Volle,
79 2018) and flexible and persistent meta-control states (Nijstad, de Dreu, Rietzschel, & Baas,
80 2010; Zhang, Sjoerds, & Hommel, 2020). In addition, significant efforts have been made to
81 formalize and standardize the ontology used by NCR researchers (Gabora, 2018; Kenett et
82 al., 2020; Simonton, 2013, 2022; Sowden, Pringle, & Gabora, 2015). However,

83 considerable work remains to move the field away from loosely defined verbal accounts
84 toward mechanistic theories of creative cognition, complete with causal hypotheses
85 regarding the cognitive operations that produce creative ideas.

86 We argue that the wider adoption of computational modeling can help greatly in
87 achieving this aim. Computational modeling involves formalizing a theory into a set of
88 algorithmic operations (Farrell & Lewandowsky, 2015; Maia, Huys, & Frank, 2017). This
89 process requires the theory to be fully described in explicit terms, which can expose
90 assumptions that might otherwise remain hidden, and lends considerable clarity, rigor,
91 and reproducibility to the development of theories and hypotheses (Farrell &
92 Lewandowsky, 2015; Guest & Martin, 2021). Computational models also allow causal
93 hypotheses to be formulated and tested, helping researchers to establish relationships
94 between neurocognitive factors and creative behavior (Blohm, Kording, & Schrater, 2020;
95 Wiggins & Bhattacharya, 2014). Indeed, calls for greater modeling within psychology as a
96 whole are growing (Blohm et al., 2020; Guest & Martin, 2021; Smaldino, 2020), yet
97 modeling is rarely used in NCR. Meanwhile, though computational creativity is itself a
98 growing field (e.g., Carnovalini & Rodà, 2020; Gatti, Stock, & Strapparava, 2021; Mekern,
99 Hommel, & Sjoerds, 2019a) with its own annual conference (the International Conference
100 on Computational Creativity), it has developed in relative isolation from NCR, with little
101 cross-pollination between the two fields. Increased collaboration could lead to both a
102 clearer understanding of human creativity and more human-like artificial creative systems
103 (Chateau-Laurent & Alexandre, 2021; Dipaola, Gabora, & McCaig, 2018; Gobet & Sala,
104 2019). Critically, however, very few computational models exist that both embody a
105 theoretical account from NCR and can perform (and thus, be validated on) common lab-
106 based creativity tasks.

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

115

116 **Neurocognitive creativity research (NCR)**

117 NCR aims to uncover the neural and cognitive processes that underlie creative cognition
118 (Benedek & Fink, 2019). To this end, NCR researchers have explored how creative
119 performance relates to numerous cognitive and psychological factors. Here, we briefly
120 review some of this work. For example, attention research suggests that while real-world

121 creative achievement may relate to leaky attention (Zabelina, 2018), in-lab creative
122 performance may relate to selective (Vartanian, 2009) or flexible attention (Zabelina,
123 O’Leary, Pornpattananangkul, Nusslock, & Beeman, 2015; Zabelina, Saporta, & Beeman,
124 2016). Meanwhile, research into the link between creative cognition and intelligence has
125 found considerable overlap between the two in terms of lab-based performance (Frith et
126 al., 2021a; Karwowski et al., 2016; Karwowski, Czerwonka, & Kaufman, 2020), and
127 suggests that they may depend on shared neural regions (Benedek, Jung, & Vartanian,
128 2018; Frith et al., 2021a). Research has also examined relationships between creativity
129 and executive functions, finding that switching (Krumm, Arán Filippetti, & Gutierrez, 2018;
130 Nusbaum & Silvia, 2011; Pan & Yu, 2018; Zabelina & Ganis, 2018), updating (Benedek et
131 al., 2014b; Stolte, García, van Luit, Oranje, & Kroesbergen, 2020; Zabelina, Friedman, &
132 Andrews-Hanna, 2019), and inhibition (Camarda et al., 2018a; Kaur, Weiss, Zhou, Fischer,
133 & Hildebrandt, 2021; Zabelina et al., 2019) all relate to aspects of creative performance.

134 Considering the relationship between creative cognition and memory, some studies report
135 that creative cognition may benefit from greater working memory (WM) abilities
136 (Benedek et al., 2014b; de Dreu, Nijstad, Baas, Wolsink, & Roskes, 2012; Stolte et al.,
137 2020), while other studies report mixed findings (de Vink, Willemsen, Lazonder, &
138 Kroesbergen, 2021; Krumm et al., 2018) indicating that the role of WM in creative
139 cognition may be task-dependent (Krumm et al., 2018). Meanwhile, studies using network
140 science methods have indicated that more creative individuals may have more flexible and
141 interconnected semantic memory structures (He et al., 2020; Kenett, Anaki, & Faust, 2014;
142 Kenett et al., 2018; Ovando-Tellez et al., 2022). Research has also probed less direct links
143 between creativity and neurocognitive processes, examining how creativity relates to
144 variation in personality traits such as risk-taking (Dewett, 2007; Harada, 2020; Shen,
145 Hommel, Yuan, Chang, & Zhang, 2018) and openness to experience (Batey & Furnham,
146 2006; Kaufman et al., 2016; Lloyd-Cox, Pickering, & Bhattacharya, 2022b; Oleynick et al.,
147 2017), and how neurodevelopmental conditions including ADHD (Fugate, Zentall, &
148 Gentry, 2013; Hoogman, Stolte, Baas, & Kroesbergen, 2020) and schizophrenia (Sampedro
149 et al., 2020a, 2020b) impact creative cognition.

150 Further research has explored how creative performance relates to motivation (Benedek,
151 Bruckdorfer, & Jauk, 2020; Xue et al., 2020) and the activities of the dopaminergic (Lin &
152 Vartanian, 2018; Zhang et al., 2020), and noradrenergic systems (Beverdors, 2019; Boot
153 et al., 2017; Flaherty, 2005). Considering other neural correlates of creativity, fMRI
154 research has consistently found that creative cognition involves increased cooperation
155 between the default mode (DMN), executive control (ECN), and salience networks (Beaty,
156 Benedek, Silvia, & Schacter, 2016; Green, Cohen, Raab, Yedibalian, & Gray, 2015; Lloyd-
157 Cox, Chen, & Beaty, 2022a; Mayseless et al., 2015). In addition, EEG research has found
158 that greater creative performance relates to greater cortical alpha synchronization (Agnoli
159 et al., 2020; Camarda et al., 2018b; Fink et al., 2018; Rominger et al., 2019; Stevens &
160 Zabelina, 2020), while research using transcranial brain stimulation has found that

161 increasing alpha power over the prefrontal cortex can improve the creative quality of
162 ideas (Lustenberger, Boyle, Foulser, Mellin, & Fröhlich, 2015), while stimulation over
163 temporal sites supports the inhibition of non-creative ideas (Luft, Zioga, Thompson,
164 Banissy, & Bhattacharya, 2018).

165

166

The theories that guide NCR

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

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

189 In the years since Guilford, the divergent and convergent thinking constructs have
190 gradually evolved and been reinterpreted, with researchers now arguing that both play
191 important roles in creative cognition (Basadur, 1995; Brophy, 2001; Caughron, Peterson, &
192 Mumford, 2011; Cropley, 2006; Jung, Mead, Carrasco, & Flores, 2013; Runco, 2012, 2014).
193 Indeed, many researchers have shifted away from defining divergent and convergent
194 thinking in terms of the number of solutions they produce, toward defining divergent
195 thinking as a generative process that produces novel ideas, and convergent thinking as an
196 evaluative process that selects and refines ideas (Basadur, 1995; Brophy, 2001; Cropley,
197 2006; Lee & Therriault, 2013). These generation-evaluation definitions of divergent and
198 convergent thinking can be seen in numerous recent NCR articles (e.g., de Vink et al.,

199 2021; Eskine, Anderson, Sullivan, & Golob, 2020; Gabora, 2018; Jung et al., 2013;
200 Kleinmintz, Ivancovsky, & Shamay-Tsoory, 2019; Lee & Therriault, 2013), although
201 Guilford's original definitions (many solutions vs. a single solution) also remain popular
202 (e.g., Gilhooly, Fioratou, Anthony, & Wynn, 2007; Lu, Akinola, & Mason, 2017; Radel,
203 Davranche, Fournier, & Dietrich, 2015; Runco, 2010; Shamay-Tsoory, Adler, Aharon-
204 Peretz, Perry, & Mayseless, 2011; Volle, 2018). This reinterpretation of divergent and
205 convergent thinking has its roots in another common framework for conceptualizing
206 creativity, which suggests that creative ideas arise from iterative cycles of generation and
207 evaluation (Basadur, 1995; Ellamil, Dobson, Beeman, & Christoff, 2012; Finke, Ward, &
208 Smith, 1992; Jung et al., 2013; Kleinmintz et al., 2019). A prominent theory of this kind is
209 the blind variation and selective retention (BVSR) model, first suggested by Campbell
210 (1960) and later expanded upon by Simonton (2013, 2022). BVSR argues that creative
211 cognition involves cycles of relatively undirected (or partially sighted; Simonton, 2013)
212 processes to produce multiple ideas, and directed processes that select the best idea to
213 develop further.

214 Among the most popular frameworks for understanding creative cognition that have
215 emerged in recent decades is the dual-process account. This argues that creative cognition
216 emerges from the interactions of spontaneous, associative processes and controlled,
217 analytic processes (Allen & Thomas, 2011; Barr, 2018; Benedek et al., 2023; Benedek &
218 Jauk, 2018; Sowden et al., 2015; Tubb & Dixon, 2014; Volle, 2018). The account is based
219 on wider dual-process theories of cognition (e.g., Evans, 2008; Evans & Stanovich, 2013;
220 Kahneman, 2011), which describe two broad categories of processes which might be
221 termed Type 1 and Type 2 (Evans & Stanovich, 2013). Type 1 processes are typically
222 described as associative, fast, unconscious, and implicit, while Type 2 processes are
223 described as controlled, slow, conscious, explicit, and dependent on WM (Evans, 2008;
224 Evans & Stanovich, 2013; Tubb & Dixon, 2014). NCR researchers have discussed the
225 overlaps between dual-process associative and controlled processes, divergent and
226 convergent thinking, and generation and evaluation (Benedek & Jauk, 2018; Goldschmidt,
227 2016; Lloyd-Cox et al., 2022a; Sowden et al., 2015), with some highlighting differences
228 between the accounts (e.g., Sowden et al., 2015; Tubb & Dixon, 2014), and others
229 concluding that they are broadly synonymous (e.g., Benedek & Jauk, 2018; Goldschmidt,
230 2016). Indeed, many NCR articles now define divergent and convergent thinking in terms
231 of associative and controlled processes (e.g., Augello et al., 2016; Cortes, Weinberger,
232 Daker, & Green, 2019; Drago & Heilman, 2012), producing a third interpretation of
233 Guilford's original constructs.

234 The accounts discussed so far are, for the most part, relatively imprecise, leaving
235 considerable room for interpretation. For example, describing creative cognition as
236 involving divergent and convergent thinking, or cycles of generation and evaluation, does
237 not greatly constrain the space of possible cognitive mechanisms that might underlie
238 creativity. However, as the findings of NCR have grown, more specific theories of creative

239 cognition have emerged. One example is the BVSR theory (Simonton, 2013, 2022), which
240 defines its variational and selective processes in formal mathematical terms. Another is
241 the contextual focus theory (Gabora, 2010, 2018) which builds on suggestions that
242 creative cognition involves switching between narrow and broad attentional states (Bristol
243 & Viskontas, 2006; Dorfman, Martindale, Gassimova, & Vartanian, 2008; Gabora, 2010;
244 Herz, Baror, & Bar, 2020; Zabelina & Robinson, 2010) to define divergent thinking as the
245 broadening of conceptual representations to include more abstract and associative
246 information, and convergent thinking as the narrowing of representations to only the
247 most relevant information (Gabora, 2010, 2018).

248 Researchers have also suggested more specific cognitive mechanisms corresponding to
249 the associative and controlled processes described by the dual-process account of creative
250 cognition (Benedek et al., 2023; Barr, 2018; Benedek & Jauk, 2018; Volle, 2018). Drawing
251 on evidence linking creative cognition to performance on free-association and verbal
252 fluency paradigms, researchers have suggested that associative creative processes may
253 include the automatic spreading of activation through semantic memory (Kenett et al.,
254 2018; Volle, 2018). Meanwhile, evidence linking creative cognition to intelligence and
255 executive functions has led to suggestions that controlled creative processes may include
256 strategic search processes (Avitia & Kaufman, 2014; Benedek & Neubauer, 2013;
257 Forthmann, Bürkner, Szardenings, Benedek, & Holling, 2019a; Lebeda & Benedek, 2023;
258 Silvia, Beaty, & Nusbaum, 2013), and the inhibition of distracting or unoriginal thoughts
259 (Beaty, Christensen, Benedek, Silvia, & Schacter, 2017a; Camarda et al., 2018a; Volle,
260 2018). The increased DMN-ECN cooperation observed during creative cognition is also
261 suggestive of interacting associative and controlled processes, and may signify the DMN
262 spontaneously activating ideas (Beaty et al., 2020; Beaty & Lloyd-Cox, 2020), while the
263 executive control network inhibits prepotent ideas (Beaty et al., 2017a; Christensen,
264 Benedek, Silvia, & Beaty, 2021; Lloyd-Cox, Christensen, Silvia, & Beaty, 2021) and
265 implements creative strategies (Benedek & Jauk, 2018). Indeed, DMN-ECN cooperation
266 during creative cognition appears to increase when there is a need for inhibition (Beaty et
267 al., 2017a; Christensen et al., 2021).

268 Another more specific account distinguishes between two opposing strategies for
269 producing creative ideas: flexibility and persistence. The former involves switching
270 between conceptual spaces to attain more diverse ideas and may depend on striatal
271 dopamine pathways, while the latter involves the persistent exploration of one conceptual
272 space and may depend on prefrontal dopamine pathways (Mekern, Sjoerds, & Hommel,
273 2019b; Nijstad et al., 2010; Zhang et al., 2020). The account has strong similarities to the
274 distinction between exploration and exploitation in creative cognition (Hart et al., 2017;
275 Lin & Vartanian, 2018), and is primarily supported by measures of clustering (i.e., the
276 generation of similar ideas) and switching (i.e., the generation of ideas from different
277 conceptual categories) in divergent thinking and cognitive search tasks (Mekern et al.,
278 2019b).

279

280

281 **How NCR can benefit from the wider adoption of computational modeling**

282 NCR has made considerable progress in uncovering a broad range of cognitive,
283 psychological, and neural correlates of creative cognition, guided by theories ranging from
284 older, broader accounts to more recent and specific accounts. However, a precise,
285 mechanistic understanding of creative cognition remains elusive. We believe that the
286 increased adoption of computational modeling can help greatly towards this goal. While
287 verbal theories are a useful and necessary part of science, they are more ambiguous and
288 open to interpretation than formal computational models, which require all elements of a
289 theory to be explicitly defined (Farrell & Lewandowsky, 2015; Fried, 2020; Guest & Martin,
290 2021; Smaldino, 2020). Defining theories in explicit and formal terms makes them more
291 falsifiable and easier to compare in terms of their predictions and assumptions. We argue
292 that NCR should continue to move towards more specific cognitive theories supported by
293 computational models.

294 For clarity, by “computational model”, we refer to dynamic computational models that
295 aim to embody a particular cognitive theory of creativity by representing how creative
296 ideas arise from cognitive processes. As such, we are not referring to statistical models of
297 human fMRI (e.g., Beaty et al., 2018a; Sunavsky & Poppenk, 2020), EEG (e.g., Rosen et al.,
298 2020; Stevens & Zabelina, 2020) or behavioral data (Beaty & Johnson, 2021; Harada, 2020;
299 He et al., 2020; Zioga, Harrison, Pearce, Bhattacharya, & di Bernardi Luft, 2020). Equally,
300 we do not include machine learning models that generate novel or interesting products
301 but in ways that do not seek to emulate human cognition, such as Google DeepDream
302 (Suzuki, Roseboom, Schwartzman, & Seth, 2017), and GPT3 (Floridi & Chiriatti, 2020). Here
303 we examine in more detail the issues that can affect purely verbal accounts, including
304 more recent and specific accounts, and how computational modeling can provide greater
305 clarity, rigor, and reproducibility to the development of cognitive theories (Farrell &
306 Lewandowsky, 2015; Guest & Martin, 2021).

307

308 **The limitations of verbal theories**

309 At the less specific end of the spectrum of theoretical accounts of creative cognition is the
310 distinction between convergent and divergent thinking. Researchers have defined these
311 constructs in several distinct ways since they first appeared. The first definition separates
312 the two constructs based on the number of ideas or solutions they produce (Guilford,
313 1959) (i.e., one solution in convergent thinking, but multiple solutions in divergent
314 thinking). A later definition focused on divergent thinking as idea generation and
315 convergent thinking as idea evaluation (Basadur, 1995; Brophy, 2001; Cropley, 2006; Lee

316 & Therriault, 2013). Finally, a third definition draws on dual process theories of cognition
317 to define divergent thinking as an unconscious, associative process and convergent
318 thinking as a conscious, analytic process (Augello et al., 2016; Cortes et al., 2019; Drago &
319 Heilman, 2012; Gabora, 2010).

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

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

348 Meanwhile, divergent thinking is typically assessed with the Alternative Uses Task (AUT;
349 Guilford, 1959, 1967), which requires participants to think of unusual uses for a given
350 object. Since the AUT involves producing multiple ideas, and undoubtedly involves
351 generative and associative thinking, it might appear to satisfy all three definitions of
352 divergent thinking. However, the AUT is also widely considered to engage evaluative and
353 analytic processes to ensure that the ideas generated are task-relevant and original
354 (Beaty, Silvia, Nusbaum, Jauk, & Benedek, 2014; Cortes et al., 2019; Gilhooly et al., 2007;

355 Nusbaum & Silvia, 2011; Volle, 2018), processes commonly associated with convergent
356 thinking (Cropley, 2006; Sowden et al., 2015). Indeed, both the AUT and RAT are now
357 thought to involve a mixture of associative and controlled processes (Cortes et al., 2019).
358 Given the difficulties in assessing divergent and convergent thinking, their varying
359 definitions, and the fact that they must be translated into more specific accounts when
360 researchers attempt to model or hypothesize about their underlying processes, NCR might
361 seek to replace these constructs with more precise subtypes of creativity defined in terms
362 of more established cognitive processes, such as memory, attention, and cognitive control
363 (Barbot, Hass, & Reiter-Palmon, 2019; Benedek & Fink, 2019; Chrysikou, 2018; Farrell &
364 Lewandowsky, 2015; Kaufman et al., 2016; Plucker, 2022; Wiggins & Bhattacharya, 2014).

365 As noted, more recent theoretical accounts of creative cognition go much further in
366 suggesting specific mechanisms that might produce creative ideas. Besides BVSR
367 (Simonton, 2022), another recent extension of the generation-evaluation account
368 describes several possible neural and cognitive mechanisms that may underlie both kinds
369 of process (Kleinmintz et al., 2019). Meanwhile, an extension of dual-process accounts has
370 suggested how creative ideas might arise from specific associative and controlled
371 processes operating on a semantic network (Volle, 2018). In addition, several recent
372 review articles have provided in-depth descriptions of the roles of distinct associative
373 (Beaty & Kenett, 2023), memory (Benedek et al., 2023), and metacognitive processes
374 (Lebuda & Benedek, 2023) in creative cognition. Researchers have also proposed
375 neurocognitive mechanisms that might underlie new conceptions of convergent and
376 divergent thinking, relating them to focused and defocused mental representations
377 (Gabora, 2010, 2018) and flexible and persistent meta-control states (Hommel & Wiers,
378 2017; Nijstad et al., 2010; Zhang et al., 2020). The latter account may soon form the basis
379 of a computational model. Finally, a recent review of the neural underpinnings of
380 divergent thinking, abstraction, and improvisation has argued that all three can arise from
381 dopaminergic novelty-seeking processes, in a framework that may soon be implemented
382 computationally (Khalil & Moustafa, 2022).

