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# The Predictive Creative Mind: A First Look at Spontaneous Predictions and Evaluations during Idea Generation

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7 **Keywords: Evaluation, Idea Generation, Prediction**

8 **Abstract**

9 Idea generation, the process of creating and developing candidate solutions that when implemented can  
10 solve ill-defined and complex problems, plays a pivotal role in creativity and innovation. The algorithms  
11 that underlie classical evolutionary, cognitive, and process models of idea generation, however, appear  
12 too inefficient to effectively help solve the ill-defined and complex problems for which one would engage  
13 in idea generation. To address this, these classical models have recently been redesigned as forward  
14 models, drawing heavily on the “predictive mind” literature. These pose that more efficiency can be  
15 achieved by making predictions based on heuristics, previous experiences, and domain knowledge about  
16 what material to use to generate ideas with, and evaluate these subsequently generated ideas based on  
17 whether they indeed match the initial prediction. When a discrepancy occurs between prediction and  
18 evaluation, new predictions are made, and thus shaping what actions, and how these actions, are  
19 undertaken. Although promising, forward models of idea generation remain theoretical and thus no  
20 empirical evidence exists about whether such predictions and evaluations indeed form part of the idea  
21 generation process. To take a first empirical look at this, a mixed methods study was conducted by  
22 analyzing people’s self-reports for the reasons of the actions that they take during an idea generation  
23 task. The results showed that predictions and evaluations are pervasive in the idea generation process.  
24 Specifically, switching between concept selection and conceptual combination and idea generation, as  
25 well as repeating idea generation based on earlier selected conceptual combination, and possibly (but to  
26 a lesser extent) concept selection and the repetition thereof, are likely to be driven by predictions and  
27 evaluations. Moreover, the frequencies of the predictions and evaluations that drive these actions  
28 influenced the amount of ideas generated, amount of concepts used, and within-concept fluency (the  
29 ratio of the amount of ideas generated per concept used). Therefore, the contribution of this paper is the  
30 first empirical evidence that indicates that the idea generation process is driven by both predictions and  
31 evaluations.

32 **1 Introduction**

33 Idea generation, the process of creating and developing candidate solutions that when implemented can  
34 solve ill-defined and complex problems, plays a pivotal role in creativity and innovation (Isaksen et al.,  
35 2010; Mumford et al., 2012). Given its central role in creativity and innovation, it forms part of the skillset  
36 that enables people to develop the products that help the economy prosper, the medical interventions  
37 that help us live longer, and the artistic expressions that move us deeply (Abraham, 2018). There is no  
38 creativity and innovation without the generation of ideas (Isaksen et al., 2010; Mumford et al., 2012). It is

39 therefore not surprising that research about creativity and innovation has always focused strongly on  
40 uncovering how idea generation works, and with that knowledge, how it can be best supported (Sawyer,  
41 2011).

42 Classical evolutionary, cognitive, and creative process models that aim to explain the idea generation  
43 process, however, have recently been argued to have limited explanatory power (Dietrich, 2015; Dietrich  
44 & Haider, 2015; Gabora, 2011; Yang & Li, 2018). To address their limitations, a recent trend has been to  
45 redesign these classical models as forward models by explicitly including prediction and evaluation as  
46 part of the idea generation process (Abraham, 2018). In these models, prediction entails the pro-active  
47 anticipation of the consequences of a possible action for achieving a goal, whereas evaluation serves to  
48 assess whether the results of an action helped to achieve a goal as previously predicted (Dietrich, 2015;  
49 Dietrich & Haider, 2015). Discrepancies between prediction and evaluation, in turn, determine if and how  
50 an action is taken.

51 For example, when asked to develop original ideas for a viral online marketing campaign, one's previous  
52 experiences may suggest that combining humorous content with shareable video are a recipe for  
53 success. When this prediction is confirmed, i.e., the ideas generated based on these concepts are  
54 evaluated as having a high potential for going viral, one is likely to continue this approach. However,  
55 when there is a negative discrepancy between this prediction and the evaluation of the generated ideas,  
56 i.e., combining humorous content with shareable video is evaluated to (no longer) lead to ideas that are  
57 likely to go viral, one is likely to change one's approach and look for other concepts to work with.

58 Although this approach appears promising, it has remained purely theoretical until now. In the present  
59 paper, it is proposed the manner in which the idea generation process is executed, which according to  
60 creative process models involves concept selection, conceptual combination, and the generation of ideas  
61 based on combined concepts (Mumford & McIntosh, 2017), are driven by prediction and evaluation. It is  
62 theorized that prediction and evaluation determine the degree of switching between concept selection  
63 and conceptual combination and idea generation, concept selection (and the repetition thereof), and  
64 conceptual combination and the generation of ideas (as well as the repetition thereof) – which affects  
65 how ideas are generated, cf. (Nijstad et al., 2010).

66 To provide empirical evidence for the developed conjectures, a first look is taken at whether and where  
67 predictions and evaluations are made during the idea generation process, and it is explored if and how  
68 these affect the way that the idea generation process is executed.

## 69 **1.1 From blind variation to prediction-action-evaluation cycles**

70 Early models of the idea generation process were modelled after algorithms that also underlie biological  
71 evolution. Campbell (1960) proposed that creativity emerges from two alternating actions: 1) Blind  
72 variation, i.e., the undirected generation of variations on ideas (based on chance), and 2) selective  
73 retention, i.e., selecting generated ideas according to standards, of which new variations can be blindly  
74 generated in a subsequent iteration (BVSR model). A defining feature of the BVSR theory is that it  
75 assumes that selection imposes direction on variation, and that variation and selection are completely  
76 uncorrelated, i.e., not coupled in any way (Dietrich, 2015; Dietrich & Haider, 2015; for a thorough  
77 discussion see Carruthers, 2018). The idea that variation is blind has been restated and adopted by  
78 many other scholars of creativity (see Simonton, 2011 for a review). However, recent work also suggests  
79 that models that propose that the generation of ideas and their evaluation are uncoupled, are problematic  
80 (Gabora, 2011).

81 Dietrich & Haider (2015), for example, proposed that variation cannot be completely undirected and  
82 uncorrelated with selection. They argued that completely undirected variation would entail a too  
83 ineffective way to traverse the type of search space that characterizes the ill-defined and complex  
84 problems for which we engage in idea generation to solve. They therefore proposed to redesign the  
85 BVSR as a forward model based on the “predictive mind” literature (Clark, 2015; Hohwy, 2013). That is, if  
86 and how the actions that form part of the idea generation process are executed depends on ongoing  
87 predictions about what type of action is most likely to help achieve the best problem solution (Dietrich,  
88 2015; Dietrich & Haider, 2015). Changing what and how an action is executed depends on the deviation  
89 of the evaluated outcomes of an action from what was previously predicted. Whether actions are  
90 invigorated, simply sustained, or abandoned depends on whether they are evaluated to be better, the  
91 same, or worse than previously predicted. Inclusion of prediction in variation can help explain how  
92 heuristics, previous experiences, and domain knowledge can play a role in effectively executing the idea  
93 generation process, as predictions made based thereupon can help traverse the type of search space  
94 needed to solve ill-defined and complex problems in a more efficient way.

95 Redesigning the BVSR as a forward model can explain this increased efficiency in the following way.  
96 First, generating variation is preceded by predictions that are based on heuristics, previous experiences,  
97 and domain knowledge that inform one about if, what, and how variation can help to best achieve the  
98 generation an appropriate idea. For example, one could favour making remote associations when  
99 producing variations to increase the likelihood that original ideas are generated, when the latter is one’s  
100 goal (Gibbert et al., 2012). This informs how variation is executed, i.e., though making remote  
101 associations. Second, the resulting variation that is produced is then evaluated on the basis of previously  
102 made predictions. For example, if making remote associations has led to the generation of original ideas,  
103 as predicted, one can continue with this way of producing variation. If it has led to more original ideas  
104 than expected, one may invigorate this approach. If this has not led to the predicted original ideas a  
105 revision of the used strategy is needed, and thus the manner in which variation is executed needs to  
106 change, leading to renewed predictions and renewed execution of variation based on these predictions.  
107 This contrasts with blind variation because here, variation and selection are strongly coupled; and  
108 heuristics, previous experiences, and domain knowledge are used to traverse through the search space  
109 in a more effective way than would be possible when people would generate variations blindly.

