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What drives us to search for creative ideas, and why does it feel good to find one? While previous studies demonstrated the positive influence of motivation on creative abilities, how reward and subjective values play a role in creativity remains unknown. This study proposes to characterize the role of individual preferences (how people value ideas) in creative ideation via behavioral experiments and computational modeling. Using the Free Generation of Associates Task coupled with rating tasks, we demonstrate the involvement of valuation processes during idea generation: Preferred ideas are provided faster. We found that valuation depends on the adequacy and originality of ideas and guides response selection and creativity. Finally, our computational model correctly predicts the speed and quality of human creative responses, as well as interindividual differences in creative abilities. Altogether, this model introduces the mechanistic role of valuation in creativity. It paves the way for a neurocomputational account of creativity mechanisms.

Public Significance Statement
This study addresses the role of individual preferences in creativity. It demonstrates that preferences for ideas energize creative idea production: the more participants like their ideas, the faster they provide them. Moreover, preferences rely on an equilibrium between the adequacy and originality of ideas and vary across individuals. This study introduces a computational model that incorporates individual preferences and correctly predicts the speed and quality of responses in a creative idea generation task, as well as interindividual differences in creative abilities. Comparison of several versions of this model demonstrated that preferences guide the selection of creative responses.

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Creativity is a core component of our ability to promote and cope with change. Creativity is defined as the ability to produce an object (or an idea) that is both original and adequate to the context (Dietrich, 2004; Jung & Vartanian, 2018; Runco & Jaeger, 2012). The cognitive mechanisms underlying the production of an original and adequate idea are yet to be elucidated.

It is largely admitted that creativity involves two interacting phases: generation and evaluation (Beaty et al., 2016; Benedek & Jauk, 2018; Dietrich, 2004; Ellamil et al., 2012; Guo et al., 2022; Kleinmintz et al., 2019; Lin & Vartanian, 2018; Mekern et al., 2019; Sowden et al., 2015). Theoretical models including these two processes have been proposed, such as the "twofold model of creativity" (Kleinmintz et al., 2019) or the "blind-variation and selective retention model" (Campbell, 1960; Simonton, 1998; Sowden et al., 2015), a Darwinian-inspired theory stating that ideas are generated and evaluated on a trial and error basis, similarly to a variation-selection process. However, what kind of processes underlies evaluation in the context of creativity (in other words, what evaluative processes drive selection) remains overlooked.

Previous frameworks assumed that the originality and adequacy of ideas are evaluated to drive the selection of an idea during idea production (Donzallaz et al., 2021; Khalil & Moustafa, 2022; Lin & Vartanian, 2018). Existing theories also usually align evaluation with controlled or metacognitive processes (i.e., detecting relevant ideas, monitoring, and applying some control to select or inhibit early thoughts and adapt to the context) and align them to the salience and executive control networks (ECN; Beaty et al., 2014; Ellamil et al., 2012; Huang et al., 2015, 2018; Kleinmintz et al., 2019; Lin & Vartanian, 2018; Mayseless et al., 2014; Rataj et al., 2018; Ren et al., 2020; Rominger et al., 2020; Sowden et al., 2015). However, how these processes work and result in idea selection remains unknown.

Because evaluative processes in other domains involve that subjective values are assigned to options to guide selection (Rushworth & Behrens, 2008), we hypothesize that evaluation in the context of creativity also requires building a subjective value. As previous work highlighted the importance of adequacy and originality in idea evaluation, we propose that this value is based on a combination of originality and adequacy of candidate ideas. Hence, we introduce valuation in the ideation process and dissociate them from other evaluation and generation processes. Valuation can be defined as a quantification of the subjective desire or preference for an entity (Redish et al., 2016) and consists in assigning a subjective value to an option, that is, to define how much it is "likeable" or "desirable."