383 For the most part, however, these are still verbal accounts, and thus they retain a degree
384 of ambiguity that can make them difficult to falsify and leaves them open to
385 reinterpretation. Another key issue for verbal theories is that they can be difficult to
386 compare in terms of their predictions or internal consistency. Despite recent efforts
387 (Kenett et al., 2020), there is no commonly accepted ontology for conceptualizing
388 creativity (Kenett et al., 2020; Puryear & Lamb, 2020; Saggar, Volle, Uddin, Chrysikou, &
389 Green, 2021). Researchers tend to employ different accounts to guide their research
390 (Abraham, 2013; Hennessey & Amabile, 2010; Wiggins & Bhattacharya, 2014), and it is not
391 always clear to what extent these accounts are synonymous or overlapping. For example,
392 it is unclear whether associative and controlled processes are synonyms for constructs like
393 generation and evaluation and implicit and explicit thought, or in fact underlie them.
394 Another example is the overlap between theories of flexibility vs. persistence (Nijstad et

395 al., 2010; Zhang et al., 2020) and exploration vs. exploitation (Hart et al., 2017; Lin &
396 Vartanian, 2018), which both distinguish between the tendency to shift between
397 conceptual spaces and the tendency to exploit a single conceptual space. Similarities also
398 exist between accounts linking different forms of creativity to different forms of attention
399 (Gabora, 2010, 2018; Zabelina et al., 2016; Zabelina & Robinson, 2010). However, without
400 formal models, it is difficult to say whether these theories are broadly equivalent or
401 describe fundamentally different kinds of operation.

402

403

404 **The benefits of modeling**

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

422 The detail required by computational modeling can also reveal weak points, dubious
423 assumptions, or outstanding questions in theories (Blohm et al., 2020), which can then
424 direct empirical work. For example, modeling creative cognition as involving cycles of
425 generation and evaluation would involve deciding how frequently the model should
426 switch between the two modes. Researchers might also consider whether movement
427 along a continuum between generation and evaluation (or even simultaneous generation
428 and evaluation) is preferable to a binary switch. These decisions might inform, and be
429 informed by, empirical research (e.g., Goldschmidt, 2016; Kleinmintz et al., 2019; Lloyd-
430 Cox et al., 2022a).

431 In addition, modeling provides a way to demonstrate and test hypotheses for how
432 variation in a neurocognitive factor leads to variation in behavioral outcomes. Indeed,

433 creative cognition is a particularly high-level construct, and there are likely to be a large
434 number of factors that can impact creative outcomes, including a person's attention,
435 memory, cognitive control, and personality (Beaty et al., 2014; Benedek & Fink, 2019;
436 Oleynick et al., 2017). With modeling, these factors can be represented as sets of
437 operations within a computational system, enabling researchers to examine the causal
438 pathways by which they can impact creative performance. For example, researchers might
439 hypothesize that individuals higher in the personality trait openness to experience
440 produce more creative ideas by engaging in broader attentional states (Gabora, 2010,
441 2018). This hypothesis might then be embodied in a computational model by defining
442 "openness" as a set of parameters governing the propensity to use broad instead of
443 narrow conceptual representations. The hypothesis can then be tested by adjusting the
444 parameters reflecting openness and observing whether the changes in simulated creative
445 outcomes are in line with those observed among human participants with varying
446 openness scores.

447 Moreover, modeling several contrasting theories can provide researchers with a more
448 concrete basis for comparing their empirical predictions, internal consistency, and
449 theoretical complexity (with less complex models being favorable; Farrell & Lewandowsky,
450 2015), allowing researchers to combine similar theories and select or reject opposing
451 theories. As noted, there appear to be strong similarities between several accounts of
452 creative cognition, such as those that describe generative and evaluative states (Jung et
453 al., 2013; Kleinmintz et al., 2019), and those that describe associative and controlled
454 processes (Benedek & Jauk, 2018; Volle, 2018), but it is hard to say whether these
455 accounts are equivalent. Translating each account into a computational model could
456 reveal opposing predictions about the role of a particular factor in creative cognition, or
457 might instead indicate that the two accounts are referring to the same underlying
458 mechanisms.

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

473 from the center outward and controlled processes strategically pushing activation along
474 one dimension (e.g., thinking of exotic locations to access more unusual fruits; Benedek &
475 Neubauer, 2013).

476 To further demonstrate how a creative task can be modeled computationally, we have
477 included an implementation of this simple model in MATLAB code in the Supplementary
478 Material, together with a detailed overview. We have made the code accessible to
479 researchers with minimal modeling experience, implementing a major recommendation
480 made by Barton et al. (2022) to enhance the usability of computational models. Of note,
481 this toy model is by no means intended as a definitive model of creativity, but simply as an
482 example of how verbal theories of creative task performance can be translated into formal
483 models for researchers who may have limited or no prior experience in computational
484 modeling.

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

498

499

500

Varieties of computational model

501 Computational models can come in a large variety of forms. However, as noted, we
502 primarily focus on computational models embodying specific theories of human cognition.
503 These are distinct from statistical models used to analyze empirical data, and
504 mathematical models that outline algorithmic hypotheses concerning human cognition,
505 but which are not implemented computationally (though these also help increase the
506 specificity and falsifiability of theories; e.g., MacGregor, Ormerod, & Chronicle, 2001;
507 Simonton, 2013; 2022). Indeed, recent years have seen numerous computational creative
508 systems being developed (see Carnovalini & Rodà, 2020; Gatti et al., 2021; Mekern et al.,
509 2019a), but many of these primarily aim to create products or behaviors that humans
510 would consider creative, such as stories (Concepción, Gervás, & Méndez, 2020), paintings

511 (Colton, 2012; Yalcin, Abukhodair, & DiPaola, 2020), and music (Anderson, Eigenfeldt, &
512 Pasquier, 2013; Todd & Miranda, 2006; Yang, Choi, & Yang, 2017), without necessarily
513 creating these in a human-like way. By contrast, the models we refer to focus on
514 emulating human cognition, with less regard for the creative quality of the products that
515 are generated (Hélie & Sun, 2010; Oltețeanu & Falomir, 2016; Schatz, Jones, & Laird, 2018;
516 Wiggins, 2020).

517 Even among computational models of human cognition, however, there is considerable
518 variation in terms of the goals and levels of representation pursued by modelers (Kording,
519 Blohm, Schrater, Kendrick, & Kay, 2020; Palminteri, Wyart, & Koechlin, 2017). Different
520 modelers may have very different aims, leading to considerable variation in how models
521 are evaluated (Kording et al., 2020). For example, some modelers may primarily aim to
522 inspire new empirical research, but could equally be most interested in the efficiency of a
523 model, or how clear and interpretable its predictions are. An important distinction can
524 also be drawn between descriptive and normative computational models. Descriptive
525 models aim to represent our best guess at what the brain is doing, while normative
526 models aim to represent an optimal way to solve a problem based on assumptions of
527 rationality. Existing models of creative cognition arguably fall into both camps, and both
528 are useful to NCR. While descriptive models are crucial for a precise understanding of
529 human creative cognition, normative models can demonstrate how a particular creative
530 task could be optimally performed, inspiring the development of descriptive models and
531 guiding empirical research efforts (Veale & Perez y Perez, 2020).

532 Models can also vary in their level of representation (Palminteri et al., 2017). Cognitive-
533 level models operate at a high level of abstraction, illustrating how cognitive factors such
534 as attention, inhibition, and associative thought might produce creative ideas (e.g., Lopez-
535 Persem et al., 2022; Schatz, Jones, & Laird, 2018). By contrast, neural models operate at
536 the level of neurons, demonstrating how neuronal populations can give rise to the
537 processes underlying creative cognition (e.g., Kajic et al., 2017). Both levels of
538 representation are important for NCR. However, neural models face greater
539 computational challenges and may not be as useful for making specific predictions about
540 creative cognition, due to the high-level nature of creativity as a construct. Among
541 cognitive-level models, a further distinction can be made between broader models that
542 encompass creativity as well as other cognitive features (e.g., Hélie & Sun, 2010; Wiggins,
543 2020), and narrower models that focus on how humans perform a single creative task
544 (e.g., Oltețeanu & Falomir, 2016; Schatz, Jones, & Laird, 2018). Again, both types of
545 models are useful. Broader models provide a holistic understanding of how creativity fits
546 together with more general cognition, while narrower models of specific tasks provide an
547 effective means to test cognitive theories of creativity since their performance can be
548 readily compared to human data. While few middle-ground models of creative cognition
549 exist currently (Mekern et al., 2019a), demonstrating how the same cognitive processes
550 can be employed in multiple distinct creative tasks would greatly contribute to our

551 understanding of human creativity. We will consider some existing models of creative
552 cognition in greater detail below.

553

554 **Challenges for computational models of creativity**

555 One reason why computational modeling has yet to have a significant impact on NCR may
556 be that models of creative cognition face key challenges not encountered by models in
557 other areas of cognitive science. For example, creative cognition is a high-level and
558 complex construct involving many cognitive and psychological factors (Benedek & Fink,
559 2019; Volle, 2018). While this complexity makes computational modeling all the more
560 important to NCR, simulating creative cognition effectively may be considerably more
561 difficult than modeling processes like memory retrieval. In addition, creative performance
562 can be assessed with a wide range of tasks, across verbal, visual, and auditory domains
563 (Plucker, 2022; Puryear & Lamb, 2020). Consequently, a precise model of creative
564 processing in one specific task or domain may not easily generalize to others, making it
565 difficult to build a comprehensive and cohesive model of creative cognition as a whole.

566 These challenges, while significant, need not deter NCR researchers from developing new
567 models. Models do not need to account for every factor that might affect creative
568 cognition. All models are simplifications (Smaldino, 2018), and representing a few
569 processes effectively is often more useful than trying to simulate all possible relevant
570 factors, especially when the goal is to create models that are easily understandable and
571 which generate clear predictions (Farrell & Lewandowsky, 2015; Guest & Martin, 2021).
572 Likewise, the diversity of creative tasks implies that NCR may require a corresponding
573 diversity of models, at least initially (Poile & Safayeni, 2016; Wilson & Collins, 2019). While
574 a single model capable of explaining performance across multiple tasks or domains would
575 be a significant advance for the field, models focusing on individual creative tasks have
576 proved highly useful to our understanding of how creative outcomes can arise from
577 cognitive processes (Lopez-Persem et al., 2022; Oltețeanu & Falomir, 2016; Schatz, Jones,
578 & Laird, 2018).

579 An additional challenge for modeling in NCR relates to the nature of creativity data, which
580 does not readily lend itself to simulation. Computational models of human cognition
581 typically need to simulate data from participants to allow the model to be evaluated.
582 Models of perception or memory often aim to simulate data such as reaction time,
583 perceptual or recall accuracy, or patterns of neural activity (Kahana, 2020; Karimi-
584 Rouzbahani, Bagheri, & Ebrahimpour, 2017; Pramod, & Arun, 2016; Rotaru, Vigliocco, &
585 Frank, 2018). Within NCR, however, the main measure of interest is often the subjective
586 creativity rating of generated ideas, drawings, or musical sequences (Amabile, 1982; Cseh
587 & Jeffries, 2019). While models can be developed to generate such products, which can
588 then also be rated for creativity, this requires incorporating knowledge of sentence

589 construction, or artistic or musical composition into the model. These tasks pose
590 significant challenges even for highly skilled computational modelers.

591 One alternative for modelers is to simulate specific features of creative output without
592 simulating the output itself (e.g., response times, number of responses made, or number
593 of concepts included in a drawing). Researchers can also focus on simpler creative tasks.
594 For example, paradigms such as free association and the RAT have just single words as
595 input and output, removing the need to model sentence generation. Indeed, several
596 recent models of creative cognition have investigated the generation of single words using
597 semantic networks, as an effective means to study creativity quantitatively (Lopez-Persem
598 et al., 2022; Oltețeanu & Falomir, 2015; Schatz, Jones, & Laird, 2018). Semantic networks
599 are formed of nodes representing concepts, and edges representing associative links, and
600 can simulate how activation spreads from a cue to a response (Beaty & Kenett, 2023).

601 Fitting semantic networks to participant data can be done in various ways. One approach
602 is to divide participants into low and high creative groups, and then construct group-level
603 semantic networks based on participants' free association data (Kenett et al., 2018). By
604 comparing the properties of these networks, researchers can then identify differences in
605 semantic memory structure between the groups. Another approach is to construct
606 networks from individual participant data, and explore their structural properties in
607 relation to measures of creative cognition (Benedek et al., 2017; He et al., 2021). A further
608 option for semantic network models is to build a single, standard network using free
609 association data (Nelson, McEvoy, & Schreiber, 2004) or distributional semantics methods
610 (Rotaru et al., 2018), and then fit the model to individual participants by modifying the
611 simulated processes that operate on this network (e.g., Lopez-Persem et al., 2022; see
612 also Benedek & Neubauer, 2013; Volle, 2018). This involves defining a set of processes
613 that determine how activation spreads through memory, such as associative and
614 controlled processes, and then adjusting the parameters governing these processes to fit
615 an individual participant's data and mimic their creative behavior. Semantic networks,
616 thus, provide a promising means to examine the production of qualitative ideas as a
617 quantitative process (Beaty & Kenett, 2023; Kenett & Faust, 2019).

618 In summary, despite the challenges, computational modeling remains a useful and
619 enlightening approach for NCR. While creativity is a complex and multifaceted construct,
620 simple models focusing on specific instances of creativity can still be useful (Smaldino,
621 2018). Given the diversity of creative tasks, NCR will likely require numerous models to
622 explore how cognitive processes operate in different contexts. In addition, since any task
623 can be modeled in various ways, it is important to develop multiple models of each task
624 and then compare their performance to human data (Poile & Safayeni, 2016; Wilson &
625 Collins, 2019). For example, semantic memory retrieval can be modeled as a random walk
626 (Kenett & Austerweil, 2016; Lopez-Persem et al., 2022) or as an exploratory process of
627 optimal foraging (Hills, Jones, & Todd, 2009). By comparing the goodness of fit of different

628 models to human data, we can determine which model and its underlying hypotheses are
629 more supported, leading to the development of further models and empirical research
630 questions. As models become more sophisticated, identifying commonalities across
631 models of distinct tasks might allow researchers to simulate multiple tasks using a single
632 model, demonstrating how the same cognitive processes operate in different creative
633 contexts. Finally, though creative outcomes are often qualitative in nature and
634 subjectively evaluated, there are methods available for simulating quantitative aspects of
635 creative performance.

636

637

638 **Existing computational models of creativity**

639 Having discussed the theoretical accounts that guide NCR and how these might benefit
640 from the increased adoption of computational modeling, we now consider some recent
641 computational models of creativity, and the steps that might be taken to improve these
642 and better integrate them with NCR. Computational models of human creative cognition
643 come in two main forms: broader models and cognitive architectures that focus on
644 creativity as a general feature of cognition (e.g., Hélie & Sun, 2010; Wiggins, 2020), and
645 narrower models that aim to simulate human performance in specific lab-based creative
646 tasks (e.g., Oltețeanu & Falomir, 2016; Schatz, Jones, & Laird, 2018).

647 Examples of broader models include recent attempts to model conceptual blending - the
648 creative association of ideas or features from two distinct conceptual spaces (Falomir &
649 Plaza, 2020; Schorlemmer & Plaza, 2021), and the simulation of both individual and
650 cultural creativity using autocatalytic networks (Gabora, Beckage, & Steel, 2022; Gabora &
651 Steel, 2020). Other examples include the Copycat (Hofstadter & Mitchell, 1994) and
652 Metacat systems (Marshall, 2006), which focus on simulating analogical thought.

653 Meanwhile, the CLARION cognitive architecture draws on Type 1 and Type 2 processes
654 (Evans & Stanovich, 2013) to model creative thinking as the outcome of both associative,
655 implicit processes and rule-based, explicit processes (Hélie & Sun, 2010). Researchers have
656 also adapted the ACT-R cognitive architecture to simulate aspects of creativity including
657 conceptual blending (Guhe, Smaill, & Peace, 2010). Finally, the IDyOT model, inspired by
658 theories of predictive intelligence (Clark, 2013; Friston, 2010) and global workspace theory
659 (Baars, 1988), focuses on cognition as the hierarchical prediction of perceptual input, with
660 creativity emerging from the system “free-wheeling” in the absence of an external
661 stimulus (Wiggins, 2020).

662 Although informative, the generality of these broad-focus models means that they are not
663 best placed to model the cognitive theories of NCR, which typically focus on how humans
664 perform specific lab-based creative tasks. For example, Copycat and Metacat operate on a
665 limited set of abstract symbolic concepts, far removed from a human-like associative

666 memory. Meanwhile, CLARION has only modeled elements of cognition relevant to
667 incubation and insight, and must be set up and trained in a specific way for each task.
668 Finally, IDyOT focuses on the perception and generation of sequential information such as
669 music. Critically, these models lack the specific input/output components needed to
670 simulate standard laboratory-based measures of creativity.

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

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

694 In contrast to the neural-level model of Kajić et al. (2017), Oltețeanu and Falomir (2015)
695 developed a cognitive-level model of RAT performance in which concepts were
696 represented as sets of associations to other concepts. The model's memory was
697 constructed from a database of unique 2-word phrases (i.e., 2-grams), with the strengths
698 of associations between words (i.e., associative strength) defined by the frequency of
699 their co-occurrence in 2-grams. When solving RAT problems, all three cues and their
700 associated concepts were activated in memory simultaneously (again in contrast with the
701 sequential activation employed by Kajić and colleagues, 2017). Solutions were then
702 selected from the most strongly activated associated concepts. While the authors did not
703 directly compare the model to humans in terms of the number of RAT problems it could
704 solve, model performance suggested that the difficulty of RAT items relates to both the

705 strength of associations between cues and solutions, and the number of associations each
706 cue word has (known as “fan”). Since these properties impact how activation spreads
707 automatically between ideas in memory, these findings emphasize the role of automatic
708 associative processes in the RAT.

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

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

731 Another recent model of creative idea generation, this time focusing on free association,
732 comes from Lopez-Persem et al. (2022). The model included separate modules for
733 exploration, valuation, and selection. The exploration module simulated activation
734 spreading through a semantic network using random walks biased by associative strength
735 (defined using a database of word associations). The valuation module then calculated the
736 value of activated ideas based on their novelty and appropriateness (estimated as linear
737 and quadratic functions of the associative strength between each idea and the cue word).
738 Finally, the selection module selected a word from among activated ideas according to
739 their value. The authors then adjusted parameters of the model, and compared the
740 resulting changes in performance to the performance of human participants. They found
741 that certain model parameters were more relevant to the performance of individual
742 modules than others, indicating the processes that may underlie these different
743 components of creative cognition. For example, the exploration module performed well

744 (i.e., matched human performance well) using just associative strength, and was not
745 improved by considering the value of ideas, which only played a role in the subsequent
746 valuation stage. The performance of the exploration module was also unaffected by
747 whether human participants were asked to produce the first response that came to mind
748 or an original but still associated response. These findings indicate that the initial
749 activation of ideas during exploration does not depend on how valuable ideas are, and
750 does not vary depending on the specific task being performed. By contrast, the selection
751 module performed better when considering appropriateness more among first responses,
752 and value more among original responses.

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

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770

771

Future steps for computational models of creative cognition

772 We have argued that NCR would benefit greatly from the increased adoption of
773 computational modeling. To this end, the neurocognitive theories that guide NCR should,
774 where possible, be formally defined in computational models that can simulate
775 performance in typical lab-based tasks. Hypotheses can then be developed with the aid of
776 computational models, with models adjusted on the basis of empirical data. This approach
777 would bring considerable clarity to our understanding of creative cognition, allowing
778 researchers to rigorously compare different theories and make inferences about
779 underlying processes. Such integration between NCR and computational modeling would,
780 in turn, aid the development of artificial creative systems (Chateau-Laurent & Alexandre,
781 2021; Wiggins & Bhattacharya, 2014) since a more algorithmic understanding of human

782 creative cognition could inform models of autonomous creativity (Dipaola et al., 2018;
783 Veale & Pérez y Pérez, 2020).