110 Complementarily, cognitive models of the idea generation process have been developed to explain how  
111 cognitive functions utilize knowledge as part of the generation of ideas (Abraham, 2018). Finke et al.  
112 (1992) proposed that ideas emerge via iteration through generative and exploratory phases under  
113 constraints imposed by knowledge about a product or problem solution that needs to be developed. In  
114 the generative phase, people generate various kinds of mental representations based on existing  
115 knowledge. The cognitive processes involved can include associative thinking (Mednick, 1962), retrieval  
116 (Perkins, 1994), and conceptual combination (Mobley, Doares & Mumford, 1992). In the exploratory  
117 phase, people evaluate their ideas, which may include hypothesis testing and testing for limitations, and  
118 develop solutions from the evaluated mental representations. The exact thinking processes and actions  
119 used during different iterations depend on the state of development of a problem solution (Finke et al.,  
120 1992). For example, where early stages of the idea generation process may involve the generation of  
121 many basic representations through association, in later stages evaluated associations can be  
122 recombined into new and more elaborate ideas (de Rooij & Vromans, 2018). As such, iteration though  
123 these two phases enables convergence upon creative ideas that help achieve set goals, by shifting the  
124 cognitive processes required to effectively execute each phase, and evaluating their success in terms of  
125 providing a solution within the given constraints.

126 Cognitive models such as those by Finke et al. (1992) were theoretically extended by Yang and Li (2018)  
127 and Wiggins and Bhattacharya (2014) to include prediction, to explain how constraints imposed by  
128 knowledge about a product or problem shape the idea generation process. That is, also classical  
129 cognitive models such as these have been recently redesigned as a forward model, and for the same  
130 reasons as the BVSR was redesigned. Specifically, it has been proposed that prediction, association,  
131 and selection shape the idea generation process (Wiggins & Bhattacharya, 2014; Yang & Li, 2018). The  
132 key assumption is that memory, and more broadly knowledge, serves prediction (Schacter & Addis,  
133 2007). It has therefore been proposed that the key associations that underlie idea generation are learned  
134 during the idea generation process, and in turn enable convergence toward ideas that align with the  
135 goals and standards (e.g., standards of originality and effectiveness) of the person engaged in the idea  
136 generation process (Wiggins & Bhattacharya, 2014; Yang & Li, 2018). That is, predictions about the  
137 likelihood that associations between concepts enable the generation of ideas that align with the goals  
138 and standards of a person, inform what material is selected for idea generation. Subsequently, ideas are  
139 generated based on the selected material. This makes up the generative phase. The exploratory phase  
140 that follows consists of evaluating the generated ideas with regards to whether applied standards are  
141 met, and goals are likely to be achieved. In turn, the discrepancy between the initial predictions and later  
142 evaluations inform the value of the used associations in the idea generation process, and thus what  
143 material is selected in further iterations of the idea generation process. Indeed, when evaluation suggests  
144 that the generated idea is less likely to help achieve set goals than predicted, the associations used  
145 during idea generation will be less likely used in subsequent idea generation, whereas if associations  
146 used to achieve a goal as predicted they are more likely to be used in subsequent idea generation, and  
147 further built upon.

148 Process models of creativity define the actions that are commonly involved in creative problem solving,  
149 i.e., that lead to complete solutions that are both original and appropriate (Lubart, 2001). Consensus has  
150 been emerging about the actions that form part of the creative process (Lubart, 2001). Typically, these  
151 actions enable an individual to understand the problem that needs to be solved, generate ideas, and  
152 prepare for implementing one or more selected ideas; and evaluation is explicitly done after  
153 understanding the problem and after idea generation, to determine whether the problem is sufficiently  
154 understood and whether there are sufficiently suitable ideas, to continue with the next steps in the  
155 creative process (Isaksen et al., 2010). As such, the idea generation process forms part of the larger  
156 creative process (Mumford & McIntosh, 2017). The idea generation process, within these broader  
157 creative process models, is typically characterised by three actions: concept selection, concept  
158 combination, and idea generation (Mumford et al., 2012). Based on the knowledge obtained about a  
159 problem, people select concepts, which can include basic categories that associate with a problem,  
160 previous experiences, and cases related to the problem at hand. Selection matters, as the kinds of  
161 concepts that are later combined have implications for the originality and appropriateness of the ideas  
162 that are generated (Gibbert et al., 2012; Mumford et al., 1996). Selected concepts are then combined to  
163 create new knowledge (Abraham, 2018), on the basis of which ideas can be generated (Mumford et al.,  
164 1997). Note that idea generation, in the present paper, is therefore seen as only one action that forms  
165 part of a larger idea generation process (as is the case in evolutionary and cognitive models of the idea  
166 generation process).

167 The actions that form part of the creative process are not executed in a linear way (Mumford & McIntosh,  
168 2017). Rather, people move back and forth between the actions taken, often for reasons yet unknown  
169 (Mumford et al., 2012). Interestingly, forecasting, the deliberate anticipation of potential consequences of  
170 the implementation of an idea, is studied as a technique aimed to support the execution of the creative  
171 process (McIntosh et al., 2019; Todd, Higgs, & Mumford, 2019). Specifically, forecasting has been  
172 studied as a technique to support idea evaluation, where forecasting the consequences of implementing

173 ideas is used to gather information in order to decision making about what ideas can be implemented,  
 174 should be revised, or not pursued at all (Bruijnickx & de Rooij, unpublished manuscript). Note that,  
 175 indeed, the definitions of forecasting and prediction as used in the present paper overlap, with the  
 176 distinction that prediction, as used in the present paper, is not necessarily deliberate nor used as a  
 177 creative technique, but rather as a key psychological process that is needed to generate ideas. However,  
 178 these same creative process models also propose that one moves forward and backward in non-linear  
 179 ways between the actions that form part of the idea generation process (Mumford et al., 2012). Surely,  
 180 there must also be reasons for why concepts are selected or not for subsequent conceptual combination  
 181 and idea generation, and why ideas are being generated based on the same conceptual combinations or  
 182 not. Indeed, executing the steps in the idea generation process in a non-linear fashion likely requires that  
 183 prediction and evaluation are a pervasive part of this process – for the same reasons that evolutionary  
 184 (Dietrich, 2019; Dietrich, 2015; Dietrich & Haider, 2015) and cognitive models of idea generation  
 185 (Wiggins & Bhattacharya, 2014; Yang & Li, 2018) require prediction to couple generation to evaluation.

186 As such, it is clear that the prediction and evaluation are likely a necessary component of the idea  
 187 generation process, and more recent theoretical models of the idea generation process acknowledge  
 188 this. Empirical evidence for these conjectures, however, is still lacking.

## 189 **1.2 The present study**

190 In the present study, a first look is therefore taken at whether and where spontaneous predictions and  
 191 evaluations may drive changes in the actions that form part of the idea generation process, and if and  
 192 how these affect the way that the idea generation process is executed. It is proposed that how people  
 193 cycle through the actions concept selection and conceptual combination and idea generation, shapes the  
 194 idea generation process through prediction and evaluation in at least three ways:

- 195 1. Switching between concept selection and conceptual combination and idea generation.
- 196 2. Concept selection (and the repetition thereof)
- 197 3. Conceptual combination and idea generation (and the repetition thereof)

198 Firstly, during concept selection predictions are made about the likelihood that a concept (in combination  
 199 with other concepts) will facilitate conceptual combination in a manner that enables effective idea  
 200 generation (Isaksen et al., 2010) or the emergence of ideas that solve a given problem (Mumford et al.,  
 201 1996). If this likelihood appears high, the concept is selected for conceptual combination, and one or  
 202 more ideas are generated based thereupon. That is, one switches from concept selection to conceptual  
 203 combination and idea generation. Ideas that are generated (or the lack thereof) are subsequently  
 204 evaluated. When the selected concepts do not (any more) facilitate the generation of ideas in a manner  
 205 as previously predicted, i.e., there is a discrepancy between the predictions made about the selected  
 206 concept(s) and the evaluation of ideas that can be generated based thereupon, one switches back from  
 207 conceptual combination and idea generation to concept selection to retrieve different concepts to  
 208 continue the idea generation process. As such, it is conjectured that prediction and evaluation drive  
 209 switching between the actions concept selection and conceptual combination and idea generation.

210 Secondly, during concept selection predictions are made on the basis of certain heuristics, previous  
 211 experiences, and domain knowledge. When it is assumed that concepts should facilitate the execution of  
 212 such heuristics (e.g., selecting remote associations), or need to match previous experiences (e.g., similar  
 213 concepts have not worked well during the present idea generation process), and domain knowledge  
 214 (e.g., previous experiences indicate that a concept is commonly found in failed solutions) about what is

215 likely to solve a given problem (Gibbert et al., 2012; Mumford et al., 1996), selecting or not selecting a  
 216 concept can also be based on evaluations of whether predictions about the efficacy of one's heuristics,  
 217 previous experiences and domain knowledge match with a concept that is retrieved or not. When this is  
 218 not the case, we expect to observe the action that people continue their search for suitable concepts, i.e.,  
 219 execute the action of concept selection (and the repetition thereof).