Previous studies assessing the role of evaluation in creativity (Ellamil et al., 2012; Huang et al., 2015, 2018; Mayseless et al., 2014; Rataj et al., 2018; Ren et al., 2020; Rominger et al., 2020) did not dissociate the valuation processes per se from the ones associated with controlled or metacognitive processes (i.e., evaluation, monitoring, and applying some control to select or inhibit early thoughts and adapt to the context). However, the neuroscience of value-based decision-making demonstrated that they are distinct, experimentally dissociable, and have separate brain substrates (Shenhav & Karmarkar, 2019). Indeed, valuation processes have been investigated for centuries by philosophers, economists, psychologists, and more recently by neuroscientists (Levy & Glimcher, 2012), outside of the creativity field. Advances in the neuroscience of decision-making have allowed the identification of a neural network, the brain valuation system (BVS), representing the subjective value of options an agent considers (Levy & Glimcher, 2012). The BVS activity reflects values in a generic (independent of the kind of items) and automatic (even when we are engaged in another task) manner (Lopez-Persem et al., 2016). Interestingly, the BVS is often coupled with the ECN when a choice has to be made in two different ways. First, in a top-down manner, the ECN modulates values according to the context (Hare et al., 2009); and second, in a bottom-up way, it drives the choice selection by integrating decision values (Domenech et al., 2018). The new framework that we propose through the present study is that evaluation processes in creativity involve valuation, implemented by the BVS, in interaction with exploration and selection processes, supported by other networks.

Existing studies provide indirect arguments for the involvement of the BVS in creativity by showing a role of dopamine (Ang et al., 2018; Boot et al., 2017; Chermahini & Hommel, 2010; de Manzano et al., 2010) and of the ventral striatum in creativity (Aberg et al., 2017; Huang et al., 2015; Takeuchi et al., 2010; Tik et al., 2018). Nevertheless, very little is known about the role of the BVS in creativity, and its interaction with the commonly reported brain networks for creativity (default mode network [DMN] and ECN) has, to our knowledge, not been explored. In fact, the place for valuation processes in creativity still needs to be conceptualized and empirically investigated.

Here, we formulate the hypothesis that originality and adequacy are combined into a "subjective value" according to individual preferences and that this subjective value drives the creative degree of the output. This value can impact the selection of an idea and possibly have a motivational role (Pessiglione et al., 2018) in exploring candidate ideas. Taking into account previous research from both creativity and decision-making fields, we hypothesize that creativity involves (1) an *explorer* module that works on individual knowledge representations and provides a set of options/ideas varying in originality and adequacy, (2) a *valuator* module that computes the likeability of candidate ideas (their subjective value) based on a combination of their originality and adequacy with the goal an agent tries to reach, and (3) a *selector* module that applies contextual constraints and integrates the subjective value of candidate ideas to guide the selection. To test these hypotheses, we combined several methods of cognitive and computational neuroscience. We built a computational model composed of the explorer, valuator, and selector modules, which we modeled separately (Figure 1) as detailed below.

First, producing something new and appropriate (i.e., creative) relies in part on the ability to retrieve, manipulate, or combine elements of knowledge stored in our memory (Benedek et al., 2012; Kenett et al., 2014). Semantic memory network methods have proven valuable in studying these processes (Benedek et al., 2017; Bernard et al., 2019; Bieth et al., 2021; Ovando-Tellez et al., 2022). Semantic networks consist of a set of nodes, which represent concepts or words, interconnected by links that represent the strength of the semantic association between them. Semantic networks provide a structure on which (censored or biased) random walk approaches have been tested to mimic semantic memory search (Zemla & Austerweil, 2017). (Pseudo)random walks on a semantic network mimic path that can be taken into the network to move from one node to another one. Those models have been essentially used to explain fluency tasks (Abbott et al., 2015) and memory retrieval of remote associates (Kenett & Austerweil, 2016), but they have not yet been combined with decision models that could bring new insights into how individuals reach a creative solution. Based on this literature, we modeled the explorer module as a random walk wandering into semantic networks.

Second, valuation and selection processes are typically studied using decision models. Utility (economic term for subjective value) functions can well capture valuation of multiattribute options that weigh attributes differently depending on individuals (Lopez-Persem et al., 2017; Samuelson, 1938; Von Winterfeldt & Fischer, 1975). Hence, we modeled the valuator module of our model as a utility function that assigns subjective values to candidate ideas based on the subjective evaluation of their adequacy and originality, considered the necessary attributes of a creative idea.

Third, the computed subjective value is then used to make a decision. Simple decision models like *softmax* functions (Luce, 1959) can explain many types of choices, ranging from concrete food choices to abstract moral choices, as soon as they rely on subjective values. Briefly, a softmax function is a mathematical function that converts a decision value, that is, the subjective values of options, into a probability of choosing one option or another. Here, we reasoned that such a simple function could capture and predict creative choices (selector module) when taking subjective values of candidate ideas as input.