784 In addition to a heavier focus on modeling theories from NCR, future models of specific
785 creative tasks should aim to meet several additional criteria (see also Mekern et al.,
786 2019a). As already noted, it is highly important that computational models can simulate
787 performance on common creative tasks, to allow model output to be compared to human
788 data. This provides a means to evaluate the structure of the model, and the cognitive
789 theories and hypotheses that the model intends to represent. Different models of the
790 same task can also be compared in terms of how well they fit human data (Guest &
791 Martin, 2021; Wilson & Collins, 2019). We have suggested that smaller, narrow-focus
792 models may be best placed to simulate creative performance on lab-based tasks, though
793 the option also exists to adapt larger cognitive architectures, such as Soar and ACT-R, for
794 this purpose (e.g., Schatz et al., 2018).

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

804 Models might also seek to adopt more complex and human-like memory structures. While
805 several studies have modeled human semantic memory as a static network (see, e.g.,
806 Kenett et al., 2018; Rotaru et al., 2018), with nodes representing concepts, and edges
807 representing associations, in reality, human memory is far more complex and dynamic.
808 Building more complexity into a model's memory (or "knowledge base") provides it with
809 more information about concepts and their relationships, enabling more nuanced
810 cognitive processes to be simulated. For example, a simple network in which concepts are
811 represented in a single layer and linked by only a single kind of association does not allow
812 the simulation of search processes that might restrict activation to only one type of
813 concept (e.g., objects), or to concepts that possess a particular property (e.g., roundness)
814 rather than simply being associated with that property.

815 The benefits of more sophisticated memory structures have already been seen in a model
816 of the RAT, in which a larger memory network with multiple kinds of association produced
817 more human-like behavior than a smaller and simpler network (Schatz et al., 2018). Other
818 examples of more complex memory structures include distributed and hierarchical
819 memory. In distributed memory, concepts are represented as patterns of activity across
820 multiple nodes, where each node can form part of multiple concept representations. This

821 provides a more natural and biologically plausible basis for spreading activation, which
822 now moves between concepts that share nodes (Kajić et al., 2017). In hierarchical memory
823 (e.g., Oltețeanu & Falomir, 2016; Wiggins, 2020), concepts in each layer are represented
824 as sets of concepts in lower layers, which serve as features or properties of higher-level
825 concepts. In both cases, richer conceptual representations provide a basis for more
826 complex and flexible processes to operate on memory.

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

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

848

849 **Towards greater integration between NCR and computational modeling**

850 Progress toward a more precise, mechanistic understanding of creative cognition cannot
851 be made by modeling alone, but will require the cooperation of theorists, modelers, and
852 experimenters (Dongen et al., 2022; Hitchcock, Fried, & Frank, 2022; Wiggins &
853 Bhattacharya, 2014). How might greater integration between NCR and computational
854 modeling look? We would argue that any research group that proposes a theory of
855 creative cognition should aim to produce a computational model to demonstrate their
856 thinking explicitly. Such models would make theories more rigorous and complete, and
857 could highlight questions for future research. Following the recommendations of Barton et
858 al. (2022), these models should be easily reproducible, with publicly available code that is

859 accessible to those with minimal modeling experience, allowing them to be adapted by
 860 other researchers who wish to develop their own hypotheses. As noted, it is also
 861 important that future models can simulate performance on common creative tasks, to
 862 allow models to be readily compared to both human data and the performance of other
 863 models. While we have focused on models of the AUT and RAT, NCR makes use of a large
 864 number of other tasks, including metaphor tasks (Beaty, Silvia, & Benedek, 2017b;
 865 Benedek et al., 2014a), drawing tasks (Ellamil et al., 2012; Rominger et al., 2018), musical
 866 improvisation (Pinho, de Manzano, Fransson, Eriksson, & Ullén, 2014; Rosen et al., 2020),
 867 and story writing (Fink, Reim, Benedek, & Grabner, 2020; Prabhakaran, Green, & Gray,
 868 2014). NCR should ideally aim to model all of these tasks computationally to improve our
 869 understanding of the cognitive processes that enable creative performance in these
 870 different contexts.

871 **Designing a model**

872 Above, we have briefly considered a simple model of creative search, but to show more
 873 clearly how theories can be represented in formal models and how modeling can inform
 874 empirical research and theoretical debate, we now outline how a more complex model
 875 might be built, based on dual-process accounts (Figure 1). A simple starting point would
 876 be a semantic network, where nodes are words and edges are associative links, which
 877 could be constructed from human free-association data (e.g., Kenett et al., 2018; Schatz et
 878 al., 2018) or distributional semantics methods (e.g., Rotaru et al., 2018). The next step is
 879 to examine the literature for theoretical processes that might be represented as
 880 operations on this network. For example, the spontaneous and deliberate processes
 881 described by dual process theories might conceivably be modeled as collections of several
 882 computational elements and mechanisms (Table 1).

883 Spontaneous processes are often described as propagating through memory,
 884 reinterpreting information, and activating distant concepts (Benedek & Jauk, 2018; Volle,
 885 2018), and so could be modeled via the structure of memory itself, the automatic
 886 spreading of activation through memory, and the spontaneous activation of tangential
 887 (i.e., non-task-relevant) ideas. Deliberate processes, meanwhile, are described as
 888 inhibiting unoriginal or distracting ideas (Beaty et al., 2017a; Camarda et al., 2018a;
 889 Chrysikou, 2019) and directing thought to fulfill strategies (Forthmann et al., 2019b;
 890 Gilhooly et al., 2007; Nusbaum & Silvia, 2011). As such, modeling deliberate processes
 891 might involve specifying mechanisms that can prevent certain ideas from activating and
 892 inhibit certain associative pathways to guide thought in particular directions (Volle, 2018).

Table 1. Summary of cognitive mechanisms that might feature in a computational model of verbal creativity

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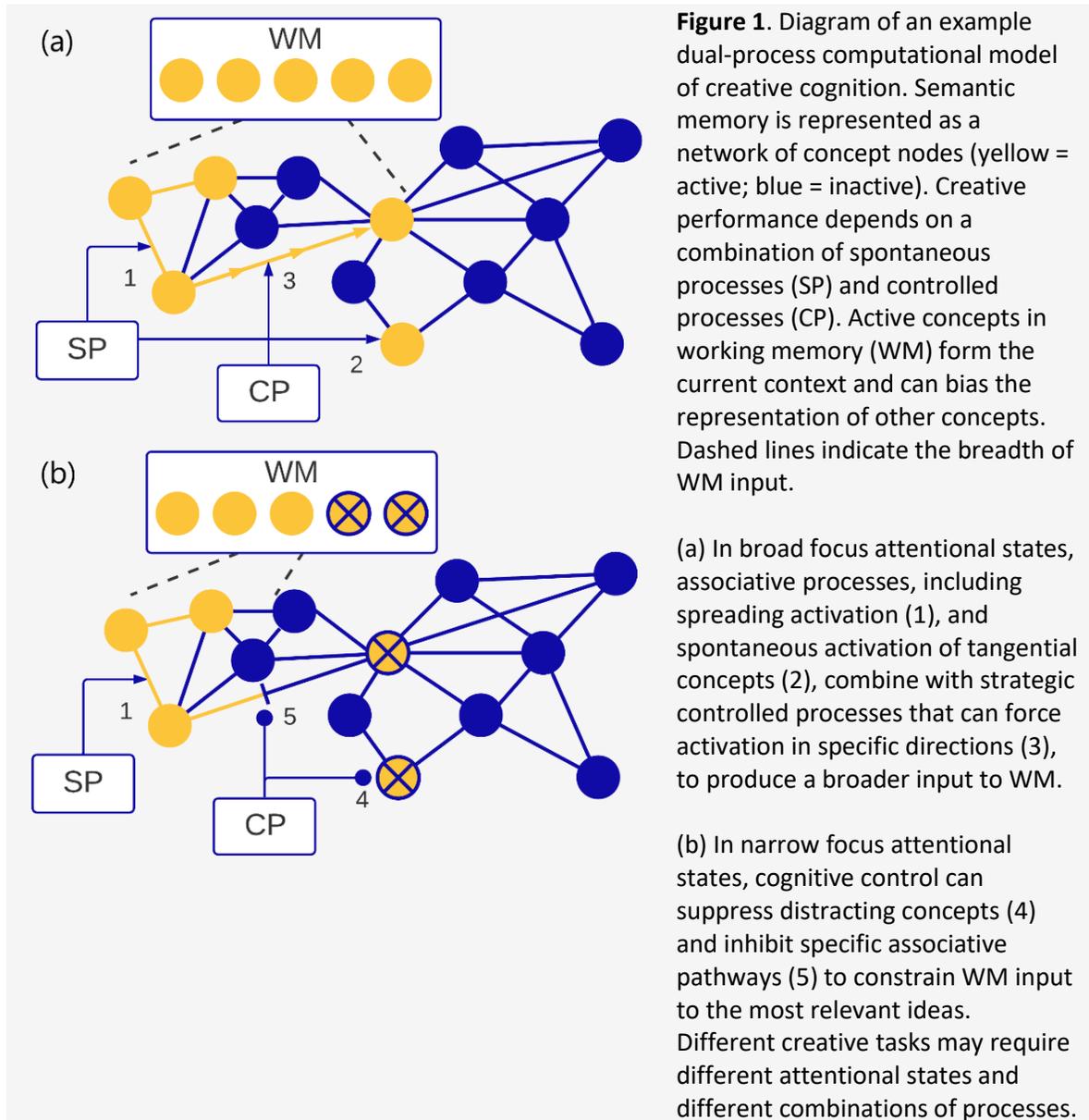
Spontaneous Associative Processes	Memory structure	Semantic memory structure relates to creative ability (Kenett et al., 2018).
	Automatic spreading of activation between concepts	Free association and verbal fluency relate to creative performance (Beaty et al., 2014; Marron et al., 2018).
	Spontaneous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

893

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

908 Modeling WM also provides a way to simulate attention. Researchers have suggested that
909 creative performance involves adjusting attention between narrower and broader states
910 (Dorfman et al., 2008; Gabora, 2010; Zabelina, 2018; Zabelina & Robinson, 2010) and
911 shifting between exploratory and exploitative search strategies (Mekern et al., 2019b;
912 Nijstad et al., 2010). Such processes might be simulated by adjusting input to WM. For
913 example, broad or exploratory attentional states might be simulated as a wider input to
914 WM, where activation flows more freely, and tangential ideas can activate spontaneously.
915 By contrast, narrow or exploitative attentional states might involve limiting WM input to
916 only closely related ideas (see Figure 1). Embodying different attention-based theories of
917 creativity in models of this general sort would allow them to be more rigorously
918 compared. Alternatively, if a single model could simulate the behavioral outcomes
919 discussed by different theoretical accounts, that would strongly suggest that the theories
920 are consistent and could be combined into one. Indeed, it is hypothetically possible that
921 all creativity-relevant control processes, including inhibition, adjustment of attentional
922 breadth, and switching between generative and evaluative modes, are based on adjusting
923 WM input, a possibility that could be investigated empirically.

924



925 In principle, such a model could meet many of the requirements for future models noted
 926 earlier. Active concepts in WM could form the current context, modifying conceptual
 927 representations in memory by changing their associative weights. Individual differences
 928 could be simulated by varying parameters governing specific features or operations in the
 929 model (e.g., WM capacity or the strength of inhibition). Finally, performance on multiple
 930 creative tasks might be achieved using spreading activation to complete RAT problems
 931 (e.g., Schatz et al., 2018) and the activation of specific associative pathways to perform
 932 strategic idea generation in the AUT.

933 **Implementing a model**

934 Before such a model can actually simulate human data, it needs to be implemented
935 computationally. This process requires several additional steps, which we now describe in
936 more detail. The first step is to construct the memory base of the model, which in the
937 current example is the semantic network. Regardless of whether this is based on human
938 free association data or distributional semantics methods, researchers would have to
939 make several decisions, such as how many words to include, whether to exclude
940 prepositions, articles, and quantifiers, whether to combine singular and plural forms of
941 words, whether to exclude associations below a certain strength threshold, and so on.
942 Researchers also have the option to create multiple semantic networks and tailor each
943 one to an individual participant (e.g., Benedek et al., 2017; He et al., 2021).

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

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

964 Finally, researchers need to consider how the model will update over time to simulate
965 cognition. One approach is to update the model in discrete time steps. At each time step,
966 activation might spread to new concepts, while the activation of previous concepts
967 gradually decays. Further, each update might involve control processes switching to
968 inhibit different concepts or pushing activation in a different direction. Once all these
969 factors and decision points have been implemented in the code, the model is ready to
970 simulate task performance. As discussed, spreading activation alone might be sufficient to
971 model performance on tasks such as chain association and the RAT (e.g., Lopez-Persem et

972 al., 2022; Schatz et al., 2017). However, simulating performance on the AUT might require
973 a slightly different model setup depending on the particular strategy used, such as object
974 replacement or object decomposition (Gilhooly et al., 2007).

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

991 This brief sketch of model development clarifies how theories of creative cognition can be
992 translated into formal models. It also demonstrates the potential of modeling to identify
993 new research avenues and the importance of cognitive factors, such as WM, that may
994 have been overlooked in verbal accounts. Importantly, this example highlights that
995 modeling inevitably requires making many reasonable assumptions to “fill the gaps” left
996 by verbal accounts. Verbal theories rarely describe all the details necessary to implement
997 a computational model, leaving the modeler to decide factors such as how exactly to
998 structure semantic memory or simulate inhibition processes. For each of these decisions,
999 alternatives are possible, and so ideally multiple models should be constructed by
1000 different research groups and their performances compared (Poile & Safayeni, 2016;
1001 Wilson & Collins, 2019). It is crucial to note that the design and implementation of the
1002 model discussed here may differ substantially from models focused on the neural level or
1003 based on alternative theories of creative cognition, such as flexibility vs. persistence
1004 (Mekern et al., 2019b; Zhang et al., 2020). This also highlights the importance of building
1005 and comparing multiple models of each creative task.

1006

1007

Concluding remarks

1008 NCR has greatly increased our understanding of creative cognition and its relations to
1009 psychological phenomena, including memory, attention, and cognitive control (Beaty et

1010 al., 2021; Benedek & Fink, 2019; Chrysikou, 2019; Kenett et al., 2018; Kleinmintz et al.,
1011 2019; Volle, 2018). However, the field remains far from a mechanistic understanding of
1012 creativity complete with causal hypotheses for how cognitive processes produce creative
1013 ideas and how such processes interact differently in different tasks and individuals. We
1014 believe that the increased adoption of computational modeling can significantly advance
1015 the field and bring it closer to this goal. The verbal theories that guide NCR (and
1016 psychology in general) are intrinsically more open to interpretation, more difficult to
1017 falsify, and less transparent than formal models (Farrell & Lewandowsky, 2015; Fried,
1018 2020; Guest & Martin, 2021; Smaldino, 2020). By contrast, embodying these theories in
1019 computational models can help make them more complete, accessible, and comparable.
1020 Modeling forces researchers to exchange abstract constructs for concrete definitions of
1021 cognitive processes as operations in a computational system (Benedek & Fink, 2019;
1022 Wiggins & Bhattacharya, 2014). Moreover, computational modeling can allow the
1023 complex pathways that produce creative ideas to be predicted effectively.

1024 For its part, though several computational models of creativity exist, they have been
1025 developed in relative isolation from empirical research, and surprisingly few are well-
1026 suited to modeling the cognitive theories of NCR in a way that can be easily compared to
1027 human performance. Since a clearer understanding of human creativity could lead to
1028 more creative artificial systems, further integration and collaboration between
1029 computational modeling and NCR stands to benefit both fields greatly (Chateau-Laurent &
1030 Alexandre, 2021; Dipaola et al., 2018; Veale & Pérez y Pérez, 2020; Wiggins &
1031 Bhattacharya, 2014).

1032 Indeed, among all areas of cognitive neuroscience, NCR may benefit especially well from
1033 computational modeling. After all, creativity is a complex and heterogeneous construct,
1034 and its underlying processes undoubtedly vary greatly depending on the specific task,
1035 domain, and other contextual and interpersonal factors. Ultimately, science seeks to
1036 establish cause and effect relationships, and so to truly advance, NCR needs clear
1037 hypotheses about how the same cognitive processes operate in different contexts,
1038 explicitly demonstrated in computational models. Integrating NCR with computational
1039 modeling will require considerable time and coordination between fields. The stakes,
1040 however, are high, and we fervently hope this article will help stimulate the necessary
1041 dialogue across disciplines (“Theorists and experimentalists must join forces”, 2021).

1042
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1044 helpful comments.

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1047

1048 **References**

- 1049 Abraham, A. (2013). The promises and perils of the neuroscience of creativity. *Frontiers in*
1050 *Human Neuroscience*, 7, 246. <https://doi.org/10.3389/fnhum.2013.00246>.
- 1051 Acar, S., Burnett, C., & Cabra, J. F. (2017). Ingredients of creativity: originality and more.
1052 *Creativity Research Journal*, 29(2), 133–144.
1053 <https://doi.org/10.1080/10400419.2017.1302776>.
- 1054 Agnoli, S., Zanon, M., Mastria, S., Avenanti, A., & Corazza, G. E. (2020). Predicting response
1055 originality through brain activity: An analysis of changes in EEG alpha power during
1056 the generation of alternative ideas. *NeuroImage*, 207, 116385.
1057 <https://doi.org/10.1016/j.neuroimage.2019.116385>.
- 1058 Allen, A. P., & Thomas, K. E. (2011). A dual process account of creative thinking. *Creativity*
1059 *Research Journal*, 23(2), 109–118. <https://doi.org/10.1080/10400419.2011.571183>.
- 1060 Amabile, T. M. (1982). Social psychology of creativity: A consensual assessment technique.
1061 *Journal of Personality and Social Psychology*, 43(5), 997–1013.
1062 <https://doi.org/10.1037/0022-3514.43.5.997>.
- 1063 Anderson, C., Eigenfeldt, A., & Pasquier, P. (2013). The generative electronic dance music
1064 algorithmic system (GEDMAS). In *Proceedings of the AAAI Conference on Artificial*
1065 *Intelligence and Interactive Digital Entertainment*. Palo Alto, CA.
- 1066 Augello, A., Infantino, I., Lieto, A., Pilato, G., Rizzo, R., & Vella, F. (2016). Artwork creation
1067 by a cognitive architecture integrating computational creativity and dual process
1068 approaches. *Biologically Inspired Cognitive Architectures*, 15, 74–86.
1069 <https://doi.org/10.1016/j.bica.2015.09.007>.
- 1070 Avitia, M. J., & Kaufman, J. C. (2014). Beyond g and c: The relationship of rated creativity
1071 to long-term storage and retrieval (Glr). *Psychology of Aesthetics, Creativity, and the*
1072 *Arts*, 8(3), 293–302. <https://doi.org/10.1037/A0036772>.
- 1073 Baars, B. J. (1988). *A cognitive theory of consciousness*. New York, NY: Cambridge
1074 University Press.
- 1075 Barbot, B. (2018). The dynamics of creative ideation: Introducing a new assessment
1076 paradigm. *Frontiers in Psychology*, 9, 2529.
1077 <https://doi.org/10.3389/FPSYG.2018.02529>.