220 Thirdly, during the generation of ideas predictions that are made about the likelihood that a conceptual  
 221 combination enables the (continued) generation of ideas (that are likely to help solve a given problem),  
 222 can be updated based on evaluations of whether the ideas that are generated still match earlier  
 223 predictions. As long as this is the case (they match), idea generation based on the same conceptual  
 224 combination continues, i.e. one executes the actions conceptual combination and idea generation (and  
 225 the repetition thereof).

226 If the above conjectures truly form part of the idea generation process one should be able to frequently  
 227 find these predictions and evaluation in the reasons that people report about the actions that they take as  
 228 part of the idea generation process, and affect the way in which the idea generation process is executed  
 229 as detailed in the above.

## 230 **2 Method**

231 To take a first look at spontaneous predictions and evaluations during the idea generation process the  
 232 reasons that underlie taking actions during this process were explored in a mixed method study.

### 233 **2.1 Participants**

234 Sixty<sup>1</sup> people initially participated in the study. However, the data of three participants was not used in  
 235 further analysis because these participants did not follow the instructions provided. This resulted in a  
 236 sample of fifty-seven people ( $M_{age} = 22.78$ ,  $SD_{age} = 2.65$ , 16 males, 41 females). The participants were  
 237 recruited via the participant recruitment system of the Communication and Information Science program  
 238 at Tilburg University. As a consequence, all participants were students of the Communication and  
 239 Information Science program and thus engaged in higher education. The participants received study  
 240 credits in exchange for their participation. Given that creativity depends on domain specific knowledge  
 241 (Rietzschel, Nijstad, & Stroebe, 2007), and the creative task that the participants will engage with is  
 242 marketing task, the participants were asked to self-report their marketing experience. The participant's  
 243 self-reported expertise in marketing was moderate 2.65 ( $SD = .96$ ). The study was approved by the  
 244 Research Ethics and Data Management Committee of the Tilburg School of Humanities and Digital  
 245 Sciences, Tilburg University.

## 246 **2.2 Materials and Measurements**

### 247 **2.2.1 Creative task**

248 A novel creative task was developed to enable participants to self-report the reasons for their actions  
 249 during the idea generation process. This creative task consisted of four activities: 1) reading a written  
 250 briefing about a project for which participants would generate ideas, 2) an association task, 3) the actual  
 251 idea generation task, and 4) an idea selection task.

#### 252 **2.2.1.1 Briefing**

253 The creative task started with the instruction that the participants would help to generate ideas for an  
 254 advertising campaign to promote a product for the (fictional) business Smart\_Nomad. This product was a  
 255 "personalized smart backpack". This topic was chosen because the participants to which there was

256 access to for this study all have some degree of experience in marketing, advertising, and branding due  
257 to the curriculum of the study program they are participating in. The instructions were followed by a  
258 briefing supposedly provided by Smart\_Nomad. The briefing is presented in Figure 1.

259 **Figure 1. Briefing about the creative problem that needed to be solved.**

#### 260 **2.2.1.2 Association task**

261 Before generating ideas participants were asked to write down as many associations they could come up  
262 with based on the information provided in the briefing in 10 minutes. The associations could range from  
263 basic categories, personal experiences, and elements from prior cases (e.g., in marketing or branding).  
264 We hitherto refer to these as concepts. These concepts would later be used in the idea generation task,  
265 by asking participants to select these and combine these associations into new knowledge based on  
266 which they could generate ideas (Abraham, 2018). Participants were asked to report to the researcher  
267 when they had difficulty listing (more) concepts, at which time the researcher would provide creative  
268 primes to facilitate the continued listing of associations. The primes were funny, serious, case-related or  
269 case-unrelated and were written on a sheet of paper that the participants could choose from (e.g.,  
270 millennials, prank, laptop, fire, picnic) (Brown & Bhadury, 2006). Maximizing the amount of concepts  
271 listed helped to ensure that there was enough material for the participants to combine during the  
272 subsequent idea generation task. Each concept was written down on a white memo sheet.

#### 273 **2.2.1.3 Idea generation task**

274 After the association task the participants engaged in an idea generation task. The goal of this task was  
275 to write down as many creative, innovative, original and usable solutions based on the briefing by  
276 Smart\_Nomad as possible in 15 minutes. As part of their idea generation process, the participants were  
277 instructed to select concepts that they wrote down during the association task, and combine these  
278 concepts to form new knowledge based on which to generate ideas for the problem provided in the  
279 briefing. When an idea was generated, it was written down on a red, yellow, or green memo sheet and  
280 positioned on the table. Participants were asked to place the concepts they combined into an idea with  
281 each idea on the table. Newly generated concepts that were used during the actions conceptual  
282 combination and idea generation were written down on blue memo sheets and also placed next to the  
283 ideas they were used for. This way, participants externalized their idea generation process in a manner  
284 that approaches the way people think about how concepts and ideas relate, (cf., Dove et al., 2018). This  
285 was developed through iterative pilot testing as participants initially, without this way of externalizing their  
286 idea generation process, were not sufficiently able to indicate the reasons that underlie taking actions  
287 during their idea generation process. A visual impression of the setup and use of memo sheets is  
288 presented in Figure 2.

289 **Figure 2. Table setup developed for use during the creative task.**

#### 290 **2.2.1.4 Idea selection task**

291 After the idea generation task, participants were asked to evaluate their ideas and select, based on the  
292 briefing, the one idea that they would recommend for implementation to Smart\_Nomad. This served no  
293 purpose other than to improve the construct and ecological validity of the task, as otherwise there would  
294 not be a final goal and motivator for generating ideas; which is typical for the idea generation process,  
295 because it is normally embedded in a larger creative process, and followed by an explicit idea evaluation  
296 and selection activities, and later implementation.



## 297 **2.2.2 Probing prediction and evaluation**

298 To capture the reasons that underlie taking actions during the idea generation process that could be  
 299 indicative of the presence of spontaneous predictions and evaluations therein, the idea generation task  
 300 was briefly stopped at three moments. During these moments the participants were asked to tell the  
 301 researcher about the reasons for taking specific actions during their idea generation process in the time  
 302 prior to each probe. That is, between the start of the task and probe 1, between probe 1 and probe 2, and  
 303 between probe 2 and probe 3. Questions were not explicitly formulated to address the prediction and  
 304 evaluation in order to avoid potential bias in the answers. Rather, each question asked about the reason  
 305 for a particular action done as part of the idea generation process. In particular, participants were asked  
 306 about the reasons for (not) using certain concepts for conceptual combination, and about stopping or  
 307 continuing idea generation based on the same conceptual combination. Moreover, they were asked  
 308 about the conception of new concepts and whether there was further information they wanted to provide.  
 309 Pilot testing showed that participants disclosed more about their actions if they were verbally asked to  
 310 answer the questions instead of asking them to write down an answer. For this reason, the questions  
 311 were administered verbally and transcribed by the researcher. The questions are presented in Figure 3.

### 312 **Figure 3. Probe questions used by the researcher to interrogate the reasons for actions taken** 313 **during the idea generation task.**

314 The probes occurred at random moments within the following time slots: minute 3-5, minute 8-10, and  
 315 minute 13-15. After the first probe, participants switched from writing down their idea on red to yellow  
 316 memo sheet. After the second probe, participants switched from writing down their ideas on yellow to  
 317 green memo sheets. The use of these coloured sticky notes was not counterbalanced. Directly after the  
 318 third probe the idea generation task was stopped. As part of each probe, the researcher took a picture of  
 319 the table on which the ideas and concepts were displayed, as to enable further analysis of how the idea  
 320 generation process was executed.

## 321 **2.2.3 Capturing idea generation process execution**

322 To capture how the idea generation process was executed and assess how this was affected by  
 323 prediction and evaluation, three quantitative performance metrics were coded for the output that was  
 324 generated prior to each probe: Fluency, flexibility, and within-concept fluency. Fluency was assessed by  
 325 counting the number of ideas generated by each participant (Guilford, 1967), which in the present study  
 326 simply meant counting the red, yellow, and green memo sheets. This indicates the ease with which  
 327 participants were able to generate ideas, which is commonly assumed to increase the chance that  
 328 creative ideas are developed (Plucker et al., 2011). Flexibility was assessed by counting the number of  
 329 different concepts used when producing ideas by each participant (Guilford, 1967), which in the present  
 330 study simply meant counting the amount of white memo sheets placed with the red, yellow, and green  
 331 sheets. This indicates a strategy commonly applied during the idea generation process where the  
 332 inclusion of many different concepts increases the chance of generating a creative idea (Nijstad et al.,  
 333 2010). Within-concept fluency was calculated by dividing fluency by flexibility for each participant. This  
 334 was used to indicate another strategy commonly applied during the idea generation process, where  
 335 multiple ideas are typically generated by exploiting only a few (successful) concepts (Nijstad et al., 2010).