Overall, through different approaches to test our hypotheses, we developed an original computational model (Figure 1) in which each module (explorer, valuator, selector) was modeled separately. We aimed at (a) determining whether subjective valuation occurs during idea generation (creativity task) and defining a valuator module from behavioral measures during the decision-making tasks; (b) developing the explorer and selector modules and characterizing which module(s) relies on subjective valuation (explorer and/or selector); (c) simulating surrogate data from the full model composed of the three modules and comparing it to human behavior; and (d) assessing the relevance of the model parameters for creative abilities.

Empirical Study

Method

Participants

An official ethics committee approved the study (Comité de Protection des Personnes Ouest II—Angers). Seventy-one participants were recruited and tested thanks to the Plateforme de Recherche sur les Interactions Sociales, la Motivation et les Emotions (PRISME) platform of the Paris Brain Institute. They gave informed consent and were compensated for their participation. Inclusion criteria were: being right-handed, native French speakers, between 22 and 40 years old, with correct or corrected vision, and having no history of neurological or psychiatric disease. Two participants were excluded because of a misunderstanding of the instructions, bringing the final number of participants to 69 (41 females and 28 males; M_{age}: 25.8 ± 4.5; mean level of education: number of study years following French A levels: 5.0 ± 1.6). The initial sample size was defined based on the interindividual correlations that

Figure 1
Schematic Representation of the Computational Model
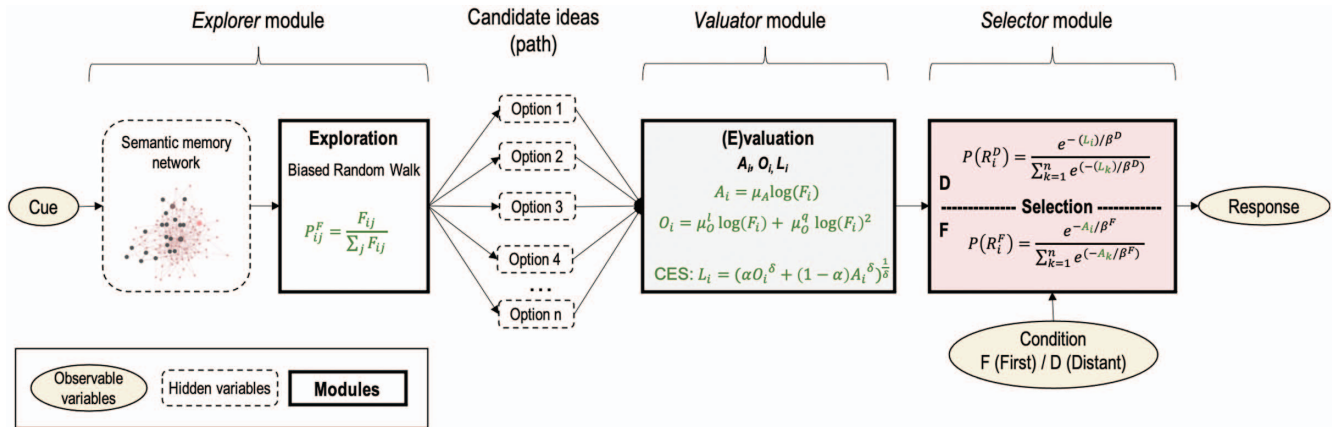
Note. The model takes as input a cue, that "activates" a semantic memory network. Semantic search (exploration) is implemented as a biased random walk, in which node transition probability P is determined by the frequency of association F between the node i and its connected nodes j. The visited nodes (options 1 to n) are evaluated in terms of adequacy (A), originality (O), and the valuator assigns a likeability (L) to each of them, CES stands for constant elasticity of substitution, see Results section. A response is selected in function of the FGAT condition: in the First condition (F), the selection is based on adequacy and in the Distant condition (D), the selection is based on likeability. Equations results from the different model comparisons conducted in the study and are detailed in the article. Text in black corresponds to our framework and hypotheses while text green corresponds to the results obtained in our study. CES = constant elasticity of substitution; FGAT = Free Generation of Associations Task.

we wanted to address between the model parameters and the creativity scores from the battery of tests. Using the software G*Power, we estimated that to detect a positive moderate effect size ($r = 0.3$) with a statistical power of 80%, for a p value threshold of .05, we needed 64 participants. As we anticipated outliers and potential exclusions, we planned to include 75 participants but four did not show up for their appointment, resulting in 71 included participants.

Experimental Design

Each participant performed three types of tasks of creative generation and evaluation of ideas, which were followed by a battery of tests classically used in the laboratory and assessing the participant's creative abilities. All tasks and tests were computerized and administered in the same fixed order for all participants.