- 1078 Barbot, B., Hass, R. W., & Reiter-Palmon, R. (2019). Creativity assessment in psychological
1079 research: (Re)setting the standards. *Psychology of Aesthetics, Creativity, and the Arts*,
1080 13(2), 233–240. <https://doi.org/10.1037/ACA0000233>.
- 1081 Barr, N. (2018). Intuition, reason, and creativity: An integrative dual-process perspective.
1082 In G. Pennycook (Ed.), *The New Reflectionism in Cognitive Psychology* (pp. 99–124).
1083 Routledge Press.
- 1084 Barton, M. C., Lee, A., Janssen, M. A., van der Leeuw, S., Tucker, G. E., ... Albert Jagers, H.
1085 R. (2022). How to make models more useful. *Proceedings of the National Academy of*
1086 *Sciences*, 119(35), e2202112119. <https://doi.org/10.1073/pnas.2202112119>.
- 1087 Basadur, M. (1995). Optimal ideation-evaluation ratios. *Creativity Research Journal*, 8(1),
1088 63–75. <https://doi.org/10.1207/s15326934crj0801>.
- 1089 Batey, M., & Furnham, A. (2006). Creativity, intelligence, and personality: A critical review
1090 of the scattered literature. *Genetic, Social, and General Psychology Monographs*,
1091 132(4), 355–429. <https://doi.org/10.3200/MONO.132.4.355-430>.
- 1092 Beaty, R. E., Benedek, M., Silvia, P. J., & Schacter, D. L. (2016). Creative cognition and brain
1093 network dynamics. *Trends in Cognitive Sciences*, 20(2), 87–95.
1094 <https://doi.org/10.1016/J.TICS.2015.10.004>.
- 1095 Beaty, R. E., Chen, Q., Christensen, A. P., Kenett, Y. N., Silvia, P. J., ... Schacter, D. L. (2020).
1096 Default network contributions to episodic and semantic processing during divergent
1097 creative thinking: A representational similarity analysis. *NeuroImage*, 209, 116499.
1098 <https://doi.org/10.1016/j.neuroimage.2019.116499>.
- 1099 Beaty, R. E., Christensen, A. P., Benedek, M., Silvia, P. J., & Schacter, D. L. (2017a). Creative
1100 constraints: Brain activity and network dynamics underlying semantic interference
1101 during idea production. *NeuroImage*, 148, 189–196.
1102 <https://doi.org/10.1016/J.NEUROIMAGE.2017.01.012>.
- 1103 Beaty, R. E., Cortes, R. A., Zeitlen, D. C., Weinberger, A. B., & Green, A. E. (2021).
1104 Functional realignment of frontoparietal subnetworks during divergent creative
1105 thinking. *Cerebral Cortex*, 31(10), 4464–4476.
1106 <https://doi.org/10.1093/cercor/bhab100>.

- 1107 Beaty, R. E., & Johnson, D. R. (2021). Automating creativity assessment with SemDis: An
1108 open platform for computing semantic distance. *Behavior Research Methods*, 53(2),
1109 757–780. <https://doi.org/10.3758/s13428-020-01453-w>.
- 1110 Beaty, R. E., Kenett, Y. N., Christensen, A. P., Rosenberg, M. D., Benedek, M., ... Silvia, P. J.
1111 (2018a). Robust prediction of individual creative ability from brain functional
1112 connectivity. *Proceedings of the National Academy of Sciences*, 115, 1087–1092.
1113 <https://doi.org/10.1073/pnas.1713532115>.
- 1114 Beaty, R. E., & Kenett, Y. N. (2023). Associative thinking at the core of creativity. *Trends in*
1115 *Cognitive Sciences*, (May). <https://doi.org/10.1016/J.TICS.2023.04.004>.
- 1116 Beaty, R. E., & Lloyd-Cox, J. (2020). The default network. In M. A. Runco & S. R. Pritzker
1117 (Eds.), *Encyclopedia of Creativity* (pp. 310–314). San Diego: Academic Press.
- 1118 Beaty, R. E., Seli, P., & Schacter, D. L. (2018b). Network neuroscience of creative cognition:
1119 mapping cognitive mechanisms and individual differences in the creative brain.
1120 *Current Opinion in Behavioral Sciences*, 27, 22–30.
1121 <https://doi.org/10.1016/j.cobeha.2018.08.013>.
- 1122 Beaty, R. E., Silvia, P. J., & Benedek, M. (2017b). Brain networks underlying novel
1123 metaphor production. *Brain and Cognition*, 111, 163–170.
1124 <https://doi.org/10.1016/J.BANDC.2016.12.004>.
- 1125 Beaty, R. E., Silvia, P. J., Nusbaum, E. C., Jauk, E., & Benedek, M. (2014). The roles of
1126 associative and executive processes in creative cognition. *Memory & Cognition*, 42(7),
1127 1186–1197. <https://doi.org/10.3758/s13421-014-0428-8>.
- 1128 Benedek, M., Beaty, R., Jauk, E., Koschutnig, K., Fink, A., ... Neubauer, A. C. (2014a).
1129 Creating metaphors: The neural basis of figurative language production. *NeuroImage*,
1130 90, 99–106. <https://doi.org/10.1016/J.NEUROIMAGE.2013.12.046>.
- 1131 Benedek, M., Beaty, R. E., Schacter, D. L., & Kenett, Y. N. (2023). The role of memory in
1132 creative ideation. *Nature Reviews Psychology*, 2, 246–257.
1133 <https://doi.org/10.1038/s44159-023-00158-z>.
- 1134 Benedek, M., Bruckdorfer, R., & Jauk, E. (2020). Motives for creativity: Exploring the what
1135 and why of everyday creativity. *Journal of Creative Behavior*, 54(3), 610–625.
1136 <https://doi.org/10.1002/jocb.396>.

- 1137 Benedek, M., Kenett, Y. N., Umdasch, K., Anaki, D., Faust, M., & Neubauer, A. C. (2017).
1138 How semantic memory structure and intelligence contribute to creative thought: A
1139 network science approach. *Thinking & Reasoning*, 23(2), 158–183.
1140 <https://doi.org/10.1080/13546783.2016.1278034>.
- 1141 Benedek, M., & Fink, A. (2019). Toward a neurocognitive framework of creative cognition:
1142 the role of memory, attention, and cognitive control. *Current Opinion in Behavioral*
1143 *Sciences*, 27, 116–122. <https://doi.org/10.1016/j.cobeha.2018.11.002>.
- 1144 Benedek, M., Franz, F., Heene, M., & Neubauer, A. C. (2012). Differential effects of
1145 cognitive inhibition and intelligence on creativity. *Personality and Individual*
1146 *Differences*, 53(4), 480–485. <https://doi.org/10.1016/J.PAID.2012.04.014>.
- 1147 Benedek, M., & Jauk, E. (2018). Spontaneous and controlled processes in creative
1148 cognition. In K. Christoff & K. C. R. Fox (Eds.), *The Oxford Handbook of Spontaneous*
1149 *Thought: Mind-Wandering, Creativity, and Dreaming* (pp. 285–298). Oxford University
1150 Press. <https://doi.org/10.1093/oxfordhb/9780190464745.013.22>.
- 1151 Benedek, M., Jauk, E., Sommer, M., Arendasy, M., & Neubauer, A. C. (2014b). Intelligence,
1152 creativity, and cognitive control: The common and differential involvement of
1153 executive functions in intelligence and creativity. *Intelligence*, 46(1), 73–83.
1154 <https://doi.org/10.1016/j.intell.2014.05.007>.
- 1155 Benedek, M., Jung, R. E., & Vartanian, O. (2018). The neural bases of creativity and
1156 intelligence: common ground and differences. *Neuropsychologia*, 118, 1–3.
1157 <https://doi.org/10.1016/j.neuropsychologia.2018.09.006>.
- 1158 Benedek, M., & Neubauer, A. C. (2013). Revisiting Mednick’s model on creativity-related
1159 differences in associative hierarchies. Evidence for a common path to uncommon
1160 thought. *Journal of Creative Behavior*, 47, 273–289. <https://doi.org/10.1002/jocb.35>.
- 1161 Beversdorf, D. Q. (2019). Neuropsychopharmacological regulation of performance on
1162 creativity-related tasks. *Current Opinion in Behavioral Sciences*, 27, 55–63.
1163 <https://doi.org/10.1016/j.cobeha.2018.09.010>.
- 1164 Blohm, G., Kording, K. P., & Schrater, P. R. (2020). A how-to-model guide for neuroscience.
1165 *ENeuro*, 7(1), 1–12. <https://doi.org/10.1523/ENEURO.0352-19.2019>.
- 1166 Bonetto, E., Pichot, N., Pavani, J. B., & Adam-Troïan, J. (2021). Creative individuals are
1167 social risk-takers: Relationships between creativity, social risk-taking and fear of

- 1168 negative evaluations. *Creativity*, 7(2), 309–320. [https://doi.org/10.2478/ctra-2020-](https://doi.org/10.2478/ctra-2020-0016)
1169 0016.
- 1170 Boot, N., Baas, M., van Gaal, S., Cools, R., & de Dreu, C. K. W. (2017). Creative cognition
1171 and dopaminergic modulation of fronto-striatal networks: Integrative review and
1172 research agenda. *Neuroscience & Biobehavioral Reviews*, 78, 13–23.
1173 <https://doi.org/10.1016/j.neubiorev.2017.04.007>.
- 1174 Borsboom, D., van der Maas, H. L. J., Dalege, J., Kievit, R. A., & Haig, B. D. (2021). Theory
1175 construction methodology: A practical framework for building theories in psychology.
1176 *Perspectives on Psychological Science*, 16(4), 756–766.
1177 <https://doi.org/10.1177/1745691620969647>.
- 1178 Bristol, A. S., & Viskontas, I. V. (2006). Dynamic processes within associative memory
1179 stores. In J. C. Kaufman & J. Baer (Eds.), *Creativity and Reason in Cognitive*
1180 *Development* (pp. 60). Cambridge: Cambridge University Press.
- 1181 Brophy, D. R. (2001). Comparing the attributes, activities, and performance of divergent,
1182 convergent, and combination thinkers. *Creativity Research Journal*, 13(3–4), 439–455.
1183 https://doi.org/10.1207/s15326934crj1334_20.
- 1184 Camarda, A., Borst, G., Agogué, M., Habib, M., Weil, B., ... Cassotti, M. (2018a). Do we
1185 need inhibitory control to be creative? Evidence from a dual-task paradigm.
1186 *Psychology of Aesthetics, Creativity, and the Arts*, 12(3), 351–358.
1187 <https://doi.org/10.1037/aca0000140>.
- 1188 Camarda, A., Salvia, É., Vidal, J., Weil, B., Poirel, N., ... Cassotti, M. (2018b). Neural basis of
1189 functional fixedness during creative idea generation: An EEG study.
1190 *Neuropsychologia*, 118, 4–12.
1191 <https://doi.org/10.1016/j.neuropsychologia.2018.03.009>.
- 1192 Campbell, D. T. (1960). Blind variation and selective retentions in creative thought as in
1193 other knowledge processes. *Psychological Review*, 67(6), 380–400.
1194 <https://doi.org/10.1037/H0040373>.
- 1195 Carnovalini, F., & Rodà, A. (2020). Computational creativity and music generation systems:
1196 An introduction to the state of the art. *Frontiers in Artificial Intelligence*, 3, 14.
1197 <https://doi.org/10.3389/frai.2020.00014>.

- 1198 Caughron, J. J., Peterson, D. R., & Mumford, M. D. (2011). Creativity Training. In M. A.
1199 Runco & S. R. Pritzker (Eds.), *Encyclopedia of Creativity* (pp. 311–317). Academic
1200 Press. <https://doi.org/10.1016/b978-0-12-375038-9.00226-0>.
- 1201 Chateau-Laurent, H., & Alexandre, F. (2021). Towards a computational cognitive
1202 neuroscience model of creativity. In *IEEE ICCI*CC'21 - 20th IEEE International*
1203 *Conference on Cognitive Informatics and Cognitive Computing* Banff, Canada.
- 1204 Chen, Q., Beaty, R. E., & Qiu, J. (2020). Mapping the artistic brain: Common and distinct
1205 neural activations associated with musical, drawing, and literary creativity. *Human*
1206 *Brain Mapping, 41*(12), 3403–3419. <https://doi.org/10.1002/hbm.25025>.
- 1207 Christensen, A., Benedek, M., Silvia, P., & Beaty, R. (2021). Executive and default network
1208 connectivity reflects conceptual interference during creative imagery generation.
1209 *PsyArxiv* (Advance online publication). <https://doi.org/10.31234/osf.io/n438d>.
- 1210 Chrysikou, E. G. (2018). The costs and benefits of cognitive control for creativity. In Rex. E.
1211 Jung & O. Vartanian (Eds.), *The Cambridge Handbook of the Neuroscience of Creativity*
1212 (pp. 299–317). Cambridge University Press.
1213 <https://doi.org/10.1017/9781316556238.018>.
- 1214 Chrysikou, E. G. (2019). Creativity in and out of (cognitive) control. *Current Opinion in*
1215 *Behavioral Sciences, 27*, 94–99. <https://doi.org/10.1016/j.cobeha.2018.09.014>.
- 1216 Clark, A. (2013). Whatever next? Predictive brains, situated agents, and the future of
1217 cognitive science. *Behavioral and Brain Sciences, 36*(3), 181–204.
1218 <https://doi.org/10.1017/S0140525X12000477>.
- 1219 Colton, S. (2012). The painting fool: Stories from building an automated painter. In J.
1220 McCormack & M. D'Inverno (Eds.), *Computers and Creativity* (pp. 3–38). Berlin:
1221 Springer Berlin Heidelberg.
- 1222 Concepción, E., Gervás, P., & Méndez, G. (2020). Exploring baselines for combining full
1223 plots into multiple-plot stories. *New Generation Computing, 38*(4), 593–633.
1224 <https://doi.org/10.1007/s00354-020-00115-x>.
- 1225 Cortes, R. A., Weinberger, A. B., Daker, R. J., & Green, A. E. (2019). Re-examining
1226 prominent measures of divergent and convergent creativity. *Current Opinion in*
1227 *Behavioral Sciences, 27*, 90–93. <https://doi.org/10.1016/j.cobeha.2018.09.017>.

- 1228 Cropley, A. (2006). In praise of convergent thinking. *Creativity Research Journal*, 18(3),
1229 391–404. https://doi.org/10.1207/s15326934crj1803_13.
- 1230 Cseh, G. M., & Jeffries, K. K. (2019). A scattered CAT: A critical evaluation of the
1231 consensual assessment technique for creativity research. *Psychology of Aesthetics,*
1232 *Creativity, and the Arts*, 13(2), 159–166. <https://doi.org/10.1037/ACA0000220>.
- 1233 de Dreu, C. K. W., Nijstad, B. A., Baas, M., Wolsink, I., & Roskes, M. (2012). Working
1234 memory benefits creative insight, musical improvisation, and original ideation
1235 through maintained task-focused attention. *Personality and Social Psychology*
1236 *Bulletin*, 38(5), 656–669. <https://doi.org/10.1177/0146167211435795>.
- 1237 de Vink, I. C., Willemsen, R. H., Lazonder, A. W., & Kroesbergen, E. H. (2021). Creativity in
1238 mathematics performance: The role of divergent and convergent thinking. *British*
1239 *Journal of Educational Psychology*, 92, 484–501. <https://doi.org/10.1111/bjep.12459>.
- 1240 Dewett, T. (2007). Linking intrinsic motivation, risk taking, and employee creativity in an
1241 R&D environment. *R and D Management*, 37(3), 197–208.
1242 <https://doi.org/10.1111/j.1467-9310.2007.00469.x>.
- 1243 Diedrich, J., Benedek, M., Jauk, E., & Neubauer, A. C. (2015). Are creative ideas novel and
1244 useful? *Psychology of Aesthetics, Creativity, and the Arts*, 9(1), 35–40.
1245 <https://doi.org/10.1037/a0038688>.
- 1246 Dietrich, A. (2019). Where in the brain is creativity: a brief account of a wild-goose chase.
1247 *Current Opinion in Behavioral Sciences*, 27, 36–39.
1248 <https://doi.org/10.1016/j.cobeha.2018.09.001>.
- 1249 Dipaola, S., Gabora, L., & McCaig, G. (2018). Informing artificial intelligence generative
1250 techniques using cognitive theories of human creativity. *Procedia Computer Science*,
1251 145, 158–168. <https://doi.org/10.1016/J.PROCS.2018.11.024>.
- 1252 Dongen, N. van, Finnemann, A., Ron, J. de, Tiokhin, L., Wang, S. B., ... Borsboom, D. (2022).
1253 Many modelers. *PsyArXiv*. <https://doi.org/10.31234/OSF.IO/R5YFZ>.
- 1254 Dorfman, L., Martindale, C., Gassimova, V., & Vartanian, O. (2008). Creativity and speed of
1255 information processing: A double dissociation involving elementary versus inhibitory
1256 cognitive tasks. *Personality and Individual Differences*, 44(6), 1382–1390.
1257 <https://doi.org/10.1016/j.paid.2007.12.006>.

- 1258 Drago, V., & Heilman, K. M. (2012). Creativity. In V. S. Ramachandran (Ed.), *Encyclopedia of*
1259 *Human Behavior: Second Edition* (pp. 606–617). Academic Press.
1260 <https://doi.org/10.1016/B978-0-12-375000-6.00112-9>.
- 1261 Ellamil, M., Dobson, C., Beeman, M., & Christoff, K. (2012). Evaluative and generative
1262 modes of thought during the creative process. *NeuroImage*, *59*, 1783–1794.
1263 <https://doi.org/10.1016/j.neuroimage.2011.08.008>.
- 1264 Eskine, K. E., Anderson, A. E., Sullivan, M., & Golob, E. J. (2020). Effects of music listening
1265 on creative cognition and semantic memory retrieval. *Psychology of Music*, *48*(4),
1266 513–528. <https://doi.org/10.1177/0305735618810792>.
- 1267 Evans, J. S. B. T. (2008). Dual-processing accounts of reasoning, judgment, and social
1268 cognition. *Annual Review of Psychology*, *59*, 255–278.
1269 <https://doi.org/10.1146/annurev.psych.59.103006.093629>.
- 1270 Evans, J. S. B. T., & Stanovich, K. E. (2013). Dual-process theories of higher cognition:
1271 Advancing the debate. *Perspectives on Psychological Science*, *8*(3), 223–241.
1272 <https://doi.org/10.1177/1745691612460685>.
- 1273 Falomir, Z., & Plaza, E. (2020). Towards a model of creative understanding: deconstructing
1274 and recreating conceptual blends using image schemas and qualitative spatial
1275 descriptors. *Annals of Mathematics and Artificial Intelligence*, *88*(5–6), 457–477.
1276 <https://doi.org/10.1007/s10472-019-09619-9>.
- 1277 Farrell, S., & Lewandowsky, S. (2015). An introduction to cognitive modeling. In *An*
1278 *Introduction to Model-Based Cognitive Neuroscience* (pp. 3–24). Springer New York.
1279 https://doi.org/10.1007/978-1-4939-2236-9_1.
- 1280 Fink, A., Reim, T., Benedek, M., & Grabner, R. H. (2020). The effects of a verbal and a
1281 figural creativity training on different facets of creative potential. *Journal of Creative*
1282 *Behavior*, *54*(3), 676–685. <https://doi.org/10.1002/jocb.402>.
- 1283 Fink, A., Rominger, C., Benedek, M., Perchtold, C. M., Papousek, I., ... Memmert, D. (2018).
1284 EEG alpha activity during imagining creative moves in soccer decision-making
1285 situations. *Neuropsychologia*, *114*, 118–124.
1286 <https://doi.org/10.1016/j.neuropsychologia.2018.04.025>.
- 1287 Finke, R. A., Ward, T. B., & Smith, S. M. (1992). *Creative cognition: theory, research, and*
1288 *applications*. Cambridge, MA: MIT Press.