## 336 **2.2.4 Socio-demographics**

337 To gain insight into the characteristics of the sample, basic socio-demographics were captured with a  
 338 questionnaire prior to the study. Specifically, participants were asked to write down their age and gender.  
 339 The participants' experience in marketing was measured on four 5-point Likert scales (1 = very  
 340 inexperienced, 5 = very experienced). Each inquiring about the participants' experience in professional  
 341 marketing, advertising, social media marketing, and branding. Cronbach alpha suggested that the  
 342 internal consistency was good,  $\alpha = .88$ .

## 343 **2.3 Procedure**

344 Upon arrival participants were seated at a table. They were provided a written information sheet about  
 345 the study and their rights related to their participation and data handling, signed informed consent, and  
 346 filled in a brief questionnaire about their socio-demographics. At this stage, information that could reveal  
 347 the true purpose of the study was withheld. Instructions about how the creative task should be executed  
 348 were provided, after which participants engaged in the creative task. First, they received the briefing and  
 349 took ample time to read and understand it. Second, instructions were briefly repeated on how to execute  
 350 the association task, and the participants executed the association task. Third, instructions were briefly  
 351 repeated on how to execute the idea generation task, after which the participants executed the idea  
 352 generation task, and during which time the three probes were administered. A researcher was present  
 353 throughout the task in case there were questions, or participants needed help with something, and to  
 354 administer the probes. After administering the third probe, the idea generation task ended. Fourth, the  
 355 participants selected one of their ideas to be recommended for implementation by Smart\_Nomad. After  
 356 the creative task ended the participants were debriefed about the aspects of the study that included  
 357 deception and its overall purpose. In total, participation took approximately 45 minutes.

## 358 2.4 Analysis

359 The self-reported reasons that underlie the actions taken during the idea generation process were coded  
 360 into variables indicative of whether a given reason indicated if a prediction happened or not, and whether  
 361 it indicated if an evaluation happened or not. The definitions of “prediction” and “evaluation” were  
 362 obtained through the grammatical interpretation of the participant’s responses. On one hand, whenever a  
 363 participant used the future tense, or modal auxiliary verbs to describe the use of a particular concept (e.g.  
 364 would), then a prediction happened (cf. Gotti, 2006; Kakzhanova, 2013). This is due to the fact that it is  
 365 used to talk about the future in the past and to express the conditional mood. On the other hand,  
 366 whenever a participant used the past or the present tense to describe concepts, ideas, or their use, an  
 367 evaluation happened (cf. Howe, 1966). When both occurred in the same response, the grammar features  
 368 related to “evaluation” outweighed the “prediction” features, therefore, the response was considered an  
 369 “evaluation”. To assess the intra-observer agreement a random selection of 15% of the responses was  
 370 recoded two weeks after the first coding. Cohen’s kappa suggested substantial intra-observer agreement  
 371 for predictions found in answers to question 1,  $\kappa = .71$ , but moderate agreement for evaluations found in  
 372 answers to question 4,  $\kappa = .43$ , and substantial agreement for predictions found in answers to question 2,  
 373  $\kappa = .76$ , and evaluations found in answers to question 2,  $\kappa = .66$ , and for predictions found in answers to  
 374 question 3,  $\kappa = .77$ , and evaluations found in answers to question 3,  $\kappa = .78$ . Answers to questions 5 and  
 375 6 were not used in the analysis.

376 To explore how prediction and evaluation correlated with the way in which the idea generation process  
 377 was executed, generalized linear mixed modelling was used. Full factorial models were calculated for the  
 378 coded predictions and evaluations that were hypothesized to relate to individual actions: Predictions  
 379 (question 1) and evaluations (question 4) conjectured to drive switching between the actions concept  
 380 selection and conceptual combination and idea generation, predictions and evaluations (question 2)  
 381 conjectured to drive concept selection (and the repetition thereof), and predictions and evaluations  
 382 (question 3) conjectured to drive the actions conceptual combination and idea generation (and the  
 383 repetition thereof). These were entered as dummy-coded nominal variables (prediction: yes = 1, no = 0;  
 384 evaluation: yes = 1, no = 0). The intercepts were modelled as random effects. Degrees of freedom were  
 385 fixed for all tests (residual method). The number of the probe (1-3) was entered as the repeated  
 386 measures variable. Note however that repeated measures were not analysed to compare differences  
 387 between the different probes, but rather for appropriate aggregation. For each full factorial model, results  
 388 were calculated for the dependent variables fluency, flexibility, and within-concept fluency. The  
 389 covariance matrix (diagonal) was selected by minimizing the Akaike information criterion, and accepting  
 390 a more complicated covariance matrix only when the additional degrees of freedom used yielded a  
 391 significant decrease in the information criterion number, following the procedure outlined in Field (2013).

## 392 3 Results

Action 1		Evaluation			Action 2		Evaluation		
		No	Yes	Total			No	Yes	Total
Prediction	No	24	37	61	Prediction	No	24	120	144
	Yes	28	82	110		Yes	2	25	27
Total		52	119	171	Total		26	145	171

393

Action 3		Evaluation		
		No	Yes	Total
Prediction	No	31	41	72
	Yes	42	57	99
Total		73	98	171

394 **Table 1. Frequencies of predictions and evaluations that were conjectured to drive switching**  
 395 **between the actions concept selection and conceptual combination and idea generation (action**  
 396 **1), concept selection (and the repetition thereof) (action 2), and conceptual combination and idea**  
 397 **generation (and the repetition thereof) (action 3). Frequencies are the counts of the responses**  
 398 **each of the three probes of the 57 participants.**

Type	Example quote
Action 1: Switching between concept selection and conceptual combination and idea generation	
Prediction	<i>“I thought about targeting the right customer, I think creating an online community as a form of organic marketing will increase positive word-of-mouth.”</i> <i>“Instagram is, like, a bigger thing, it is more useful, deep, it will make it easier to have new ideas.”</i>
Evaluation	<i>“At first I thought it could work, but now that I look at it, I think that using ads in specific magazines doesn’t convince me anymore.”</i> <i>“When I came up with it, I thought it could still come in handy, but now I think I won’t get new possibilities of use.”</i>
Action 2: Concept selection (and the repetition thereof)	
Prediction	<i>“Previously yes, but then I thought that Gamers would not fit in the ultimate product target group.”</i> <i>“I just know it will not help to have better insight on the product.”</i>
Evaluation	<i>“Fashionable doesn’t address the right audience.”</i> <i>“Gaming; Awareness in other countries, these are not prime goals, I can’t use them.”</i>
Action 3: Concept combination and idea generation (and the repetition thereof)	
Prediction	<i>“Wi-Fi and scientific improvement together will be meaningful features when communicating the product to people.”</i> <i>“I clustered them, I thought they would make more sense if used together. The same for the other clusters for the other ideas.”</i>
Evaluation	<i>“Marketing is an enormous concept, it connects with many others, that is why it was possible to get more ideas for the campaign.”</i> <i>“I think these concepts are important if taken singularly, better to focus on once concept, stress it, and then use another one to come up with strategies.”</i>

399 **Table 2. Example quotes that illustrate the type of predictions and evaluations made during the**  
 400 **idea generation process.**

401 Predictions and evaluations were frequently reported in the reasons for switching between the concept  
 402 selection and conceptual combination and idea generation. That is, predictions about what concepts  
 403 would facilitate creative idea generation were reported together with evaluations that concept  
 404 combinations do not support creative idea generation (any more) in 48% of the probes (Table 1, left). In  
 405 contrast, 16% (n = 28) only reported these predictions, 22% (n = 37) reported only these evaluations, and  
 406 14% reported neither in the probes. These findings suggest that predictions about what concepts  
 407 facilitate idea generation, and relatedly evaluations of the utility of combinations concepts for idea  
 408 evaluation commonly form part of the idea generation process. Example quotes are presented in Table 2,  
 409 component 1.

410 Prediction, but evaluations in particular were reported in the reasons for concept selection (and the  
 411 repetition thereof). That is, predictions about what concepts are unlikely to facilitate the idea generation  
 412 process were reported together with evaluations that concepts should not be selected for concept  
 413 combination and subsequent idea generation in only 15% (n = 25) of these probes (Table 1, middle).  
 414 Less than 1% (n = 2) of the probes were coded as predictions only, and 14% (n = 24) as neither. In  
 415 contrast, evaluations indicating reasons for not selecting concepts were reported in 70% (n = 120) of the  
 416 probes. This suggests that not selecting concepts was mostly driven by evaluations, at least as indicated  
 417 by the data obtained in the present study. Although, predictions, albeit less commonly, also form part of  
 418 not selecting concepts for idea generation. Example quotes are presented in Table 2, component 2.