Free Generation of Associations Task. The Free Generation of Associations Task (hereinafter referred to as FGAT) is a word association task, previously shown to capture aspects of creativity (Bendetowicz et al., 2017; Prabhakaran et al., 2014). It is composed of two conditions, presented successively and always in the same order. Cue word selection is detailed in the Supplemental Material.

FGAT First Condition. After a five-trial training session, participants performed 62 trials of the first condition block (hereafter referred to as FGAT First). They were presented with a cue word and instructed to provide the first word that came to mind after reading it. They had 10 s to find a word and press the spacebar and were allowed 10 s maximum to type it on a keyboard. This condition was used to explore the

participants' spontaneous semantic associations and served as a control condition that is not a creative task per se.

FGAT Distant Condition. In a different following block, participants were administered 62 trials of the second condition of the task (hereafter referred to as FGAT Distant). On each trial, they were presented with a cue word as in the previous condition and instructed to press the spacebar once they had thought of a word unusually associated with the cue. They were asked to find a distant but understandable associate and to think creatively. They had 20 s to think of a word, press the spacebar, and then were allowed 10 s maximum to type it. This condition measures the participants' ability to intentionally produce remote and creative associations.

Rating Tasks. After the FGAT task, participants performed two rating tasks. In the first block, they had to rate how much they liked an association of two words (likeability rating task). Then, in a separate block performed after the choice task (see below), they had to rate the originality and the adequacy (originality and adequacy rating task) of the same associations as in the likeability rating task.

Likeability Rating Task. After a five-trial training session, participants performed 197 trials in which they were presented with an association of two words (cue–response, see below) and asked to rate how much they liked this cue–response association in a creative context, that is, how much they liked it or would have liked to find it during the FGAT Distant condition. A cue–response association was displayed on the screen, and 0.3–0.6 s later, a rating scale appeared underneath it. The rating scale's low to high values were represented from left to right, without any numerical values but with 101 steps and a segment indicating the middle

of the scale (later converted in ratings ranging between 0 and 100). Participants entered their ratings by pressing the left and right arrows on the keyboard to move a slider across the rating scale, with the instruction to use the whole scale. Once satisfied with the slider's location, they pressed the spacebar to validate their rating and went on to the subsequent trial. No time limit was applied, but participants were instructed to respond as spontaneously as possible. A symbol (a heart for likeability ratings) was placed underneath the scale as a reminder of the dimension on which the words were to be rated.

Originality and Adequacy Ratings. The originality and adequacy rating task was performed after the likeability rating task and the choice task to avoid any prior influence of these dimensions on the likeability ratings and choices. After a five-trial training session, participants performed a block of 197 trials. They were asked to rate the same set of associations as in the likeability task, but this time in terms of originality and adequacy, and in a different random order. The instructions described an original association as "original, unusual, surprising." An adequate association was described as "appropriate, understandable meaning, relevant, suitable." Note that the instructions were given in French to the participants, and the adjectives used here are the closest translation we could find.

For each cue–response association, participants had to rate originality and adequacy dimensions one after the other, in a balanced order (in half of the trials, participants were asked to rate the association's adequacy before its originality, and in the other half of the trials, it was the opposite). The order was unpredictable for the participant. Similar to the likeability ratings, the rating scale appeared underneath the association after 0.3–0.6 s, with a different symbol below it: a star for originality ratings and a target for adequacy ratings, as depicted in Figure 2.