- 1289 Flaherty, A. W. (2005). Frontotemporal and dopaminergic control of idea generation and
1290 creative drive. *Journal of Comparative Neurology*, *493*(1), 147–153.
1291 <https://doi.org/10.1002/cne.20768>.
- 1292 Floridi, L., & Chiriatti, M. (2020). GPT-3: Its nature, scope, limits, and consequences. *Minds
1293 and Machines*, *30*(4), 681–694. [https://doi.org/10.1007/S11023-020-09548-
1294 1/FIGURES/5](https://doi.org/10.1007/S11023-020-09548-1/FIGURES/5).
- 1295 Forthmann, B., Bürkner, P. C., Szardenings, C., Benedek, M., & Holling, H. (2019a). A new
1296 perspective on the multidimensionality of divergent thinking tasks. *Frontiers in
1297 Psychology*, *10*(MAY), 985. <https://doi.org/10.3389/fpsyg.2019.00985>.
- 1298 Forthmann, B., Jendryczko, D., Scharfen, J., Kleinkorres, R., Benedek, M., & Holling, H.
1299 (2019b). Creative ideation, broad retrieval ability, and processing speed: A
1300 confirmatory study of nested cognitive abilities. *Intelligence*, *75*, 59–72.
1301 <https://doi.org/10.1016/j.intell.2019.04.006>.
- 1302 Fox, K., & Beaty, R. E. (2018). Mind-wandering as creative thinking: Neural, psychological,
1303 and theoretical considerations. *Current Opinion in Behavioral Sciences*, *27*, 123–130.
1304 <https://doi.org/10.1016/j.cobeha.2018.10.009>.
- 1305 Fried, E. I. (2020). Theories and models: What they are, what they are for, and what they
1306 are about. *Psychological Inquiry*, *31*(4), 336–344.
1307 <https://doi.org/10.1080/1047840X.2020.1854011>.
- 1308 Friston, K. (2010). The free-energy principle: A unified brain theory? *Nature Reviews
1309 Neuroscience*, *11*(2), 127–138. <https://doi.org/10.1038/nrn2787>.
- 1310 Frith, E., Elbich, D. B., Christensen, A. P., Rosenberg, M. D., Chen, Q., ... Beaty, R. E.
1311 (2021a). Intelligence and creativity share a common cognitive and neural basis.
1312 *Journal of Experimental Psychology: General*, *150*(4), 609–632.
1313 <https://doi.org/10.1037/xge0000958>.
- 1314 Frith, E., Kane, M. J., Welhaf, M. S., Christensen, A. P., Silvia, P. J., & Beaty, R. E. (2021b).
1315 Keeping creativity under control: Contributions of attention control and fluid
1316 intelligence to divergent thinking. *Creativity Research Journal*, *33*(2), 138–157.
1317 <https://doi.org/10.1080/10400419.2020.1855906>.
- 1318 Fugate, C. M., Zentall, S. S., & Gentry, M. (2013). Creativity and working memory in gifted
1319 students with and without characteristics of attention deficit hyperactive disorder:

- 1320 lifting the mask. *Gifted Child Quarterly*, 57(4), 234–246.
1321 <https://doi.org/10.1177/0016986213500069>.
- 1322 Gabora, L. (2010). Revenge of the “Neurds”: Characterizing creative thought in terms of
1323 the structure and dynamics of memory. *Creativity Research Journal*, 22(1), 1–13.
1324 <https://doi.org/10.1080/10400410903579494>.
- 1325 Gabora, L. (2018). The neural basis and evolution of divergent and convergent thought. In
1326 Rex. E. Jung & O. Vartanian (Eds.), *The Cambridge Handbook of the Neuroscience of*
1327 *Creativity* (pp. 58–70). Cambridge, MA: Cambridge University Press.
1328 <https://doi.org/10.1017/9781316556238.005>.
- 1329 Gabora, L., Beckage, N. M., & Steel, M. (2022). An autocatalytic network model of
1330 conceptual change. *Topics in Cognitive Science*, 14(1), 163–188.
1331 <https://doi.org/10.1111/tops.12583>.
- 1332 Gabora, L., & Steel, M. (2020). Modeling a cognitive transition at the origin of cultural
1333 evolution using autocatalytic networks. *Cognitive Science*, 44(9), e12878.
1334 <https://doi.org/10.1111/cogs.12878>.
- 1335 Gatti, L., Stock, O., & Strapparava, C. (2021). Cognition and Computational Linguistic
1336 Creativity. In M. Danesi (Ed.), *Handbook of Cognitive Mathematics* (pp. 1–39). Cham:
1337 Springer. https://doi.org/10.1007/978-3-030-44982-7_33-1.
- 1338 Gilhooly, K. J., Fioratou, E., Anthony, S. H., & Wynn, V. (2007). Divergent thinking:
1339 Strategies and executive involvement in generating novel uses for familiar objects.
1340 *British Journal of Psychology*, 98(4), 611–625. [https://doi.org/10.1111/J.2044-](https://doi.org/10.1111/J.2044-8295.2007.TB00467.X)
1341 [8295.2007.TB00467.X](https://doi.org/10.1111/J.2044-8295.2007.TB00467.X).
- 1342 Gobet, F., & Sala, G. (2019). How artificial intelligence can help us understand human
1343 creativity. *Frontiers in Psychology*, 10(JUN), 1401.
1344 <https://doi.org/10.3389/fpsyg.2019.01401>.
- 1345 Goldschmidt, G. (2016). Linkographic evidence for concurrent divergent and convergent
1346 thinking in creative design. *Creativity Research Journal*, 28(2), 115–122.
1347 <https://doi.org/10.1080/10400419.2016.1162497>.
- 1348 Gray, K., Anderson, S., Chen, E. E., Kelly, J. M., Christian, M. S., Patrick, J., et al. (2019).
1349 “Forward flow”: A new measure to quantify free thought and predict creativity.
1350 *American Psychologist*, 74(5), 539–554. <https://doi.org/10.1037/amp0000391>.

- 1351 Green, A. E., Cohen, M. S., Raab, H. A., Yedibalian, C. G., & Gray, J. R. (2015). Frontopolar
1352 activity and connectivity support dynamic conscious augmentation of creative state.
1353 *Human Brain Mapping, 36*(3), 923–934. <https://doi.org/10.1002/hbm.22676>.
- 1354 Guest, O., & Martin, A. E. (2021). How computational modeling can force theory building
1355 in psychological science. *Perspectives on Psychological Science, 16*(4), 789–802.
1356 <https://doi.org/10.1177/1745691620970585>.
- 1357 Guilford, J. P. (1950). Creativity. *American Psychologist, 5*(9), 444–454.
1358 <https://doi.org/10.4337/9781849805896.00013>.
- 1359 Guilford, J. P. (1959). Three faces of intellect. *American Psychologist, 14*(8), 469–479.
1360 <https://doi.org/10.4159/harvard.9780674864207.c5>.
- 1361 Guilford, J. P. (1967). *The Nature of Human Intelligence*. New York, NY: Mc-Graw Hill.
- 1362 Guhe, M., Smaill, A., & Pease, A. (2010). Towards a cognitive model of conceptual
1363 blending. In *10th International Conference on Cognitive Modeling*, 293–304.
1364 Philadelphia, PA: Drexel University.
- 1365 Harada, T. (2020). The effects of risk-taking, exploitation, and exploration on creativity.
1366 *PLOS ONE, 15*(7), e0235698. <https://doi.org/10.1371/JOURNAL.PONE.0235698>.
- 1367 Hart, Y., Kosoy, E., Liquin, E. G., Leonard, J. A., Mackey, A. P., & Gopnik, A. (2022). The
1368 development of creative search strategies. *Cognition, 225*, 105102.
1369 <https://doi.org/10.1016/J.COGNITION.2022.105102>.
- 1370 Hart, Y., Mayo, A. E., Mayo, R., Rozenkrantz, L., Tendler, A., ... Noy, L. (2017). Creative
1371 foraging: An experimental paradigm for studying exploration and discovery. *PLoS*
1372 *ONE, 12*(8), 1–15. <https://doi.org/10.1371/journal.pone.0182133>.
- 1373 He, L., Kenett, Y. N., Zhuang, K., Liu, C., Zeng, R., ... Qiu, J. (2020). The relation between
1374 semantic memory structure, associative abilities, and verbal and figural creativity.
1375 *Thinking and Reasoning, 27*(2), 268–293.
1376 <https://doi.org/10.1080/13546783.2020.1819415>.
- 1377 Hélie, S., & Sun, R. (2010). Incubation, insight, and creative problem solving: A unified
1378 theory and a connectionist model. *Psychological Review, 117*(3), 994–1024.
1379 <https://doi.org/10.1037/a0019532>.

- 1380 Hennessey, B. A., & Amabile, T. M. (2010). Creativity. *Annual Review of Psychology*, *61*,
1381 569–598. <https://doi.org/10.1146/annurev.psych.093008.100416>.
- 1382 Herz, N., Baror, S., & Bar, M. (2020). Overarching states of mind. *Trends in Cognitive*
1383 *Sciences*, *24*(3), 184–199. <https://doi.org/10.1016/j.tics.2019.12.015>.
- 1384 Hills, T. T., Jones, M. N., & Todd, P. M. (2012). Optimal foraging in semantic memory.
1385 *Psychological Review*, *119*(2), 431–440. <https://doi.org/10.1037/A0027373>.
- 1386 Hitchcock, P. F., Fried, E. I., & Frank, M. J. (2022). Computational psychiatry needs time
1387 and context. *Annual Review of Psychology*, *73*, 243–270.
1388 <https://doi.org/10.1146/annurev-psych-021621-124910>.
- 1389 Hofstadter, D., & Mitchell, M. (1994). The copycat project: A model of mental fluidity and
1390 analogy-making. *Advances in Connectionist and Neural Computation Theory*, *2*(31–
1391 112), 29–30.
- 1392 Hommel, B., & Wiers, R. W. (2017). Towards a unitary approach to human action control.
1393 *Trends in Cognitive Sciences*, *21*(12), 940–949.
1394 <https://doi.org/10.1016/j.tics.2017.09.009>.
- 1395 Hoogman, M., Stolte, M., Baas, M., & Kroesbergen, E. (2020). Creativity and ADHD: A
1396 review of behavioral studies, the effect of psychostimulants and neural
1397 underpinnings. *Neuroscience and Biobehavioral Reviews*, *119*, 66–85.
1398 <https://doi.org/10.1016/j.neubiorev.2020.09.029>.
- 1399 Iger, R. (2019). *The Ride of a Lifetime: Lessons in Creative Leadership from 15 Years as CEO*
1400 *of the Walt Disney Company*. London: Bantam Press.
- 1401 Jensen, A. R. (1998). *The g Factor: The Science of Mental Ability*. Westport, CT: Praeger.
- 1402 Jung, R. E., Mead, B. S., Carrasco, J., & Flores, R. A. (2013). The structure of creative
1403 cognition in the human brain. *Frontiers in Human Neuroscience*, *7*, 330.
1404 <https://doi.org/10.3389/fnhum.2013.00330>.
- 1405 Kahneman, D. (2011). *Thinking, fast and slow*. New York, NY: Farrar, Straus and Giroux.
- 1406 Kajić, I., Gosmann, J., Stewart, T. C., Wennekers, T., & Eliasmith, C. (2017). A spiking
1407 neuron model of word associations for the remote associates test. *Frontiers in*
1408 *Psychology*, *8*(FEB), 99. <https://doi.org/10.3389/fpsyg.2017.00099>.

- 1409 Karimi-Rouzbahani, H., Bagheri, N., & Ebrahimpour, R. (2017). Invariant object recognition
1410 is a personalized selection of invariant features in humans, not simply explained by
1411 hierarchical feed-forward vision models. *Scientific Reports*, *7*, 14402.
1412 <https://doi.org/10.1038/s41598-017-13756-8>.
- 1413 Karwowski, M., Czerwonka, M., & Kaufman, J. C. (2020). Does intelligence strengthen
1414 creative metacognition? *Psychology of Aesthetics, Creativity, and the Arts*, *14*(3), 353–
1415 360. <https://doi.org/10.1037/ACA0000208>.
- 1416 Karwowski, M., Dul, J., Gralewski, J., Jauk, E., Jankowska, D. M., ... Benedek, M. (2016). Is
1417 creativity without intelligence possible? A necessary condition analysis. *Intelligence*,
1418 *57*, 105–117. <https://doi.org/10.1016/j.intell.2016.04.006>.
- 1419 Kaufman, S. B., Quilty, L. C., Grazioplene, R. G., Hirsh, J. B., Gray, J. R., ... DeYoung, C. G.
1420 (2016). Openness to experience and intellect differentially predict creative
1421 achievement in the arts and sciences. *Journal of Personality*, *84*(2), 248–258.
1422 <https://doi.org/10.1111/jopy.12156>.
- 1423 Kaur, Y., Weiss, S., Zhou, C., Fischer, R., & Hildebrandt, A. (2021). Exploring neural signal
1424 complexity as a potential link between creative thinking, intelligence, and cognitive
1425 control. *Journal of Intelligence*, *9*(4), 59.
1426 <https://doi.org/10.3390/jintelligence9040059>.
- 1427 Kenett, Y. N., Anaki, D., & Faust, M. (2014). Investigating the structure of semantic
1428 networks in low and high creative persons. *Frontiers in Human Neuroscience*, *8*, 407.
1429 <https://doi.org/10.3389/fnhum.2014.00407>.
- 1430 Kenett, Y.N. & Austerweil, J.L. (2016). Examining search processes in low and high creative
1431 individuals with random walks. In *Proceedings of the 38th Annual Meeting of the*
1432 *Cognitive Science Society*. Austin, TX.
- 1433 Kenett, Y. N., & Faust, M. (2019). A semantic network cartography of the creative mind.
1434 *Trends in Cognitive Sciences*, *23*, 271–274.
1435 <https://doi.org/10.1016/J.TICS.2019.01.007>.
- 1436 Kenett, Y. N., Kraemer, D. J. M., Alfred, K. L., Colaizzi, G. A., Cortes, R. A., & Green, A. E.
1437 (2020). Developing a neurally informed ontology of creativity measurement.
1438 *NeuroImage*, *221*, 117166. <https://doi.org/10.1016/j.neuroimage.2020.117166>.

- 1439 Kenett, Y. N., Levy, O., Kenett, D. Y., Stanley, H. E., Faust, M., & Havlin, S. (2018). Flexibility
1440 of thought in high creative individuals represented by percolation analysis.
1441 *Proceedings of the National Academy of Sciences*, *115*(5), 867–872.
1442 <https://doi.org/10.1073/pnas.1717362115>.
- 1443 Khalil, R., & Moustafa, A. A. (2022). A neurocomputational model of creative processes.
1444 *Neuroscience & Biobehavioral Reviews*, *137*, 104656.
1445 <https://doi.org/10.1016/j.neubiorev.2022.104656>.
- 1446 Kleinmintz, O. M., Ivancovsky, T., & Shamay-Tsoory, S. G. (2019). The twofold model of
1447 creativity: the neural underpinnings of the generation and evaluation of creative
1448 ideas. *Current Opinion in Behavioral Sciences*, *27*, 131–138.
1449 <https://doi.org/10.1016/j.cobeha.2018.11.004>.
- 1450 Kounios, J., & Beeman, M. (2014). The cognitive neuroscience of insight. *Annual Review of*
1451 *Psychology*, *65*, 71–93. <https://doi.org/10.1146/annurev-psych-010213-115154>.
- 1452 Kording, K. P., Blohm, G., Schrater, P., & Kendrick, K. (2020). Appreciating the variety of
1453 goals in computational neuroscience. *Arxiv* (Advance online publication).
1454 <https://arxiv.org/abs/2002.03211v1>.
- 1455 Krumm, G., Arán Filippetti, V., & Gutierrez, M. (2018). The contribution of executive
1456 functions to creativity in children: What is the role of crystallized and fluid
1457 intelligence? *Thinking Skills and Creativity*, *29*, 185–195.
1458 <https://doi.org/10.1016/j.tsc.2018.07.006>.
- 1459 Lebuda, I., & Benedek, M. (2023). A systematic framework of creative metacognition.
1460 *PsyArxiv* (Advance online publication). <https://doi.org/10.31234/osf.io/s793q>
- 1461 Lee, C. S., & Theriault, D. J. (2013). The cognitive underpinnings of creative thought: A
1462 latent variable analysis exploring the roles of intelligence and working memory in
1463 three creative thinking processes. *Intelligence*, *41*(5), 306–320.
1464 <https://doi.org/10.1016/j.intell.2013.04.008>.
- 1465 Lin, H., & Vartanian, O. (2018). A neuroeconomic framework for creative cognition.
1466 *Perspectives on Psychological Science*, *13*(6), 655–677.
1467 <https://doi.org/10.1177/1745691618794945>.

- 1468 Liu, S., & Peng, M. (2020). Does scope of attention affect creativity? Testing the
1469 attentional priming hypothesis. *Journal of Creative Behavior*, *54*(2), 423–435.
1470 <https://doi.org/10.1002/jocb.378>.
- 1471 Lloyd-Cox, J., Chen, Q., & Beaty, R. E. (2022a). The time course of creativity: Multivariate
1472 classification of default and executive network contributions to creative cognition
1473 over time. *Cortex*, *156*, 90–105. <https://doi.org/10.1016/J.CORTEX.2022.08.008>.
- 1474 Lloyd-Cox, J., Christensen, A. P., Silvia, P. J., & Beaty, R. E. (2021). Seeing outside the box:
1475 salient associations disrupt visual idea generation. *Psychology of Aesthetics,*
1476 *Creativity, and the Arts*, *15*(4), 575–583. <https://doi.org/10.1037/aca0000371>.
- 1477 Lloyd-Cox, J., Pickering, A., & Bhattacharya, J. (2022b). Evaluating creativity: How idea
1478 context and rater personality affect considerations of novelty and usefulness.
1479 *Creativity Research Journal*, *34*, 373–390.
1480 <https://doi.org/10.1080/10400419.2022.2125721>.
- 1481 Lopez-Persem, A., Rodriguez, S. M., Ovando-Tellez, M., Bieth, T., Guiet, S., ... Volle, E.
1482 (2022). How subjective idea valuation energizes and guides creative idea generation.
1483 *BioRxiv*. <https://doi.org/10.1101/2022.08.02.502491>.
- 1484 Lu, J. G., Akinola, M., & Mason, M. F. (2017). “Switching On” creativity: Task switching can
1485 increase creativity by reducing cognitive fixation. *Organizational Behavior and Human*
1486 *Decision Processes*, *139*, 63–75. <https://doi.org/10.1016/j.obhdp.2017.01.005>.
- 1487 Luft, C. D. B., Zioga, I., Thompson, N. M., Banissy, M. J., & Bhattacharya, J. (2018). Right
1488 temporal alpha oscillations as a neural mechanism for inhibiting obvious associations.
1489 *Proceedings of the National Academy of Sciences*, *115*(52), E12144–E12152.
1490 <https://doi.org/10.1073/pnas.1811465115>.
- 1491 Lustenberger, C., Boyle, M. R., Foulser, A. A., Mellin, J. M., & Fröhlich, F. (2015). Functional
1492 role of frontal alpha oscillations in creativity. *Cortex*, *67*, 74–82.
1493 <https://doi.org/10.1016/j.cortex.2015.03.012>.
- 1494 Mackintosh, N. J. (1998). *IQ and Human Intelligence*. Oxford, UK: Oxford University Press.
- 1495 MacGregor, J. N., Ormerod, T. C., & Chronicle, E. P. (2001). Information processing and
1496 insight: a process model of performance on the nine-dot and related problems.
1497 *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *27*(1), 176.

- 1498 Madore, K. P., Addis, D. R., & Schacter, D. L. (2016). Creativity and memory: Effects of an
1499 episodic specificity induction on divergent thinking. *26*(9), 1461–1468.
1500 <https://doi.org/10.1177/0956797615591863.Creativity>.
- 1501 Maia, T. V., Huys, Q. J. M., & Frank, M. J. (2017). Theory-based computational psychiatry.
1502 *Biological Psychiatry, 82*(6), 382–384.
1503 <https://doi.org/10.1016/j.biopsych.2017.07.016>.
- 1504 Marron, T. R., Lerner, Y., Berant, E., Kinreich, S., Shapira-Lichter, I., ... Faust, M. (2018).
1505 Chain free association, creativity, and the default mode network. *Neuropsychologia,*
1506 *118*, 40–58. <https://doi.org/10.1016/j.neuropsychologia.2018.03.018>.
- 1507 Marshall, J. B. (2006). A self-watching model of analogy-making and perception. *Journal of*
1508 *Experimental and Theoretical Artificial Intelligence, 18*(3), 267–307.
1509 <https://doi.org/10.1080/09528130600758626>.
- 1510 Mayselless, N., Eran, A., & Shamay-Tsoory, S. G. (2015). Generating original ideas: The
1511 neural underpinning of originality. *NeuroImage, 116*, 232–239.
1512 <https://doi.org/10.1016/j.neuroimage.2015.05.030>.
- 1513 Mednick, S. A. (1962). The associative basis of the creative process. *Psychological Review,*
1514 *69*(3), 220–32. [https://doi.org/10.1016/0160-4120\(83\)90087-9](https://doi.org/10.1016/0160-4120(83)90087-9).
- 1515 Mekern, V., Hommel, B., & Sjoerds, Z. (2019a). Computational models of creativity: a
1516 review of single-process and multi-process recent approaches to demystify creative
1517 cognition. *Current Opinion in Behavioral Sciences, 27*, 47–54.
1518 <https://doi.org/10.1016/j.cobeha.2018.09.008>.
- 1519 Mekern, V. N., Sjoerds, Z., & Hommel, B. (2019b). How metacontrol biases and adaptivity
1520 impact performance in cognitive search tasks. *Cognition, 182*, 251–259.
1521 <https://doi.org/10.1016/j.cognition.2018.10.001>.
- 1522 Nelson, D. L., McEvoy, C. L., & Schreiber, T. A. (2004). The University of South Florida free
1523 association, rhyme, and word fragment norms. *Behavior Research Methods,*
1524 *Instruments, & Computers, 36*(3), 402–407. <https://doi.org/10.3758/BF03195588>.
- 1525 Nielsen, B. D., Pickett, C. L., & Simonton, D. K. (2008). Conceptual versus experimental
1526 creativity: Which works best on convergent and divergent thinking tasks? *Psychology*
1527 *of Aesthetics, Creativity, and the Arts, 2*(3), 131–138. [https://doi.org/10.1037/1931-](https://doi.org/10.1037/1931-3896.2.3.131)
1528 [3896.2.3.131](https://doi.org/10.1037/1931-3896.2.3.131).