419 Furthermore, predictions and evaluations were frequently reported in the reasons for combining concepts  
 420 and generating ideas based thereupon (and the repetition thereof). That is, predictions about the  
 421 continued use of the same concepts for idea generation were reported together with evaluations  
 422 suggesting that the same concepts can facilitate (continued) idea generation in 33% (n = 57) of the  
 423 probes (Table 1, right). In contrast, 25% (n = 42) of the probes suggested that only these predictions  
 424 occurred, whereas in 24% (n = 41) only these evaluations were reported, and in 18% (n = 31) neither  
 425 were reported. This suggests that predictions about the continued use of selected concepts for idea  
 426 generation, and evaluations about whether these concepts can be used to facilitate (continued) idea  
 427 generation, also commonly form part of the idea generation process. Example quotes are presented in  
 428 Table 2, component 3.

		Fluency		Flexibility		Within-concept fluency	
		M	SD	M	SD	M	SD
Action 1: Switching between concept selection and conceptual combination and idea generation							
Prediction	No	8.10	3.28	20.92	5.33	.40	.18
	Yes	8.25	3.06	20.55	5.61	.41	.15
Evaluation	No	8.27	3.45	21.52	6.02	.40	.16
	Yes	8.16	2.99	20.32	5.24	.41	.16
Action 2: Concept selection (and the repetition thereof)							
Prediction	No	8.15	3.12	20.69	5.38	.40	.15
	Yes	8.41	3.25	20.63	6.22	.43	.19
Evaluation	No	8.92	3.48	20.08	5.36	.45	.16
	Yes	8.06	3.06	20.79	5.53	.40	.16
Action 3: Concept combination and idea generation (and the repetition thereof)							
Prediction	No	8.50	3.38	21.33	5.97	.41	.17

Evaluation	Yes	7.97	2.93	20.21	5.11	.40	.15
	No	7.79	2.81	20.89	5.05	.38	.13
	Yes	8.49	3.33	20.53	5.83	.43	.17

429 **Table 3. Means and standard errors for fluency, flexibility, and within concept fluency for**  
 430 **predictions, evaluations, and their interaction.**

	Fluency	Flexibility	Within-concept fluency
Fluency	-		
Flexibility	.326*	-	
Within-concept fluency	.804**	-.270*	-

431 **Table 4. Pearson correlations (two-tailed) between fluency, flexibility, and within-concept fluency.**  
 432 **Note that these variables were aggregated (sum) across the three measurement times (probes). \***  
 433  **$p < .05$ , \*\*  $p < .01$ .**

434 The predictions and evaluations that underlie the actions that form part of the idea generation process  
 435 also affect the manner in which the idea generation process is executed. The descriptive statistics are  
 436 presented in Table 3 and Table 4.

437 *Model 1* tested the effects of predictions about what concepts would facilitate idea generation, and  
 438 evaluations of whether concept combinations did not support idea generation, on fluency, flexibility, and  
 439 within-concept fluency (Table 5, model 1).

440 The results showed that the occurrence of the evaluations significantly and positively correlated with  
 441 fluency,  $B = 1.47$ ,  $t(167) = 2.19$ ,  $p = .030$ .

442 Moreover, the results showed a significant interaction effect on fluency,  $B = -3.19$ ,  $t(167) = 3.03$ ,  $p = .003$ .  
 443 Pairwise comparisons (sequential Sidak) showed that when no predictions and no evaluations were  
 444 reported ( $M = 7.08$ ,  $SE = .63$ ), people had generated less ideas than when no predictions, but  
 445 evaluations were reported ( $M = 8.80$ ,  $SE = .51$ ),  $t(167) = 2.12$ ,  $p = .036$ ; and people had generated less  
 446 ideas than when predictions, but no evaluations were reported ( $M = 9.33$ ,  $SE = .58$ ),  $t(167) = 2.63$ ,  $p =$   
 447  $.009$ . Moreover, when both predictions and evaluations were reported ( $M = 7.86$ ,  $SE = .34$ ), participants  
 448 had generated less ideas than when predictions but not evaluations were reported ( $M = 9.33$ ,  $SE = .58$ ),  
 449  $t(167) = 2.19$ ,  $p = .030$ ; and when no predictions but only evaluations were reported ( $M = 8.80$ ,  $SE = .51$ ),  
 450 albeit not significantly in the latter,  $t(167) = 1.54$ ,  $p = .126$ .

451 The results also showed a significant interaction effect on within-concept fluency,  $B = -.14$ ,  $t(167) = 2.52$ ,  
 452  $p = .013$ . Pairwise comparisons (sequential Sidak) showed that when no predictions and no evaluations  
 453 were reported ( $M = .34$ ,  $SE = .03$ ) participants had generated less ideas per concept than when they  
 454 reported no predictions but only evaluations ( $M = .44$ ,  $SE = .03$ ),  $t(167) = 2.31$ ,  $p = .022$ ; and when they  
 455 reported predictions but no evaluations ( $M = .44$ ,  $SE = .03$ ),  $t(167) = 2.45$ ,  $p = .026$ . Moreover, no  
 456 significant difference was found between when both predictions and evaluations were reported ( $M = .40$ ,  
 457  $SE = .02$ ), with when predictions but no evaluations were reported ( $M = .44$ ,  $SE = .03$ ),  $t(167) = 1.16$ ,  $p =$   
 458  $.249$ ; and with when no predictions but only evaluations were reported ( $M = .44$ ,  $SE = .03$ ),  $t(167) = 1.19$ ,  
 459  $p = .237$ .

460 *Model 2* tested the effects of predictions about what concepts are unlikely to facilitate creative idea  
 461 generation, and evaluations of whether concepts should not be selected for concept combination and  
 462 subsequent idea generation, on fluency, flexibility, and within-concept fluency. The results showed no  
 463 significant effects of these predictions, evaluations, nor their interaction on fluency, flexibility, and within-  
 464 concept fluency (Table 5, model 2).

465 *Model 3* tested the effects of predictions about the continued use of the same concepts for idea  
 466 generation, and evaluations suggesting that the same concepts can facilitate (continued) idea  
 467 generation, on fluency, flexibility, and within-concept fluency (Table 5, model 3).

468 The results showed no significant correlations of predictions nor evaluations with fluency, flexibility, and  
 469 within-concept fluency. However, a not significant positive correlation between predictions and fluency,  $B$   
 470  $= 1.13$ ,  $t(167) = 1.78$ ,  $p = .077$ ; and a not significant positive correlation between predictions and within-  
 471 concept fluency,  $B = .06$ ,  $t(167) = 1.88$ ,  $p = .062$ , may be of interest.

472 The results, however, did show a significant interaction effect on flexibility,  $B = 3.38$ ,  $t(167) = 1.98$ ,  $p =$   
 473  $.049$ . Pairwise comparisons (sequential Sidak) showed that when no predictions and no evaluations were  
 474 reported people had used more concepts during idea generation ( $M = 22.65$ ,  $SE = .98$ ) than when no  
 475 predictions but only evaluations were reported ( $M = 20.35$ ,  $SE = .85$ ),  $t(167) = 1.78$ ,  $p = .077$ ; and when  
 476 predictions but no evaluations were reported ( $M = 19.59$ ,  $SE = .84$ ),  $t(167) = 2.38$ ,  $p = .019$ ; albeit not  
 477 significantly in the former. Moreover, when both predictions and evaluations were reported participants  
 478 had used more concepts ( $M = 20.66$ ,  $SE = .72$ ) than when predictions but no evaluations were reported  
 479 ( $M = 19.59$ ,  $SE = .84$ ),  $t(167) = .97$ ,  $p = .335$ ; and when no predictions but only evaluations were reported  
 480 ( $M = 20.35$ ,  $SE = .85$ ),  $t(167) = .28$ ,  $p = .780$ . These where, however, not significant.