- 1529 Nijstad, B. A., de Dreu, C. K. W., Rietzschel, E. F., & Baas, M. (2010). The dual pathway to
1530 creativity model: Creative ideation as a function of flexibility and persistence.
1531 *European Review of Social Psychology, 21*(1), 34–77.
1532 <https://doi.org/10.1080/10463281003765323>.
- 1533 Nusbaum, E. C., & Silvia, P. J. (2011). Are intelligence and creativity really so different?
1534 Fluid intelligence, executive processes, and strategy use in divergent thinking.
1535 *Intelligence, 39*(1), 36–45. <https://doi.org/10.1016/j.intell.2010.11.002>.
- 1536 Oleynick, V. C., DeYoung, C. G., Hyde, E., Barry Kaufman, S., Beaty, R. E., & Silvia, P. J.
1537 (2017). Openness/Intellect: The core of the creative personality. In G. J. Feist, R.
1538 Reiter-Palmon, & J. C. Kaufman (Eds.), *Cambridge handbook of creativity and*
1539 *personality research* (pp. 9–27). New York: Cambridge University Press.
- 1540 Oltețeanu, A. M., & Falomir, Z. (2015). ComRAT-C: A computational compound Remote
1541 Associates Test solver based on language data and its comparison to human
1542 performance. *Pattern Recognition Letters, 67*, 81–90.
1543 <https://doi.org/10.1016/j.patrec.2015.05.015>.
- 1544 Oltețeanu, A. M., & Falomir, Z. (2016). Object replacement and object composition in a
1545 creative cognitive system. Towards a computational solver of the Alternative Uses
1546 Test. *Cognitive Systems Research, 39*(January), 15–32.
1547 <https://doi.org/10.1016/j.cogsys.2015.12.011>.
- 1548 Ovando-Tellez, M., Kenett, Y. N., Benedek, M., Bernard, M., Belo, J., ... Volle, E. (2022).
1549 Brain connectivity-based prediction of real-life creativity is mediated by semantic
1550 memory structure. *Science Advances, 8*(5).
1551 https://doi.org/10.1126/SCIADV.ABL4294/SUPPL_FILE/SCIADV.ABL4294_SM.PDF.
- 1552 Pan, X., & Yu, H. (2018). Different effects of cognitive shifting and intelligence on
1553 creativity. *Journal of Creative Behavior, 52*(3), 212–225.
1554 <https://doi.org/10.1002/jocb.144>.
- 1555 Palminteri, S., Wyart, V., & Koechlin, E. (2017). The importance of falsification in
1556 computational cognitive modeling. *Trends in Cognitive Sciences, 21*, 425–433.
1557 <https://doi.org/10.1016/J.TICS.2017.03.011>.
- 1558 Pinho, A. L., de Manzano, Ö., Fransson, P., Eriksson, H., & Ullén, F. (2014). Connecting to
1559 create: Expertise in musical improvisation is associated with increased functional

- 1560 connectivity between premotor and prefrontal areas. *Journal of Neuroscience*, *34*(18),
1561 6156–6163. <https://doi.org/10.1523/JNEUROSCI.4769-13.2014>.
- 1562 Plucker, J. A. (2022). The patient is thriving! Current issues, recent advances, and future
1563 directions in creativity assessment. *Creativity Research Journal* (Advance online
1564 publication). <https://doi.org/10.1080/10400419.2022.2110415>.
- 1565 Plucker, J. A., Beghetto, R. A., & Dow, G. T. (2004). Why isn't creativity more important to
1566 educational psychologists? Potentials, pitfalls, and future directions in creativity
1567 research. *Educational Psychologist*, *39*(2), 83–96.
1568 https://doi.org/10.1207/s15326985ep3902_1.
- 1569 Poile, C., & Safayeni, F. (2016). Using computational modeling for building theory: A
1570 double edged sword. *Journal of Artificial Societies and Social Simulation*, *19*(3), 8.
1571 <https://doi.org/10.18564/jasss.3137>.
- 1572 Prabhakaran, R., Green, A. E., & Gray, J. R. (2014). Thin slices of creativity: Using single-
1573 word utterances to assess creative cognition. *Behavior Research Methods*, *46*(3), 641.
1574 <https://doi.org/10.3758/S13428-013-0401-7>.
- 1575 Pramod, R. T., & Arun, S. P. (2016). Do computational models differ systematically from
1576 human object perception? In *Proceedings of the IEEE Computer Society Conference on*
1577 *Computer Vision and Pattern Recognition*. Las Vegas, NV.
1578 <https://doi.org/10.1109/CVPR.2016.177>.
- 1579 Puryear, J. S., & Lamb, K. N. (2020). Defining creativity: How far have we come since
1580 Plucker, Beghetto, and Dow? *Creativity Research Journal*, *32*(3), 206–214.
1581 <https://doi.org/10.1080/10400419.2020.1821552>.
- 1582 Radel, R., Davranche, K., Fournier, M., & Dietrich, A. (2015). The role of (dis)inhibition in
1583 creativity: Decreased inhibition improves idea generation. *Cognition*, *134*, 110–120.
1584 <https://doi.org/10.1016/j.cognition.2014.09.001>.
- 1585 Rominger, C., Papousek, I., Perchtold, C. M., Benedek, M., Weiss, E. M., ... Fink, A. (2019).
1586 Creativity is associated with a characteristic U-shaped function of alpha power
1587 changes accompanied by an early increase in functional coupling. *Cognitive, Affective*
1588 *and Behavioral Neuroscience*, *19*(4), 1012–1021.
- 1589 Rominger, C., Papousek, I., Perchtold, C. M., Weber, B., Weiss, E. M., & Fink, A. (2018). The
1590 creative brain in the figural domain: Distinct patterns of EEG alpha power during idea

- 1591 generation and idea elaboration. *Neuropsychologia*, 118, 13–19.
1592 <https://doi.org/10.1016/J.NEUROPSYCHOLOGIA.2018.02.013>.
- 1593 Rosen, D. S., Oh, Y., Erickson, B., Zhang, F. (Zoe), Kim, Y. E., & Kounios, J. (2020). Dual-
1594 process contributions to creativity in jazz improvisations: An SPM-EEG study.
1595 *NeuroImage*, 213, 116632. <https://doi.org/10.1016/J.NEUROIMAGE.2020.116632>.
- 1596 Rotaru, A. S., Vigliocco, G., & Frank, S. L. (2018). Modeling the structure and dynamics of
1597 semantic processing. *Cognitive Science*, 42(8), 2890–2917.
1598 <https://doi.org/10.1111/cogs.12690>.
- 1599 Runco, M. (2010). Divergent thinking, creativity, and ideation. In J. C. Kaufman & R. J.
1600 Sternberg (Eds.), *The Cambridge Handbook of Creativity* (pp. 413–446). Cambridge:
1601 Cambridge University Press. <https://doi.org/10.1017/CBO9780511763205.026>.
- 1602 Runco, M. A. (2012). Creative and imaginative thinking. In V. S. Ramachandran (Ed.),
1603 *Encyclopedia of Human Behavior: Second Edition* (pp. 602–605). Academic Press.
1604 <https://doi.org/10.1016/B978-0-12-375000-6.00111-7>.
- 1605 Runco, M. A. (2014). Cognition and creativity. In M. A. Runco (Ed.), *Creativity* (pp. 1–38).
1606 Academic Press. <https://doi.org/10.1016/b978-0-12-410512-6.00001-1>.
- 1607 Runco, M. A., & Jaeger, G. J. (2012). The standard definition of creativity. *Creativity*
1608 *Research Journal*, 24(1), 92–96. <https://doi.org/10.1080/10400419.2012.650092>.
- 1609 Saggar, M., Volle, E., Uddin, L. Q., Chrysikou, E. G., & Green, A. E. (2021). Creativity and the
1610 brain: An editorial introduction to the special issue on the neuroscience of creativity.
1611 *NeuroImage*, 231(February), 117836.
1612 <https://doi.org/10.1016/j.neuroimage.2021.117836>.
- 1613 Sampedro, A., Peña, J., Ibarretxe-Bilbao, N., Sánchez, P., Iriarte-Yoller, N., ... Ojeda, N.
1614 (2020a). Mediating role of cognition and social cognition on creativity among patients
1615 with schizophrenia and healthy controls: Revisiting the Shared Vulnerability Model.
1616 *Psychiatry and Clinical Neurosciences*, 74(2), 149–155.
1617 <https://doi.org/10.1111/PCN.12954>.
- 1618 Sampedro, A., Peña, J., Ibarretxe-Bilbao, N., Sánchez, P., Iriarte-Yoller, N., ... Ojeda, N.
1619 (2020b). Neurocognitive, social cognitive, and clinical predictors of creativity in
1620 schizophrenia. *Journal of Psychiatric Research*, 129, 206–213.
1621 <https://doi.org/10.1016/J.JPSYCHIRES.2020.06.019>.

- 1622 Schatz, J., Jones, S. J., & Laird, J. E. (2018). An architecture approach to modeling the
1623 remote associates test. In *Proceedings of ICCM 2018 - 16th International Conference*
1624 *on Cognitive Modeling* (pp. 126–131).
- 1625 Schorlemmer, M., & Plaza, E. (2021). A uniform model of computational conceptual
1626 blending. *Cognitive Systems Research*, *65*, 118–137.
1627 <https://doi.org/10.1016/J.COGSYS.2020.10.003>.
- 1628 Shamay-Tsoory, S. G., Adler, N., Aharon-Peretz, J., Perry, D., & Mayseless, N. (2011). The
1629 origins of originality: The neural bases of creative thinking and originality.
1630 *Neuropsychologia*, *49*(2), 178–185.
1631 <https://doi.org/10.1016/j.neuropsychologia.2010.11.020>.
- 1632 Shang, L., Little, D. R., Webb, M. E., Eidels, A., & Yang, C.-T. (2021). The workload capacity
1633 of semantic search in convergent thinking. *Journal of Experimental Psychology:*
1634 *General*, *150*(11), 2230–2245. <https://doi.org/10.1037/xge0001045>.
- 1635 Shen, W., Hommel, B., Yuan, Y., Chang, L., & Zhang, W. (2018). Risk-taking and creativity:
1636 Convergent, but not divergent thinking is better in low-risk takers. *Creativity Research*
1637 *Journal*, *30*(2), 224–231. <https://doi.org/10.1080/10400419.2018.1446852>.
- 1638 Silvia, P. J., Beaty, R. E., & Nusbaum, E. C. (2013). Verbal fluency and creativity: General
1639 and specific contributions of broad retrieval ability (Gr) factors to divergent thinking.
1640 *Intelligence*, *41*(5), 328–340. <https://doi.org/10.1016/j.intell.2013.05.004>.
- 1641 Simonton, D. K. (2013). Creative thought as blind variation and selective retention: Why
1642 creativity is inversely related to sightedness. *Journal of Theoretical and Philosophical*
1643 *Psychology*, *33*(4), 253–266. <https://doi.org/10.1037/a0030705>.
- 1644 Simonton, D. K. (2018). Defining creativity: Don't we also need to define what is not
1645 creative? *Journal of Creative Behavior*, *52*(1), 80–90.
1646 <https://doi.org/10.1002/jocb.137>.
- 1647 Simonton, D. K. (2022). The blind-variation and selective-retention theory of creativity:
1648 Recent developments and current status of BVSR. *Creativity Research Journal*
1649 (Advance online publication). <https://doi.org/10.1080/10400419.2022.2059919>.
- 1650 Smaldino, P. E. (2017). Models are stupid, and we need more of them. In R. Vallacher, S.
1651 Read, & A. Nowak (Eds.), *Computational Models in Social Psychology* (pp. 311–331).
1652 Psychology Press. <https://doi.org/10.4324/9781315173726-14>.

- 1653 Smaldino, P. E. (2020). How to translate a verbal theory into a formal model. *Social*
1654 *Psychology*, 51(4), 207–218. <https://doi.org/10.1027/1864-9335/a000425>.
- 1655 Sowden, P. T., Pringle, A., & Gabora, L. (2015). The shifting sands of creative thinking:
1656 Connections to dual-process theory. *Thinking and Reasoning*, 21(1), 40–60.
1657 <https://doi.org/10.1080/13546783.2014.885464>.
- 1658 Stein, M. I. (1953). Creativity and culture. *The Journal of Psychology*, 36(2), 311–322.
- 1659 Stevens, C. E., & Zabelina, D. L. (2020). Classifying creativity: Applying machine learning
1660 techniques to divergent thinking EEG data. *NeuroImage*, 219, 116990.
1661 <https://doi.org/10.1016/j.neuroimage.2020.116990>.
- 1662 Stolte, M., García, T., van Luit, J. E. H., Oranje, B., & Kroesbergen, E. H. (2020). The
1663 contribution of executive functions in predicting mathematical creativity in typical
1664 elementary school classes: A twofold role for updating. *Journal of Intelligence*, 8(2),
1665 1–20. <https://doi.org/10.3390/JINTELLIGENCE8020026>.
- 1666 Storm, B. C., Angello, G., & Bjork, E. L. (2011). Thinking can cause forgetting: Memory
1667 dynamics in creative problem solving. *Journal of Experimental Psychology: Learning*
1668 *Memory and Cognition*, 37(5), 1287–1293. <https://doi.org/10.1037/a0023921>.
- 1669 Sunavsky, A., & Poppenk, J. (2020). Neuroimaging predictors of creativity in healthy adults.
1670 *NeuroImage*, 206, 116292. <https://doi.org/10.1016/j.neuroimage.2019.116292>.
- 1671 Suzuki, K., Roseboom, W., Schwartzman, D. J., & Seth, A. K. (2017). A deep-dream virtual
1672 reality platform for studying altered perceptual phenomenology. *Scientific Reports*,
1673 7(1), 1–11. <https://doi.org/10.1038/s41598-017-16316-2>.
- 1674 Theorists and experimentalists must join forces. (2021). *Nature Computational Science*,
1675 1(5), 299. <https://doi.org/10.1038/s43588-021-00082-3>.
- 1676 Tik, M., Sladky, R., Di, C., Luft, B., Willinger, D., ... Windischberger, C. (2018). Ultra-high-
1677 field fMRI insights on insight: Neural correlates of the Aha!-moment. *Human Brain*
1678 *Mapping*, 39, 3241–3252. <https://doi.org/10.1002/hbm.24073>.
- 1679 Todd, P. M., & Miranda, E. R. (2006). Putting some (artificial) life into models of musical
1680 creativity. In I. Deliège & G. A. Wiggins (Eds.), *Musical Creativity: Multidisciplinary*
1681 *Research in Theory and Practice* (pp. 376–396). Psychology Press.

- 1682 Tubb, R., & Dixon, S. (2014). A four strategy model of creative parameter space
1683 interaction. In *Proceedings of the 5th International Conference on Computational*
1684 *Creativity, ICCV 2014*.
- 1685 Undheim, J. O., & Horn, J. L. (1977). Critical evaluation of Guilford's structure-of-intellect
1686 theory. *Intelligence*, 1(1), 65–81. [https://doi.org/10.1016/0160-2896\(77\)90027-7](https://doi.org/10.1016/0160-2896(77)90027-7).
- 1687 Vartanian, O. (2009). Variable attention facilitates creative problem solving. *Psychology of*
1688 *Aesthetics, Creativity, and the Arts*, 3(1), 57–59. <https://doi.org/10.1037/a0014781>.
- 1689 Veale, T., & Pérez y Pérez, R. (2020). Leaps and bounds: An introduction to the field of
1690 computational creativity. *New Generation Computing*, 38(4), 551–563.
1691 <https://doi.org/10.1007/s00354-020-00116-w>.
- 1692 Volle, E. (2018). Associative and controlled cognition in divergent thinking: Theoretical,
1693 experimental, neuroimaging evidence, and new directions. In Rex. E. Jung & O.
1694 Vartanian (Eds.), *The Cambridge handbook of the neuroscience of creativity* (pp. 333–
1695 360). New York, NY, US: Cambridge University Press.
- 1696 Wallas, G. (1926). *The Art of Thought*. New York: Harcourt Brace.
- 1697 Wiggins, G. A. (2020). Creativity, information, and consciousness: The information
1698 dynamics of thinking. *Physics of Life Reviews*, 34–35, 1–39.
1699 <https://doi.org/10.1016/j.plrev.2018.05.001>.
- 1700 Wiggins, G. A., & Bhattacharya, J. (2014). Mind the gap: An attempt to bridge
1701 computational and neuroscientific approaches to study creativity. *Frontiers in Human*
1702 *Neuroscience*, 8(JULY), 540. <https://doi.org/10.3389/fnhum.2014.00540>.
- 1703 Wilson, R. C., & Collins, A. G. E. (2019). Ten simple rules for the computational modeling of
1704 behavioral data. *Elife* 8:e49647. <https://doi.org/10.7554/ELIFE.49547>.
- 1705 Xue, Y., Gu, C., Wu, J., Dai, D. Y., Mu, X., & Zhou, Z. (2020). The effects of extrinsic
1706 motivation on scientific and artistic creativity among middle school students. *Journal*
1707 *of Creative Behavior*, 54(1), 37–50. <https://doi.org/10.1002/jocb.239>.
- 1708 Yalcin, O. N., Abukhodair, N., & DiPaola, S. (2020). Empathic AI painter: A computational
1709 creativity system with embodied conversational interaction. In *JMLR: Workshop and*
1710 *Conference Proceedings* (pp. 1–11). Available at: <http://arxiv.org/abs/2005.14223>.

- 1711 Yang, L.-C., Choi, S.-Y., & Yang, Y.-H. (2017). MidiNet: a convolutional generative
1712 adversarial network for symbolic-domain music generation. *ArXiv*. 1703.10847.
- 1713 Zabelina, D. L. (2018). Attention and creativity. In R. E. Jung & O. Vartanian (Eds.), *The*
1714 *Cambridge Handbook of the Neuroscience of Creativity* (pp. 161–179). Cambridge
1715 University Press. <https://doi.org/10.1017/9781316556238.010>.
- 1716 Zabelina, D. L., Friedman, N. P., & Andrews-Hanna, J. (2019). Unity and diversity of
1717 executive functions in creativity. *Consciousness and Cognition*, 68, 47–56.
1718 <https://doi.org/10.1016/j.concog.2018.12.005>.
- 1719 Zabelina, D. L., & Ganis, G. (2018). Creativity and cognitive control: Behavioral and ERP
1720 evidence that divergent thinking, but not real-life creative achievement, relates to
1721 better cognitive control. *Neuropsychologia*, 118, 20–28.
1722 <https://doi.org/10.1016/j.neuropsychologia.2018.02.014>.
- 1723 Zabelina, D. L., O’Leary, D., Pornpattananangkul, N., Nusslock, R., & Beeman, M. (2015).
1724 Creativity and sensory gating indexed by the P50: Selective versus leaky sensory
1725 gating in divergent thinkers and creative achievers. *Neuropsychologia*, 69, 77–84.
1726 <https://doi.org/10.1016/j.neuropsychologia.2015.01.034>.
- 1727 Zabelina, D. L., & Robinson, M. D. (2010). Creativity as flexible cognitive control.
1728 *Psychology of Aesthetics, Creativity, and the Arts*, 4(3), 136–143.
1729 <https://doi.org/10.1037/a0017379>.
- 1730 Zabelina, D. L., Saporta, A., & Beeman, M. (2016). Flexible or leaky attention in creative
1731 people? Distinct patterns of attention for different types of creative thinking. *Memory*
1732 *and Cognition*, 44(3), 488–498. <https://doi.org/10.3758/s13421-015-0569-4>.
- 1733 Zhang, W., Sjoerds, Z., & Hommel, B. (2020). Metacontrol of human creativity: The
1734 neurocognitive mechanisms of convergent and divergent thinking. *NeuroImage*, 210,
1735 116572. <https://doi.org/10.1016/j.neuroimage.2020.116572>.
- 1736 Zioga, I., Harrison, P. M. C., Pearce, M. T., Bhattacharya, J., & di Bernardi Luft, C. (2020).
1737 From learning to creativity: Identifying the behavioral and neural correlates of
1738 learning to predict human judgements of musical creativity. *NeuroImage*, 206,
1739 116311. <https://doi.org/10.1016/j.NEUROIMAGE.2019.116311>.
- 1740
- 1741

1742 *Supplementary Information:*

1743 **Towards Greater Computational Modeling in Neurocognitive Creativity**
1744 **Research**

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1746

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1750

1751 The attached code (in MATLAB®; see [https://github.com/Alan-Pickering/example-creativity-](https://github.com/Alan-Pickering/example-creativity-model)
1752 [model](https://github.com/Alan-Pickering/example-creativity-model)) implements a simple toy model of within-category search processes. We have left
1753 extensive comments in the code but this supplementary text explains in greater detail how the
1754 provided model code works and how one might experiment with it. In the spirit noted in the main
1755 article, our primary objective in this exercise is to demonstrate a simple but formal model related
1756 to creative cognition. We have tried to do this in the most accessible and transparent fashion. The
1757 hope is to enable those new to formal computational modeling to get a clearer insight into the
1758 modeling process, rather than making any major claims for the specific features of this particular
1759 model. It also makes transparent the process of making assumptions and modeling choices
1760 inherent in every formal model.

1761 This model was designed to simulate creativity tasks in which the instructions are to search a
1762 conceptual space for an unusual item or response (e.g., trying to come up with an unusual
1763 exemplar from the category of “fruit”, where unusual is defined as a response that would have
1764 been suggested by very few people when asked to generate fruit exemplars).

1765

1766 *Concept network as a multidimensional space*

1767 The central idea in this model is to represent the concept network (e.g., fruits) as an n -dimensional
1768 space. In the code provided, we simplify this space to just two dimensions (in the code $ndims=2$).
1769 Our first assumption (A1) is that the number of dimensions will not affect the qualitative behavior
1770 of the model. We should investigate that assumption by running simulations using higher-
1771 dimensional models. In general, we recommend starting with simplifying assumptions but, where
1772 possible, one should test the impact of each assumption one makes.

1773 The model's key feature is that each exemplar is represented as a unique point in the space and
1774 the Euclidean distance¹ between any two exemplars reflects the overall strength of association

¹ See https://en.wikipedia.org/wiki/Euclidean_distance.

1775 between the exemplars. Our second assumption (A2) is that the free-wheeling, undirected flow of
1776 thought in this space will more likely move between exemplars strongly associated with one
1777 another (e.g., apple and orange; these examples will have a small Euclidean distance between the
1778 points they occupy). The construction of the model as outlined below ensures that the model
1779 generally behaves according to assumption A2.

1780 In this model space, the dimensions might be considered features over which items such as fruits
1781 might be associated. For example, one dimension might be “size”, and because apple and orange
1782 are similar in size, the distance between them on the size dimension would be small; alternatively
1783 put, their association in terms of size would be strong. Consider another dimension, “citrus-ness”;
1784 here, we expect the distance to be larger as oranges are citrus fruits but apples are not. However,
1785 it seems likely that orange and apple would be close together on most of the model dimensions,
1786 so the overall Euclidean distance separating them (across dimensions) would be small in our
1787 model space. Thus, when one thinks of apple (as an example from the fruit category), one is likely
1788 to spontaneously think of orange, and vice versa.

1789 We have used a simple formal feature in our model (the Euclidean distance between items) to
1790 capture the relatedness of two items, which seems a “reasonable”² approach. In defense of this
1791 claim, we would argue that the associative strengths of a set of items should have “distance-like”
1792 properties. For example, if the associative strength between items apple and orange is 1
1793 (arbitrary) unit and the associative strength between orange and pear is 1.5 units, then the
1794 associative strength of apple and pear should be less than or equal to 2.5 units. We would
1795 refine/change this basic feature if the model based upon it was shown to be unable to simulate
1796 some aspects of observed behavior in creative tasks.

1797

1798 *Simulating the concept network using multivariate normal distributions*

1799 To generate the position of the items in the model space, we use a random number generation
1800 process. Specifically, we generated the exemplars using a multivariate normal (MVN) random³
1801 generator (bivariate in this case as our space has two dimensions). This is a key mathematical
1802 choice which we have adopted because it is mathematically simple and well-understood. By doing
1803 so, we are not saying that the positions of items in a conceptual space always behave exactly as if
1804 they follow a MVN distribution but that it will usually be close enough to the true distribution so as
1805 to have little effect on the accuracy of the simulations we are going to perform. If the model
1806 simulations fail to capture observed behavior accurately, then we would revisit this choice for our
1807 model.

1808 Before explaining the simple implementation procedure to generate an MVN distribution in
1809 MATLAB (of note, the procedure will be similarly easy in most other coding languages), we need to

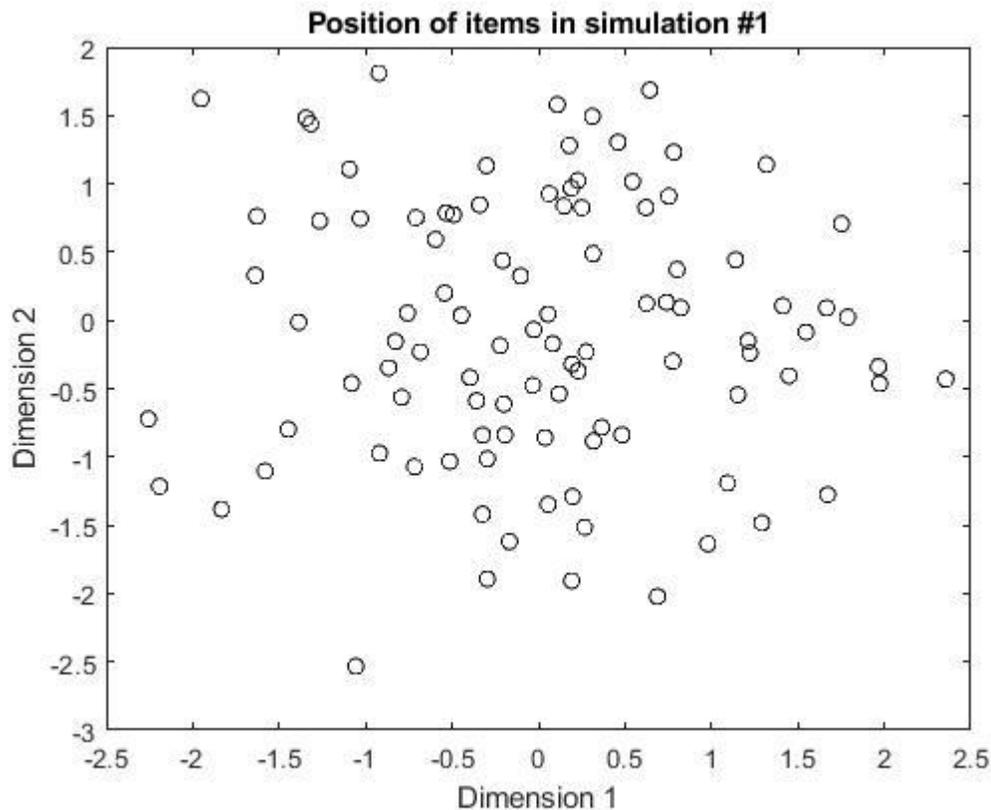
² The somewhat subjective notion of reasonableness will crop up more than once and so we will try to give a flavor of how one can justify something as reasonable.

³ See https://en.wikipedia.org/wiki/Multivariate_normal_distribution

1810 check the reasonableness of our decision to use an MVN distribution. Supplementary Figure 1
1811 (SF1) shows an example of a multivariate normal random sample of 100 items using 2 dimensions.
1812 One can see different samples by changing the *plot2show* control variable in the code provided.
1813 SF1 was generated using *plot2show*=1 and is the set of items used in simulation number 1.

1814 SF1 shows that most items are clustered close to the center of the space, and the density of items
1815 gets less as we move outwards from 0 on either dimension. This implies that the sample items at
1816 the center of the space have lots of closely associated items and that as one moves towards the
1817 edge of the space, each item has fewer close associates. This seems to capture the associative
1818 properties of sets of items such as fruits in a reasonable way: there will be some items in the set
1819 with lots of strongly associated items (apple, pear, orange etc.), but others will be associated
1820 closely with only a small number of items (jackfruit for example).

1821



1822

1823 *Supplementary Figure 1: A random sample of 100 items generated using a multivariate normal*
1824 *random number generation process in 2 dimensions. The distances along each dimension are*
1825 *arbitrary and standardized.*

1826 We are trying to use our model to simulate the search for unusual items, where unusual items are
1827 those that few other people would think of in a limited period of time. Good answers will be items

1828 that have few strong associates because people will generate candidate items by searching
1829 associatively through the space. Thus, people will be less likely to come up with items towards the
1830 periphery of the space.

1831 In Figure SF1 we used 100 items (in the code, *nitems*=100). Once again, we felt that this was
1832 reasonable: it should be roughly equal to the total number of fruits an adult human might be able
1833 to name given enough time. Our third assumption (A3) relates to this choice of number; namely,
1834 that the precise number chosen is not going to change the way the model would behave, so long
1835 as we avoid really small values (<10). Such small values are unreasonable for the sorts of sets of
1836 items we might use in the task we are simulating.

1837 The multivariate normal (MVN) random process means that, along each dimension, the
1838 distribution of item positions follows a univariate normal distribution. While a univariate random
1839 variable has a mean and a standard deviation (0 and 1 respectively, for a standard normal
1840 distribution), the MVN distribution has a mean vector and a variance-covariance matrix (*mu* and
1841 *sigma*, respectively, in the code). We set the means to be zero on each dimension and the item
1842 variances to be 1 (*itemvar* in the code). These are just standardized values and are not important.
1843 Nevertheless, they do allow us to scale other parameters in our model easily, given that we know,
1844 with these choices, that roughly 5% of our items will lie outside the values of -2 and 2 on each
1845 dimension.

1846 We also can choose whether there is any covariation between the values on the separate
1847 dimensions of our space. In the model code, this is specified via *itemcov*. Our next assumption (A4)
1848 is that these two dimensions are not related; therefore, we set *itemcov* = 0. This ensures that the
1849 cloud of points in our 2-d space is roughly circular; non-zero values for the covariance would
1850 stretch the cloud of points into an elliptical shape. This is, of course, an initial simplifying
1851 assumption which we believe is *almost certainly wrong* even if the other aspects of the model
1852 might be useful. Over all of the dimensions on which fruits can vary, we feel confident that the
1853 associative distance between pairs of items on some dimensions will be correlated with their
1854 distances along some other dimensions (e.g., fruit size will be somewhat inversely correlated with
1855 the intensity of flavor, think melon vs blackcurrant or raspberry). Once again, tests of the impact of
1856 adopting assumption A4 should be made if the simpler model proves useful. We need to use >2
1857 dimensions to explore this assumption properly; with >2 dimensions, we can arrange it so that the
1858 degree of covariation between pairs of dimensions can vary over different pairs of dimensions.

1859 As already noted, generating the MVN distributed items is simple: it is a single line of code once
1860 we have the parameters described above. In MATLAB, we use the *mvnrnd* command and write
1861 (line 105):-

```
1862 itemvals=mvnrnd(mu, sigma, nitems);
```

1863

1864 It is important to note that we do not specify a precise set of fruits in this model or try to set their
1865 associative closeness to one another to reflect some objective reality. Our assumptions and model
1866 specification create a set of exemplars that we propose could represent any set of exemplars in a

1867 category of finite size that is broadly similar to the category of fruits. We could test this by seeing if
1868 the real behavior on this task was similar irrespective of the specific set of items being employed
1869 (e.g. fruits, or British Olympic gold medalists at London 2012).

1870 An obvious alternative approach would be to create an associative network for a specific category
1871 with the weights of association (distances) between items being set to “realistic” values. This could
1872 be done by evaluating the associative strength between exemplar pairs for real categories using
1873 lexical databases, or by collecting suitable experimental data from human participants. The
1874 weights used would then be set to be proportional to the measures of associative strength
1875 obtained. This sort of approach has been used in past computational models of creativity see
1876 section “Existing computational models of creativity” in the main text for examples. This is a more
1877 complex approach, and we could test whether our simplifying assumptions lead to a model which
1878 is capable of producing simulated behavior similar to that produced using a more elaborate model
1879 based on “real” associative weights.

1880
1881
1882

1883 *Modeling free-wheeling associative thoughts*

1884

1885 The next key aspect of the model is our choice for implementing the free association of thoughts.
1886 This is intended to capture one facet of the dual-process models discussed in the main text (see
1887 Box 1 in particular): the “spontaneous”, or “generative”, or “automatic” flow of ideas during the
1888 search for a creative response. We did this using a random walk⁴. Random walks have been used
1889 quite extensively in modeling behavior in varied fields within psychology [1-5]. Once again, this is
1890 probably because their basic mathematical processes are well-understood. We leave it to the
1891 reader to decide if a random walk is a reasonable choice for this aspect of our model.

1892

1893 In the model, there is a loop of 200 simulations (*nsims*=200), and each simulation can be thought
1894 of as a different simulated participant attempting to generate an unusual fruit (one that would be
1895 thought of by as few other participants as possible). The choice of 200 is fairly arbitrary but, given
1896 the extensive use of random variables in the model, it needs to be large enough to give
1897 representative outcomes when aggregated across all simulations. Within each simulation, there is
1898 an inner loop of up to 10000 steps (*nsteps*=10000). Each step is one step of the random walk. The
1899 number of steps is initially set to be large, although we adjust this to a lower number (1500) for
1900 reasons explained below. The length of a timestep is arbitrary, but one could rescale the numbers
1901 of steps into response times (e.g., 100 steps equates to 1 second) so that the simulated response
1902 times are of the right magnitude. The walk has to start at an initial position. In the simplest version
1903 of the model, we assume (A5) that the walk starts at the center of the space: (0,0) in two
1904 dimensions (coded as *mystart*). This seems reasonable because, if we are asked to think of fruits, it
1905 is highly likely that we would first think of common exemplars at the center of our space.

1906

1907 Another feature is the walk step size, i.e., the amount that the walk might move in each direction
1908 on a single step. Bearing in mind that 95% of the items lie along values in the range -2 to 2 on each
1909 dimension (see above), we set the step size to 0.05 for each dimension (coded as *stepsize*). To
1910 make the walk random, we used a uniform random number generator to create a random move
1911 direction for each of the *nsteps* (=10000) steps of a simulation along each of the *ndims* (=2)
1912 dimensions. The direction for each step on each dimension was either -1, 0 or +1 (each occurring
1913 randomly with equal probability), generating 9 possible moves on each step (3*3 over the two
1914 dimensions). To do this, we used the *randi* command in MATLAB to create a matrix of values with
1915 10000 rows and 2 columns for each simulation (called *mymoves*):

1916

```
1917 mymoves=randi([-1 1],nsteps,ndims);
```

1918

1919 The actual walk is thus a combination of the direction specified by *mymoves* multiplied by the
1920 amount moved in that direction, specified by *stepsize*. On the *k*-th step of the walk, the variable
1921 *currpos* keeps track of the current 2-d position of the walk iteratively, thus:-

```
1922 currpos=currpos+stepsize.*(mymoves(k,:));
```

1923

⁴ https://en.wikipedia.org/wiki/Random_walk

1924 Clearly, the larger the values used for *stepsize*, the more space will be covered by the random
1925 walk. All other things being equal, our *model intuition*⁵ is that larger *stepsize* values will enable the
1926 simulated participant to encounter more unusual (peripheral) items more quickly.

1927

1928

1929 *Retrieval of candidate items*

1930

1931 The next aspect of the model is how we interrupt the free-associative process of the random walk
1932 with attempts to retrieve candidate items. The way we capture this in our model is that, every so
1933 often, the walk pauses and the simulated participant attempts to retrieve an example item from
1934 the current position of the random walk in our space of items. The frequency with which this
1935 attempt at retrieval occurs is controlled by a parameter in the code called *walkfor* (a default value
1936 of 50 steps). This means that after every *walkfor* random walk steps, an attempt at item retrieval is
1937 made. This feature of the model embeds another assumption (A6); namely, that the spontaneous
1938 free-association processes are in alternating phases with memory retrieval and subsequent
1939 evaluative processes. This is a feature present in some theoretical accounts in the literature (see
1940 [33] in the main article).

1941

1942 Which items might be retrieved at each attempt? Following the underpinning logic of the model –
1943 i.e., that the distance in the model space represents the closeness of the association of an item –
1944 we implemented this using a competitive probabilistic retrieval process based on the relative
1945 distance of items from the current position of the walk. This means that the items nearest to the
1946 current position are compared in terms of their relative distances, and the probability of their
1947 retrieval is directly linked to those relative distances (closer items being more likely to be
1948 retrieved). The retrieval competition is limited to those items which are within a specific Euclidean
1949 distance of the current position. This selection of potential items for retrieval is controlled by a
1950 parameter, denoted *closeto* in the code (default =1 distance unit). This parameter is used by
1951 computing the Euclidean distance between each item in the space and the current position
1952 (computed as *euclidist*, see line 140), and then computing a “logical filter” (*choicefilt* in the code)
1953 with value = 1 for those items with a Euclidean distance (ED) less than *closeto*, and 0 otherwise.
1954 The filter is used later on in the code to restrict the choice function to apply to only those items
1955 with values of *choicefilt*=1. In mathematical terms, we can define a set *S* of potentially retrievable
1956 items where the Euclidean distance of item *i* from the current walk position, ED_i is smaller than
1957 *closeto* for all items *i* in the set *S*.⁶

1958

1959 The default value of *closeto* represents a wide search radius given that 95% of the items are within
1960 a circle of radius 2 units from the center of the space. One might imagine that different individuals
1961 might vary in the value of *closeto* that they use. Our next model intuition is that someone with an
1962 ability to think more creatively might have a higher value of *closeto*, than their less creative
1963 counterpart, and so such a person would include more potential items in their retrieval searches.

⁵ A model intuition is what effect we think the model parameter will have. Even if these intuitions seem reasonable, it is important to test these out. Formal modeling allows one to move from intuitions to clear predictions when we run the simulations.

⁶ In mathematical notation if item *i* is a member of a set *S*, this can be written as $i \in S$

1964 The more creative person (based upon their higher value of *closeto*) would, according to the
 1965 model, be more likely to alight upon a more creative (unusual) choice of fruit in a fixed amount of
 1966 thinking time.