481 Because flexibility positively correlates with fluency (Table 4), it was also explored whether the found  
 482 effects of predictions about the continued use of the same concepts for idea generation, and evaluations  
 483 suggesting that the same concepts can facilitate (continued) idea generation, on flexibility were not  
 484 driven by fluency. This to help rule out alternative explanations. This was done by adding fluency as a  
 485 covariate to *model 3*. The results again showed no significant coefficients for predictions,  $B = -1.01$ ,  
 486  $t(166) = -.96$ ,  $p = .340$ , nor evaluations,  $B = -1.01$ ,  $t(166) = -.97$ ,  $p = .335$ . However, in this model, the  
 487 correlation between fluency and flexibility was replicated,  $B = .61$ ,  $t(166) = 4.79$ ,  $p < .001$ . Moreover, the  
 488 results replicated the interaction effect,  $B = 4.23$ ,  $t(166) = 2.62$ ,  $p = .010$ . These findings suggest that the  
 489 found effects of prediction and evaluation on flexibility are not only driven by fluency.

490 Complementarily, the results showed a significant interaction effect on within-concept fluency,  $B = -.12$ ,  
 491  $t(167) = 2.53$ ,  $p = .013$ . Pairwise comparisons (sequential Sidak) showed that when no predictions and  
 492 no evaluations were reported ( $M = .35$ ,  $SE = .03$ ) participants had generated less ideas per concept than  
 493 when no predictions but only evaluations were reported ( $M = .46$ ,  $SE = .02$ ),  $t(167) = 3.17$ ,  $p = .002$ ; and  
 494 when predictions but no evaluations were reported ( $M = .41$ ,  $SE = .02$ ),  $t(167) = 1.72$ ,  $p = .088$ ; albeit not  
 495 significantly in the latter. However, when both predictions and evaluations were reported ( $M = .40$ ,  $SE =$   
 496  $.02$ ), participants generated a similar amount of ideas per concept when prediction but no evaluation was  
 497 reported ( $M = .41$ ,  $SE = .02$ ),  $t(167) = .18$ ,  $p = .861$ ; and generated less ideas per concept when no  
 498 predictions but only evaluations were reported ( $M = .46$ ,  $SE = .02$ ),  $t(167) = 1.88$ ,  $p = .062$ . However,  
 499 these were also not significant.

	Fluency	Flexibility	Within-concept fluency
<i>Model 1: Switching between concept selection and conceptual combination and idea generation</i>			
Intercept	7.86** (.34)	20.05** (.60)	.40** (.02)
Predictions	.94 (.61)	.83 (1.10)	.04 (.03)
Evaluations	<b>1.47* (.67)</b>	1.93 (1.20)	.04 (.03)
Predictions x Evaluations	<b>-3.19** (1.05)</b>	-1.73 (1.89)	<b>-.14* (.05)</b>

*Model 2: Concept selection (and the repetition thereof)*

Intercept	8.47** (.63)	20.87** (1.11)	.43** (.03)
Predictions	-.50 (.69)	-.09 (1.22)	-.04 (.04)
Evaluations	-.98 (2.31)	-3.40 (4.06)	-.01 (.12)
Predictions x Evaluations	2.05 (2.41)	2.90 (4.24)	.06 (.12)

*Model 3: Concept combination and idea generation (and the repetition thereof)*

Intercept	8.02** (.41)	20.66** (.72)	.40** (.02)
Predictions	<b>1.13† (.64)</b>	-.31 (1.12)	<b>.06† (.03)</b>
Evaluations	-.12 (.63)	-1.07 (1.11)	.01 (.03)
Predictions x Evaluations	-1.38 (.97)	<b>3.78* (1.71)</b>	<b>-.12* (.05)</b>

500 **Table 5. Results of the generalized linear mixed model analysis for the correlations between**  
 501 **predictions and evaluations with fluency, flexibility, and within-concept fluency. †  $p < .10$ , \*  $p <$**   
 502 **.05, \*\*  $p < .01$ .**

## 503 4 Discussion

504 The presented study aimed to take a first look at whether and where predictions and evaluations are  
 505 made about the actions taken during the idea generation process, and if and how these affect the way  
 506 that the idea generation process is executed.

### 507 4.1 Summary and interpretation of the results

508 The results showed overall that predictions and evaluations happen spontaneously and frequently during  
 509 the idea generation process. The results furthermore confirm our conjectures that different patterns of  
 510 predictions and evaluations exist within the idea generation process and underlie a specific set of  
 511 actions.

512 First, the results indicated that switching between the actions concept selection and conceptual  
 513 combination and idea generation is driven by both predictions and evaluations. That is, predictions about  
 514 what concepts would facilitate idea generation, and evaluations of whether concept combinations did not  
 515 support idea generation (any more) occurred frequently in the participant's reports about the reasons for  
 516 their actions taken during the idea generation process. These predictions and evaluations also correlated  
 517 with how the idea generation process was executed. Participants that reported evaluations more  
 518 frequently also generated more ideas. When participants reported no evaluations and no predictions,  
 519 they had also generated less ideas than when they reported only predictions or only evaluations.  
 520 Moreover, when both predictions and evaluations were reported, they had generated less ideas than  
 521 when predictions but not evaluations were reported. No correlations were found of these predictions and  
 522 evaluations with the amount of concepts used. Complementarily, when participants reported no  
 523 evaluations and no predictions, they had generated less ideas per selected concept than when they  
 524 reported only predictions or only evaluations. However, no differences were found for the amount of  
 525 ideas generated per concept between participants that reported both predictions and evaluations, with  
 526 reporting predictions or reporting evaluations only.

527 Speculatively, these findings can be explained in the following ways. The found relationship between a  
 528 lack of predictions and evaluations and the generation of less ideas and lowered within-concept fluency  
 529 may simply suggest that the idea generation process is stagnating. Whereas being actively engaged in  
 530 the idea generation process involves predictions and evaluations. This conjecture is supported further by

531 a positive correlation between evaluations and the amount of generated ideas. Interestingly, the finding  
532 that when participants reported both predictions and evaluations, they had generated less ideas than  
533 when only predictions but no evaluations were reported, suggests that frequent switching may be the  
534 consequence of a problematically executed idea generation process. That is, when prediction in one  
535 probe did not coincide with an evaluation this may indicate continued idea generation thereafter, and vice  
536 versa, may indicate that continued idea generation preceded sustained idea generation. Thus, when both  
537 prediction and evaluation happen as frequently as to report them in the same probe, this may signal  
538 issues during the execution of the idea generation process. This is in line with previous research that  
539 suggests that the frequency of switching between concept selection and subsequent conceptual  
540 combination and idea generation can affect the generation of ideas (e.g., Beaty et al., 2014; Nusbaum &  
541 Silvia, 2011). The findings of the present study add that switching can be driven explicitly by spontaneous  
542 predictions about the likelihood that a concept will facilitate the generation of ideas, and evaluations that  
543 a conceptual combination will not facilitate creative idea generation (any more).

544 Second, the results obtained in the present study indicated that the action of concept selection (and the  
545 repetition thereof) can be driven by predictions and evaluations in particular. That is, predictions about  
546 what concepts are unlikely to facilitate creative idea generation occurred, but not frequently. Rather,  
547 participants frequently reported evaluations of whether concepts should not be selected for concept  
548 combination and subsequent idea generation. Despite the presence of predictions, and evaluations in  
549 particular, no measurable impact on how the idea generation process was executed was found.

550 Speculatively, this finding can be interpreted as evidence that predictions and evaluations that form part  
551 of concept selection do not necessarily affect how the idea generation process is executed, as measured  
552 with fluency, flexibility, and within-concept fluency. This, of course, does not mean that there is no effect  
553 on idea generation whatsoever. Previous research, for example, found that selecting concepts that are  
554 semantically further apart affect the originality and usefulness of ideas that are generated as a result of  
555 conceptual combination (Gibbert et al., 2012). Given previous research, it may be the case that  
556 predictions and evaluations that form part of concept selection (and the repetition thereof) have more a  
557 qualitative than a quantitative effect (which was assessed in the present study) on idea generation.

558 Third, the results indicated that the actions conceptual combination and idea generation (and the  
559 repetition thereof) is also driven by both predictions and evaluations. That is, predictions about the  
560 continued use of the same concepts for idea generation, and evaluations suggesting that the same  
561 concepts can facilitate (continued) idea generation, occurred frequently in the participant's reports about  
562 the reasons for their actions taken during the idea generation process. These predictions and evaluations  
563 also correlated with how the idea generation process was executed. Participants that reported  
564 predictions tended to generate more ideas, and more ideas per concept used. However, these findings  
565 were not significant. When participants reported no predictions and no evaluations they had also used  
566 fewer concepts than when they reported only predictions or only evaluations. Although the latter was not  
567 significant. Moreover, despite a positive correlation between the amount of ideas generated and the  
568 amount of concepts used, a rough comparison between their results show that the effects of predictions  
569 and evaluations differ (Table 5, model 3), and adding the amount of ideas as a covariate to that same  
570 model did not change the results. This suggested that, indeed, these effects were not driven by the  
571 amount of ideas that were generated. Complementarily, when participants reported no predictions and no  
572 evaluations, they also generated less ideas per concept. Although the former was not significant. In all  
573 cases, no differences were found for the amount of ideas generated, the amount of concepts used, and  
574 the amount of ideas generated per concept, when comparing reports that contained only predictions or  
575 only evaluation, with reports that contained both predictions and evaluations.