1967 The actual formula used to compute the probabilities of retrieval of the items lying within *closeto*
 1968 distance units of the current position was based upon a widely adopted choice function in
 1969 psychological modeling: the softmax function.⁷ Specifically, the softmax formula used to define the
 1970 probability of retrieving item *i*, given that *i* is a member of the set *S* of competing potentially
 1971 retrievable items, is as follows: -
 1972

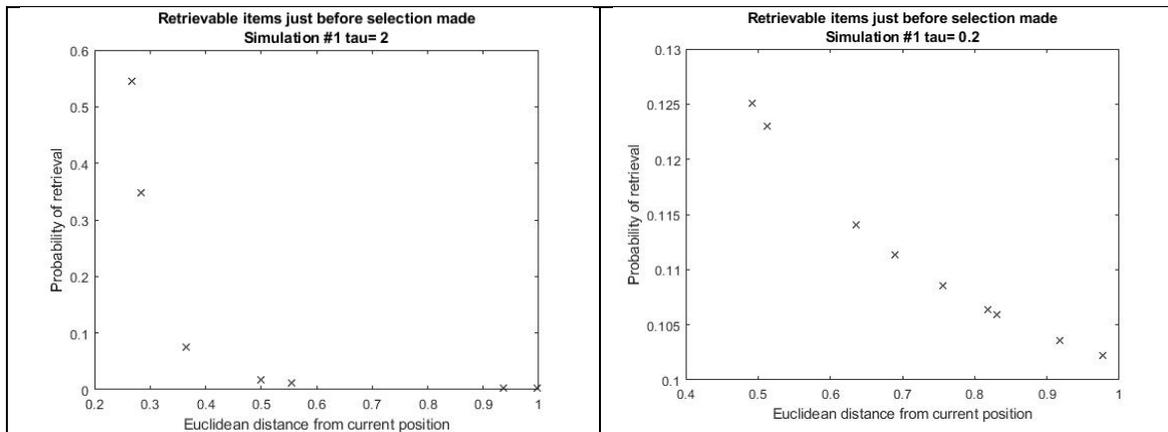
1973
$$p(R_i | i \in S) = \frac{e^{\tau/ED_i}}{\sum_{j \in S} e^{\tau/ED_j}}$$

1974

1975 The above formula suggests that the smaller the Euclidean distance of a candidate item *i* from the
 1976 current position, the higher the probability that it is retrieved amongst all the competitor items in
 1977 set *S*. In the code, it is computed across lines 157-159. The following lines of code (165-167) use a
 1978 random number generator to retrieve a specific item in accordance with the probabilities returned
 1979 by the softmax function.

1980 A key parameter in the softmax function is τ (in the code, this is *tau*), and it can take values of zero
 1981 or greater. This parameter has different names in modeling contexts (e.g., inverse temperature,
 1982 stochasticity or exploration-exploitation parameter), but it simply controls how noisy the choice
 1983 process is. As τ gets larger then the closest item is more and more likely to be retrieved (i.e., a
 1984 more deterministic choice), even when it is only slightly closer than the next nearest competitor.
 1985 By contrast, as τ approaches zero, all competitor items tend to be chosen with similar probabilities
 1986 irrespective of their relative distances (more random, noisy choice). We can see this effect of τ in
 1987 Supplementary Figure 2 (SF2) during one retrieval decision during simulation number 1.

1988



⁷ https://en.wikipedia.org/wiki/Softmax_function

1989

1990 *Supplementary Figure 2: The effect of parameter τ on retrieval probabilities as a function of*
1991 *Euclidean distance (ED) from the current walk position. Note the difference in y-axis scale across*
1992 *the two panels. In the left panel ($\tau = 2$), there are 7 potentially retrievable items, but the closest*
1993 *two, with EDs < 0.3 have the greatest chance of being retrieved (0.55 and 0.35 approximately).*
1994 *Items with ED ≥ 0.5 have virtually a zero probability of retrieval. In the right panel ($\tau = 0.2$) all 9*
1995 *potentially retrievable items have a similar probability of being retrieved ($0.1 < p < 0.13$)*
1996 *irrespective of their EDs from the current position, even though the range of EDs goes from just*
1997 *below 0.5 to almost 1.*

1998

1999 Once again, one has a strong model intuition that the parameter τ should directly affect the
2000 breadth of the search of the category space and thus the ability to generate more creative
2001 solutions. When τ is smaller, then more items can be retrieved at any position of the random walk
2002 than for higher values of τ . This means that, over a fixed period, the random walk has a greater
2003 chance of retrieving more peripheral items (i.e., more unusual, creative choices) for lower values
2004 of τ , all other things being equal. We can think of τ in conjunction with the value of *closeto*
2005 (already discussed) as opening up the retrieval process to a broader range of possible items. In
2006 terms that have been widely used in the creativity literature, one might view these two
2007 parameters as reflecting the degree of inhibition in memory retrieval; specifically, the combination
2008 of large *closeto* and low τ equates to weak inhibition.

2009

2010 *Response selection as a controlled decision process*

2011 The final part of the model is the decision process used to decide if a retrieved item is “unusual
2012 enough” to be worthy of being given as a response. This represents the other facet of dual-process
2013 theories: the “deliberate”, or “evaluative”, or “controlled” process.

2014 If a retrieved item is considered unusual enough, then it will be given as a response (e.g., I have
2015 thought of the fruit “durian” and I am happy to give this as my example of an unusual fruit). If it is
2016 not deemed unusual enough, then the random walk resumes *from the position of the retrieved*
2017 *item*⁸ until a future retrieval attempt is made, *walkfor* random walk steps later. What decision rule
2018 might a participant use to decide that a retrieved item was unusual enough? We considered that it
2019 must be some simple property of the retrieved item that a simulated participant could use to
2020 decide upon unusualness. For example, perhaps after retrieving an item, the participant finds that

⁸ The position of the random walk is supposed to represent where one’s thoughts currently are at within the category space. Thus, if one has retrieved an item then the position of that item seems a reasonable choice for the current “position” of your thoughts. In the code the current walk position is moved to the position of the retrieved item on line 177. So, strictly, the model is a random walk punctuated with jumps to retrieved items.

2021 it brings to mind very few close associates, then one might decide that it is worth offering as a
2022 creative response. As a simple proxy for this, we used an alternative related decision rule
2023 (controlled in the code by the parameter *respmethod* taking a value of 1; *respmethod*=2 has a
2024 different effect see below): the retrieved item has to be more than a threshold Euclidean distance
2025 from the center of the space. The threshold distance is specified by a parameter called *respthresh*
2026 in the code. At the start of each simulation, *respthresh* is set to *respthreshbase* (=2.0 by default).
2027 We chose this value in light of the parameters chosen for the multivariate normal distribution of
2028 the items (which force 95% of the items to lie between -2 and 2 on each dimension). If the
2029 retrieved item has an ED from the center which exceeds the value of *respthresh*, then the
2030 response is made and the current random walk stops (controlled in the code by setting *endkflag* to
2031 1). The simulation loop records the response information and then moves on to the next simulated
2032 participant.

2033 To reflect the potential effect of time pressure on the task we assumed (A7) that participants
2034 might relax their decision threshold the longer they could not produce a suitable response. We
2035 simulated this by having a decrement to the value of *respthresh* (called *threshdrop* in the code,
2036 default value =0.01). The decrement is applied every 100 steps of the random walk if a response
2037 has not been made (in the code this is controlled by setting a parameter, *threshtime* = 100). This is
2038 a minor feature of the model and we can explore its effect by setting *threshdrop*=0 in the model.

2039

2040 *Exploring the effects of parameters*

2041 It is relatively easy to explore the effect of the model parameters, which are likely to affect the
2042 ability to give more creative responses. As noted above, for example, we have clear model
2043 intuitions for the effects of *stepsize*, *closeto*, and *tau*. Thus, it is essential to test these model
2044 intuitions, along with the effects of the assumptions listed above. For example, below, we show
2045 the effect of changing the value of *tau*.

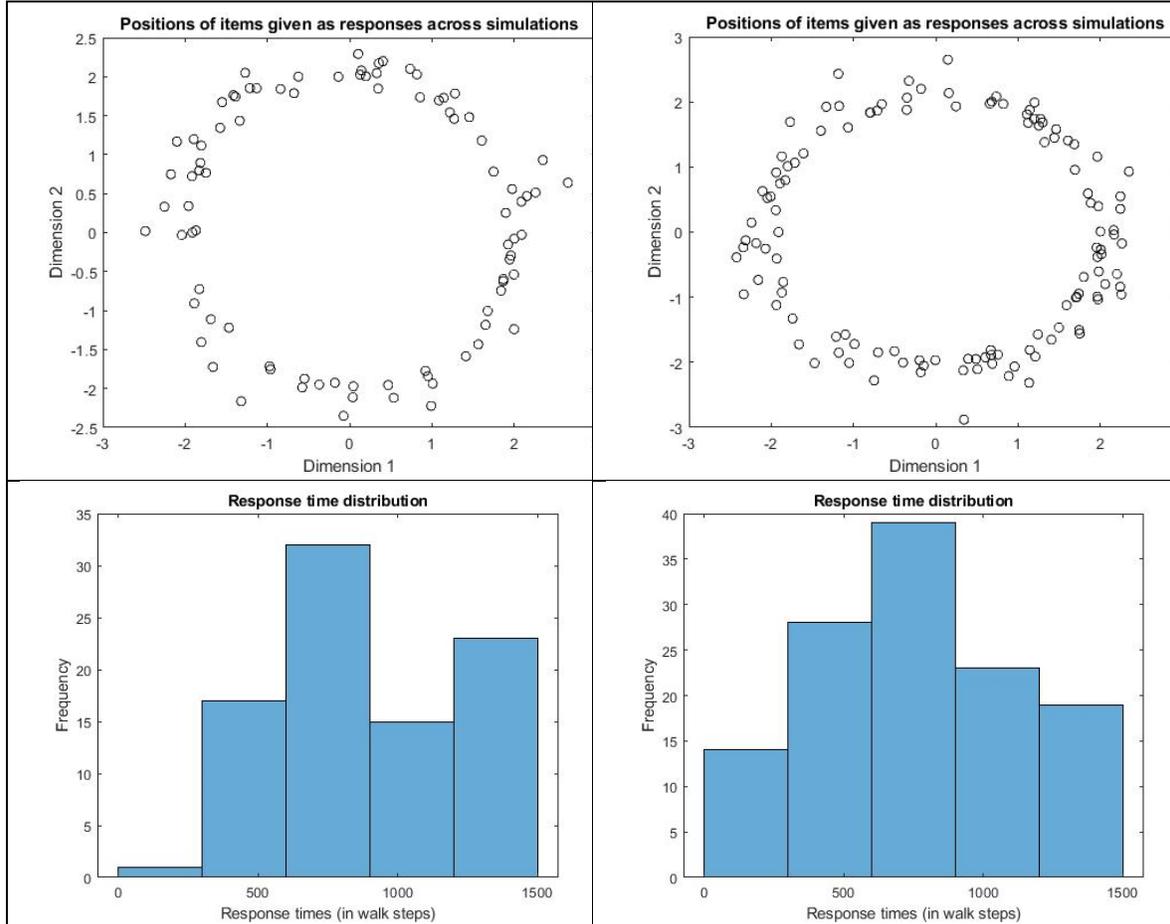
2046 It was noted above that the maximum number of time steps (*nsteps*) per simulation was set to
2047 10000. This large value was used to develop and set the values of the model parameters. This
2048 parameter setting was chosen because it allowed every simulated subject to retrieve an unusual
2049 item across the whole range of *tau* values used (0.2 to 2). To test the model, we inspected the
2050 response time distributions achieved when 10000 walk steps per simulation were permitted.
2051 Based on the mean response times over 200 simulations (generally around 1600-1700 steps), we
2052 set the maximum response time to 1500 timesteps in our test simulations. This change was made
2053 to reflect our assumption (A8) that, under a small amount of time pressure, not all subjects would
2054 be able to select a genuinely unusual response (using the *respthresh* decision rule). That is, they
2055 feel that all the candidate responses they thought of in the time allowed are likely to have been
2056 thought of by lots of other people as well. The model does not yet implement what response they
2057 offer in these circumstances. Perhaps they would give one of the less unusual items previously
2058 retrieved but still in their (working) memory. As the simulations below confirm, using the 1500

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2059 step maximum per simulation ensures that not every simulated participant can produce an
2060 unusual item (i.e., one that passes the decision threshold) in the time allowed.

2061 Supplementary Figure 3 (SF3) shows the simulation results for two very different τ values (0.2
2062 vs. 2.0). Our model intuition above was that a lower value of τ would lead to more creative
2063 responses. In our simulation, this intuition would be confirmed if a higher proportion of the 200
2064 simulated participants (with $\tau=0.2$) can give a response that passes the *respthresh* decision rule
2065 compared with 200 simulated participants (with $\tau=2$). The simulation confirmed our intuition:
2066 88/200 simulated participants (with $\tau=2$) were able to generate an unusual response. By
2067 comparison, 123/200 simulated participants (with $\tau=0.2$) were able to generate an unusual
2068 response. The responses made were generally in very similar average positions in the model space
2069 (see SF3) and were all towards the periphery of the space, in keeping with the nature of the
2070 *respthresh* decision rule. In addition to the greater number of responses in the low τ condition,
2071 SF3 shows that the responses were made more rapidly in the low τ simulations (an average of
2072 734 random walk steps, s.d.=358) compared with the high τ simulations (average= 878
2073 walksteps, s.d.=364). Thus, in respect of τ , our model intuitions are confirmed. We leave it as an
2074 exercise for the interested reader to explore the effects of *stepsize* and *closeto* in relation to the
2075 model intuitions offered above.

2076



2077

2078 *Supplementary Figure 3: The effect of parameter τ on the ability to make an unusual category*
 2079 *response in the time allowed. The leftmost panels are for $\tau = 2.0$, and the rightmost panels are*
 2080 *for $\tau = 0.2$. The upper row records the position of the response items made (note the greater*
 2081 *number of responses made for the 200 simulations with $\tau = 0.2$). The bottom row records the*
 2082 *distribution of response times for the responses given.*

2083

2084 *Making new predictions with the model and testing them*

2085 It is an essential first step to show that the model behaves in the ways our intuitions suggested it
 2086 would. As already noted, one must also explore, as fully as possible, the impact of the numerous
 2087 assumptions and choices made in developing the model. However, for the model to be useful, it
 2088 should lead to novel predictions for real creative behaviors that can be tested in actual human
 2089 participants. Below we illustrate how even this simple model can generate testable predictions.

2090 The model can easily be made to simulate a fluency task as well (where one has to name as many
 2091 exemplars of the category as one can in a fixed time). In fact, the provided code already records

2092 the number of category exemplars retrieved during the “think of an unusual fruit” simulation. To
2093 simulate a fluency task, the “unusual response” decision process must be turned off. This can be
2094 achieved by setting *respmethod* to have a value of 2 (instead of the usual value of 1;
2095 *respmethod*=2 makes no decision about whether a retrieved item is unusual). Then one can run
2096 the code with *nsteps*=1500 (to represent the fixed amount of response time for the fluency task)
2097 with *tau*=0.2 vs 2.0. Across 200 simulations, the mean number of unique items retrieved for
2098 *tau*=0.2 was 22.1 (s.d.=2.5). For *tau*=2.0, the average number of unique items retrieved was 16.9
2099 (s.d.=3.5). The model thus shows that variation in parameter *tau* can underlie an ability to
2100 generate an unusual response more often and be more fluent in generating category exemplars.
2101 We leave it as an exercise for the interested reader to see if the same patterns over both tasks can
2102 be obtained using variation in the parameters *closeto* and *stepsize*.

2103 Of course, one might argue that by using verbal reasoning alone, one could have arrived at the
2104 prediction that more creative people would generate more unusual responses and also be more
2105 fluent (i.e., retrieving more exemplars from the category). Having a formal model allows one to
2106 explore this predicted effect more rigorously and thoroughly. In the main article, the idea was
2107 briefly noted that a strategic search along one dimension of the category might help find unusual
2108 items. For example, one might think of exotic locations that one has visited and thereby recall
2109 unusual fruits experienced specifically in those locations. A simple way to give dimensional
2110 directionality (of this kind) in the search could be to make the step sizes for the random walk
2111 different for each dimension. In the code provided, the step size along dimensions 1 and 2 was
2112 equal (0.05). With the same average stepsize, a more directed walk would be achieved with step
2113 sizes of 0.025 and 0.075 (or vice versa). For low *tau* settings (*tau*=0.2), this had little effect on the
2114 number of unusual responses made (in fact, they decreased slightly to 118/200 simulations c.f.
2115 123/200 simulations with equal step sizes). For high *tau* settings (*tau*=2.0), unequal stepsizes
2116 increased the number of unusual responses achieved to 103/200 (c.f. 88/200 with equal
2117 stepsizes). This is a novel prediction of the model: in the “find an unusual exemplar task”, people
2118 with lower creativity (higher *tau*) are more likely than their more creative counterparts (low *tau*)
2119 to benefit from a suggestion to use a strategy of focusing their search along one/some specific
2120 feature dimension(s). This prediction could be tested with actual participants by testing them
2121 under conditions when provided with a dimensional search strategy by the experimenter and
2122 comparing the results with performance under a control condition where no such strategy was
2123 given. Strictly the prediction applies only to those whose high vs. low creativity stems from
2124 processes captured by the parameter *tau* (which controls the noisiness of the exemplar retrieval
2125 process).

2126

2127 *Model limitations*

2128 There are many limitations and unrealistic features of the current model. There is not space here
2129 to consider them all. Two striking illustrative examples of limitations are noted. First, the random
2130 walk phases in each simulation are of a fixed duration (controlled by the parameter *walkfor*). If

2131 these phases are intended to represent periods of mind-wandering around the conceptual space,
2132 then it seems unreasonable that these periods would all be of the same duration. An easy fix
2133 would be to use a Gaussian random variable (with mean and standard deviation) for *walkfor*, so
2134 that in a particular simulation, the number of steps of the random walk between each retrieval
2135 attempt would vary randomly about the mean value. The parameters of the random variable
2136 could vary across different simulated individuals.

2137 Secondly, and more importantly, the item retrieval process takes no time in the model. Therefore,
2138 the model should be extended to include a retrieval time component. Such a component should
2139 ensure that the pattern of Euclidean Distances (EDs) of potentially retrievable items influences the
2140 time taken for the retrieval in a principled way. For example, one would imagine that a pattern of
2141 EDs in the left panel of SF2 (two exemplars with small EDs and high probabilities of retrieval; the
2142 rest further away and with very low probabilities of retrieval) would lead to quite different
2143 retrieval times than the pattern in the right panel (no close exemplars and all exemplars have a
2144 similar probability of retrieval). A pervasive finding is that response times are slower for more
2145 difficult decisions [6]. It is relatively straightforward to incorporate retrieval times into the model
2146 in a realistic way; for example, one might use a so-called accumulator model [7].

2147

2148 **Supplementary References**

- 2149 1) Mathys, C., Daunizeau, J., Friston, K. J., & Stephan, K. E. (2011). A Bayesian foundation for
2150 individual learning under uncertainty. *Frontiers in Human Neuroscience*, 5, 39.
2151
- 2152 2) Nosofsky, R. M., & Palmeri, T. J. (1997). An exemplar-based random walk model of speeded
2153 classification. *Psychological Review*, 104(2), 266–300.
2154
- 2155 3) Ratcliff, R. (1978). A theory of memory retrieval. *Psychological Review*, 85, 59-108.
2156
- 2157 4) Simkin, M. V., & Roychowdhury, V. P. (2014). Stochastic modeling of a serial killer. *Journal of*
2158 *Theoretical Biology*, 355, 111–116.
2159
- 2160 5) Tuerlinckx, F., Maris, E., Ratcliff, R., & De Boeck, P. (2001). A comparison of four methods for
2161 simulating the diffusion process. *Behavior Research Methods, Instruments, & Computers: A*
2162 *Journal of the Psychonomic Society*, 33(4), 443–456.
2163
- 2164 6) Ratcliff, R., & McKoon, G. (2008). The diffusion decision model: theory and data for two-choice
2165 decision tasks. *Neural Computation*, 20(4), 873–922.
2166
- 2167 7) Ratcliff, R., & Starns, J. J. (2013). Modeling confidence judgments, response times, and multiple
2168 choices in decision making: Recognition memory and motion discrimination. *Psychological*
2169 *Review*, 120(3), 697–719.