576 Speculatively, these findings can be explained in the following ways. One way to explain the results is  
577 that the reports about predictions about the continued and successful use of the same concepts for idea  
578 generation, and positive evaluations drive a dual process that is commonly hypothesized to characterize  
579 the way in which an idea generation process is executed (Nijstad et al., 2010). That is, people tend to  
580 either produce more ideas through the persistent use of a few concepts, raising within-concept fluency.  
581 This can be explained by the finding that possibly, participants that reported predictions had also  
582 generated more ideas and had generated more ideas per concept used. Or people tend to produce more  
583 ideas though the use of many different concepts, lowering within-concept fluency. This can be explained  
584 by the finding that when participants reported no prediction and no evaluations, less concepts, but not  
585 less ideas were produced, than when they reported only predictions or only evaluations. In these cases,  
586 within-concept fluency was also lowered. Another way to explain these results is that, as in our  
587 explanation about the results about switching between concept selection and conceptual combination  
588 and idea generation, no predictions and no evaluations signal stagnation somewhere in the idea  
589 generation process. However, in this case they may also signal increased switching itself – indicating the  
590 production of more ideas through the use of more different concepts. As such, this finding aligns with  
591 previous research on dual process models of idea generation (Nijstad et al., 2010). The findings of the  
592 present study add that conceptual combination and idea generation (and the repetition thereof) can be  
593 driven explicitly by spontaneous predictions about the continued use of the same concepts for idea  
594 generation, and evaluations suggesting that the same concepts can facilitate (continued) idea  
595 generation.

## 596 **4.2 Limitations**

597 Of course, there are several limitations to the presented study. This is partly due to the exploratory nature  
598 of the study, and partly due to other more specific methodological choices that were made. Some of  
599 which, we wish to discuss in more detail.

600 First, the use of three probes to capture predictions and evaluations during the idea generation task  
601 affects the validity of the results. It could for example be argued that after the first probe was presented,  
602 participants were primed to think about predictions and evaluations during idea generation, in preparation  
603 for the next probe. This could have helped to capture predictions and evaluations but could also have  
604 steered participants into applying predictions and evaluations more frequently, and thereby confounding  
605 the results. Moreover, because of using only three probes, and dummy-coding their results into nominal  
606 variables, the exact relationships between the predictions and evaluations made could not easily be  
607 assessed. Indeed, one would expect that what truly drives idea generation are predictions and  
608 evaluations of whether actions taken match or mismatch with these predictions, and is further influences  
609 by their frequency (Dietrich, 2015; Dietrich & Haider, 2015; Yang & Li, 2018). Capturing the relationships  
610 between predictions, actions, and evaluations, would therefore require a higher resolution than can be  
611 achieved with probes, as increasing the number of probes would be at the cost of the ability to actually  
612 execute the idea generation process. As such, a different method is needed to achieve this increased  
613 resolution.

614 Second, and related, one limitation was also due to the questions that formed part of the administered  
615 probes. That is, the relatively few predictions that were reported about concept selection (and the  
616 repetition thereof) could well be an artefact of the way that the present study was set up. It may well be  
617 that, counter to our initial conjectures, simply asking participants why they decided not to use certain  
618 concepts (Figure 3, question 2) did not capture the phase in which predictions occur during concept  
619 selection, but rather only the phase in which evaluations occurred. For example, people apply a range of  
620 heuristics during concept selection, such as concept selection based on similarity judgments (Gibbert et  
621 al., 2012), use their experiences they gain during idea generation, and domain knowledge. Asking people

622 why they applied a particular heuristic may have yielded better insight into the type of predictions that  
 623 occurred, whereas asking why they decided to use certain concepts would help capture the subsequent  
 624 evaluations that would have taken place.

625 Third, the way the creative task was structured helped participants to report the reasons for their actions  
 626 taken, which could then be coded into predictions and evaluations. The use of probes, for example,  
 627 interrupts the idea generation process at random times. However, regular interruption is something that  
 628 one attempts to prevent during idea generation (Madjar & Shalley, 2008). Moreover, to facilitate insight  
 629 for both the participants and the researchers into how concept selection, conceptual combination, and  
 630 idea generation took place, concepts were elicited as part of an association task, and this was done prior  
 631 to and thus separately from the idea generation task. Although it is common to attempt to understand a  
 632 problem prior to idea generation, this was made a linear step-wise process in the present study, whereas  
 633 in real-world creative processes people are free to move between the thinking processes and actions  
 634 involved in understanding the problem they are working on, and the generation of ideas (Isaksen et al.,  
 635 2011; Mumford et al., 2012). This freedom to integrate new associations that arise during idea generation  
 636 into our understanding of a problem, to later help facilitate the emergence of new conceptual  
 637 combinations and idea generation, may in itself lead to (different kinds of) predictions and evaluations. As  
 638 a consequence, these predictions and evaluations may not have occurred during the presented study,  
 639 which affects the ecological validity of the study presented here.

640 Finally, there are several other limitations that should be mentioned that have implications for interpreting  
 641 and building further upon the results. First, the study was conducted by using a marketing task only.  
 642 Although this choice likely improved external validity as the participants were known to have at least  
 643 some knowledge about marketing, a basic requirement for effective idea generation (Abraham, 2018;  
 644 Mumford et al., 2012), this also introduced some uncertainty about the degree to which these results can  
 645 be generalized to idea generation in other domains than marketing. Secondly, due to the presence of the  
 646 researcher during the study we cannot rule out any effects on the results due to possible socially  
 647 desirable behaviours by the participants. Third, differently coloured sticky notes were used by the  
 648 participants to self-report the reasons for the actions taken. However, these were not counterbalanced. In  
 649 light of recent findings of colour effects on idea generation (e.g., Lichtenfeld et al., 2012), it can therefore  
 650 not be ruled out that these may have affected the results. Fourth, the novelty of the method led to  
 651 difficulties in justifying statistically the sample size needed for the study (see footnote 1). The choice not  
 652 to statistically justify the sample size, however, does introduce uncertainty about whether the study is  
 653 sufficiently powered. Subsequently introducing uncertainty about the likelihood that type I and type II  
 654 errors may have occurred (Cohen, 1992). Fifth, please note that when interpreting the correlations  
 655 between fluency, flexibility and within-concept fluency presented in Table 4, and when comparing further  
 656 results that involve these variables, that fluency and flexibility are confounded (Forthmann, Szardening, &  
 657 Holling, 2018). This introduces uncertainty about how these results should be interpreted. That said,  
 658 further testing also suggested that effects of prediction and evaluation on flexibility that were found, were  
 659 unlikely to be driven by fluency.

### 660 **4.3 Future work**

661 After taking this first look at the predictions and evaluations that drive the idea generation process, a  
 662 second and third look seem justified.

663 Firstly, we propose that future work should investigate the function of predictions and evaluations in the  
 664 idea generation process in more detail. Previous research outside the domain of creativity suggests that  
 665 predictions about the consequences of thinking processes and actions serve to reduce uncertainty about  
 666 whether these actions help achieve a set goal (Clark, 2015; Hohwy, 2013). In other words, these are the

667 mechanisms that help select and learn about what strategies are effective for solving a given problem.  
668 One unpublished study within the domain of creativity supports this to some extent, as it showed that that  
669 instructing participants to form predictions about an idea in light of its possible future implementation,  
670 reduced uncertainty (Bruijninx & de Rooij, unpublished manuscript). In line with this, Dietrich & Haider  
671 (2015) proposed that how predictions and evaluations form part of the idea generation process reflects  
672 different strategies that people undertake to produce creative ideas. The results of the present study  
673 already provide preliminary evidence for this. For example, in the present study people tended to either  
674 produce more ideas through the persistent use of a few concepts, raising within-concept fluency; or  
675 produced (more) ideas through the inclusion of more different categories, decreasing within-concept  
676 fluency, reflecting two different idea generation strategies that appeared to be driven by different  
677 combinations of predictions and evaluations (Table 5, bottom); which aligns with Nijstad et al.'s (2010)  
678 dual pathway model of idea generation. Opportunities for future work therefore lie in the further  
679 investigation of the function of predictions and evaluations in the idea generation process.

680 Secondly, and related to this opportunity, we propose that future work should investigate the typology of  
681 predictions and evaluations that occur. Although not reported in detail in the present paper, the  
682 participants reported a rich variety of reasons for the actions they undertook during idea generation.  
683 Intuitively, this suggests that there are different types of predictions and evaluations that commonly form  
684 part of the idea generation process. Table 2 already showed this to some extent, where some predictions  
685 and evaluations were explicitly about the consequences of using a concept or generating an idea for its  
686 implementation, e.g., predictions about whether a concept would facilitate the generation of ideas that will  
687 sufficiently reach a target group; and other predictions and evaluations were explicitly about maintaining  
688 the idea generation process itself, e.g., predictions about whether a concept is likely to enable the  
689 sustained production of ideas. Understanding details of the contents of predictions and evaluations can  
690 therefore not only help to uncover how the creative process is executed, but also how these shape  
691 specific qualities of ideas, e.g. originality and effectiveness. Indeed, previous scholars have also hinted  
692 upon the relevance of such a study, suggesting that relatively little is known about what process  
693 evaluations are involved in it (Mumford et al., 2012). Opportunities for future work therefore also lie in the  
694 further investigation of the different types of predictions and evaluations that underlie the idea generation  
695 process.

#### 696 **4.4 Contribution statement**

697 As such, the contribution of this study is the presentation of empirical evidence that shows that  
698 predictions and evaluation drive different aspects of idea generation. This supports empirically, and for  
699 the first time, previous intuitions by scholars such as Dietrich & Haider (2015), Yang & Li (2018), and  
700 Wiggins & Bhattacharya (2014) and about the potentially central role of spontaneous predictions and  
701 evaluations during idea generation.

#### 702 **5 Conflict of Interest**

703 The authors declare that the research was conducted in the absence of any commercial or financial  
704 relationships that could be construed as a potential conflict of interest.

#### 705 **6 Author Contribution**

706 JV and AR wrote the article, JV and AR developed the theory and method, JV produced the materials  
707 and collected the data, JV conducted the qualitative analysis, AR conducted the statistical analysis.

#### 708 **7 Data Availability Statement**

709 The data supporting the conclusions of this manuscript will be made available by the authors, upon  
710 request, and without undue reservation, to any qualified researcher.

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799

800 **9 Tables**

Action 1		Evaluation			Action 2		Evaluation			Action 3		Evaluation		
		No	Yes	Total			No	Yes	Total			No	Yes	Total
Prediction	No	24	37	61	Prediction	No	24	120	144	Prediction	No	31	41	72
	Yes	28	82	110		Yes	2	25	27		Yes	42	57	99
Total		52	119	171	Total		26	145	171	Total		73	98	171

801 **Table 1. Frequencies of predictions and evaluations that were conjectured to drive switching**  
 802 **between concept selection and conceptual combination and idea generation (action 1), concept**  
 803 **selection (and the repetition thereof) (action 2), and conceptual combination and idea generation**  
 804 **(and the repetition thereof) (action 3).**

Type	Example quote
Action 1: Switching between concept selection and conceptual combination and idea generation	
Prediction	<i>“I thought about targeting the right customer, I think creating an online community as a form of organic marketing will increase positive word-of-mouth.”</i> <i>“Instagram is, like, a bigger thing, it is more useful, deep, it will make it easier to have new ideas.”</i>
Evaluation	<i>“At first I thought it could work, but now that I look at it, I think that using ads in specific magazines doesn’t convince me anymore.”</i>  <i>“At first I thought it could work, but now that I look at it, I think that using ads in specific magazines doesn’t convince me anymore.”</i> <i>“When I came up with it, I thought it could still come in handy, but now I think I won’t get new possibilities of use.”</i>
Action 2: Concept selection (and the repetition thereof)	
Prediction	<i>“Previously yes, but then I thought that Gamers would not fit in the ultimate product target group.”</i> <i>“I just know it will not help to have better insight on the product.”</i>
Evaluation	<i>“Fashionable doesn’t address the right audience.”</i> <i>“Gaming; Awareness in other countries, these are not prime goals, I can’t use them.”</i>
Action 3: Concept combination and idea generation (and the repetition thereof)	
Prediction	<i>“Wi-Fi and scientific improvement together will be meaningful features when communicating the product to people.”</i> <i>“I clustered them, I thought they would make more sense if used together. The same for the other clusters for the other ideas.”</i>
Evaluation	<i>“Marketing is an enormous concept, it connects with many others, that is why it was possible to get more ideas for the campaign.”</i> <i>“I think these concepts are important if taken singularly, better to focus on once concept, stress it, and then use another one to come up with strategies.”</i>

805 **Table 2. Example quotes that illustrate the type of predictions and evaluations made during the**  
 806 **idea generation process.**

Fluency		Flexibility		Within-concept fluency	
M	SD	M	SD	M	SD

Action 1: Switching between concept selection and conceptual combination and idea generation

Prediction	No	8.10	3.28	20.92	5.33	.40	.18
	Yes	8.25	3.06	20.55	5.61	.41	.15
Evaluation	No	8.27	3.45	21.52	6.02	.40	.16
	Yes	8.16	2.99	20.32	5.24	.41	.16

Action 2: Concept selection (and the repetition thereof)

Prediction	No	8.15	3.12	20.69	5.38	.40	.15
	Yes	8.41	3.25	20.63	6.22	.43	.19
Evaluation	No	8.92	3.48	20.08	5.36	.45	.16
	Yes	8.06	3.06	20.79	5.53	.40	.16

Action 3: Concept combination and idea generation (and the repetition thereof)

Prediction	No	8.50	3.38	21.33	5.97	.41	.17
	Yes	7.97	2.93	20.21	5.11	.40	.15
Evaluation	No	7.79	2.81	20.89	5.05	.38	.13
	Yes	8.49	3.33	20.53	5.83	.43	.17

807 **Table 3. Means and standard errors for fluency, flexibility, and within concept fluency for**  
 808 **predictions, evaluations, and their interaction.**

	Fluency	Flexibility	Within-concept fluency
Fluency	-		
Flexibility	.326*	-	
Within-concept fluency	.804**	-.270*	-

809 **Table 4. Pearson correlations (two-tailed) for fluency, flexibility, and within-concept fluency. \*  $p <$**   
 810 **.05, \*\*  $p <$  .01.**

811 However, these were also not significant.

	Fluency	Flexibility	Within-concept fluency
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*Model 1: Switching between concept selection and conceptual combination and idea generation*

Intercept	7.86** (.34)	20.05** (.60)	.40** (.02)
Predictions	.94 (.61)	.83 (1.10)	.04 (.03)
Evaluations	<b>1.47* (.67)</b>	1.93 (1.20)	.04 (.03)
Predictions x Evaluations	<b>-3.19** (1.05)</b>	-1.73 (1.89)	<b>-.14* (.05)</b>

*Model 2: Concept selection (and the repetition thereof)*

Intercept	8.47** (.63)	20.87** (1.11)	.43** (.03)
Predictions	-.50 (.69)	-.09 (1.22)	-.04 (.04)
Evaluations	-.98 (2.31)	-3.40 (4.06)	-.01 (.12)
Predictions x Evaluations	2.05 (2.41)	2.90 (4.24)	.06 (.12)



*Model 3: Concept combination and idea generation (and the repetition thereof)*

Intercept	8.02** (.41)	20.66** (.72)	.40** (.02)
Predictions	<b>1.13† (.64)</b>	-.31 (1.12)	<b>.06† (.03)</b>
Evaluations	-.12 (.63)	-1.07 (1.11)	.01 (.03)
Predictions x Evaluations	-1.38 (.97)	<b>3.78* (1.71)</b>	<b>-.12* (.05)</b>

812 **Table 5. Results of the generalized linear mixed model analysis for the correlations between**  
 813 **predictions and evaluations with fluency, flexibility, and within-concept fluency. † p < .10, \* p <**  
 814 **.05, \*\* p < .01.**

815

816 **10 Footnotes**

817 <sup>1</sup> Note that the sample size for this study was not statistically justified. Firstly, this was not done because  
818 the novelty of the method used, and the topic of the study, did not enable us to use data from prior work  
819 to do a power analysis (Cohen, 1992). Secondly, as the study also has a substantial qualitative  
820 component, sample size also needs to be determined by following conventions of qualitative research,  
821 e.g. reaching saturation. Thirdly, heuristics for mixed method studies exist (Onwuegbuzie & Collins,  
822 2007), but again are difficult to interpret given the novelty of the method used. Therefore, the sample size  
823 was a judgment call made by the authors that aimed to collect a dataset that allowed us to take a first  
824 quantitative and qualitative look at the occurrence and functioning of predictions and evaluations during  
825 idea generation, within the constraints of available time and other resources.