Figure 2
Experimental Design
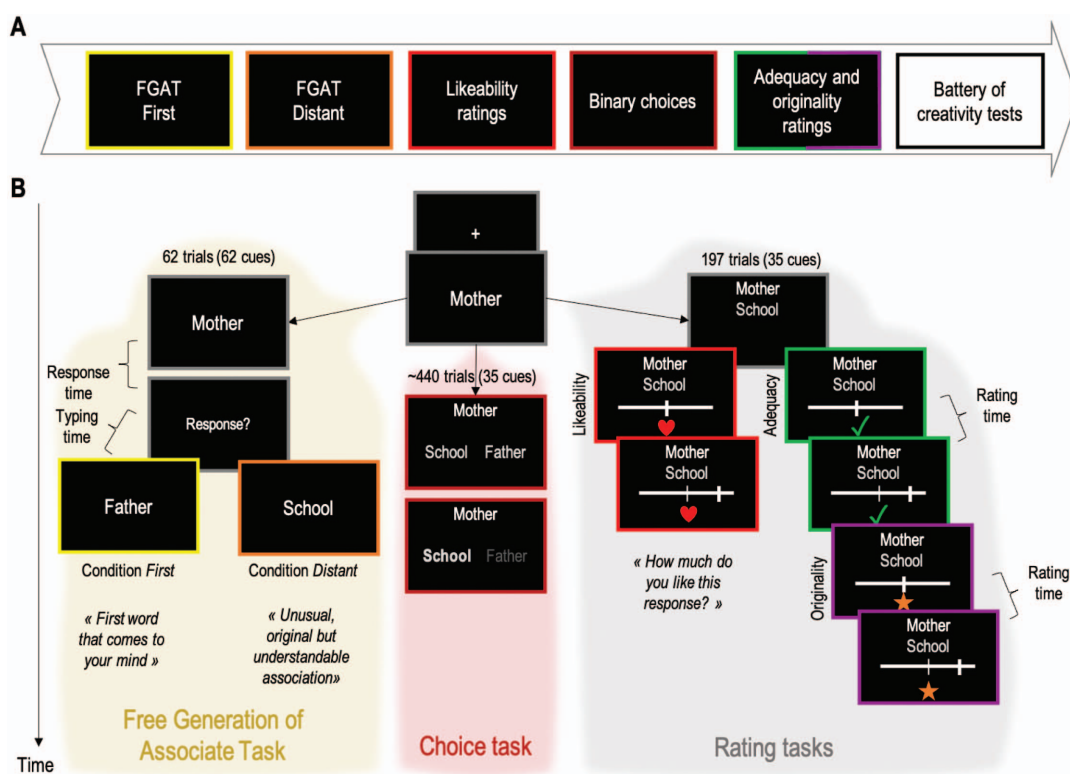
Note. (A) Chronological order of successive tasks. (B) From top to bottom, successive screenshots of example trials are shown for the three types of tasks (left: FGAT task, middle: choice task, right: rating tasks). Every trial started with a fixation cross, followed by one cue word. In the *FGAT* task, when participant had a response in mind, they had to press the space bar and the word "Response?" popped out on the screen. The FGAT task had two conditions. Participants had to press a space for providing the first word that came to their mind in the First condition and an unusual, original but associated word in the Distant condition. In the *choice* task, two words were displayed on the screen below the cue. Participants had to choose the association they preferred using the arrow keys. As soon as a choice was made, another cue appeared on the screen and the next trial began. In the *rating* tasks, one word appeared on the screen below the cue. Then a scale appeared on the screen, noticing subjects that it was time for providing a response. In the likeability rating task, participants were asked to indicate how much they liked the association in the context of FGAT Distant. In the adequacy and originality rating tasks, each association was first rated on either adequacy and originality and then on the remaining dimension. Order was counterbalanced (see the Method section, for details). FGAT = Free Generation of Associations Task.

Cue–Word Associations in the Rating Tasks. The 197 cue–response associations presented in the rating were built with 35 FGAT cue words randomly selected for each participant after they performed the FGAT task. We used a Matlab script that implemented an adaptive design with the following rules. Each of the 35 cue words was paired with seven different words, amounting to 245 possible associations in total. We paired each cue word with (a) the participant response to the cue FGAT First, (b) the participant's response to the cue in FGAT Distant, (c) one word selected randomly from the most common FGAT first responses from another data set collected previously in the lab that gathers the responses of 96 independent and healthy participants on a similar FGAT task, (d) one word selected randomly from the less common FGAT First responses from this other data set, (e) one word selected randomly from the most common FGAT Distant responses from the same other data set, (f) one word selected randomly from the less common FGAT Distant responses from the same other data set, and (g) one unrelated association for each cue ("cow" with "inverse," for instance; see Supplemental Methods, for a full description).

We used these word associations from another study and unrelated associations to obtain a sufficient sampling of all possible combinations of adequacy and originality ratings (to estimate likeability with sufficient statistical power).

Choice Task. Participants performed a binary choice task between the likeability rating task and the adequacy–originality rating task. They had to choose between two words the one they preferred to be associated with a cue in a creative context, that is, in the FGAT Distant context. Instructions were as follows: "For example, would you have preferred to answer 'silver' or 'jewelry' to 'necklace' when generating original associations during the previous task?" (There was additionally a reminder of the FGAT Distant condition in the instructions.) Details of the task and how the items were selected can be found in Supplemental Methods.

Battery of Creativity Tests. A battery of creativity tests and questionnaires run on Qualtrics followed the previous tasks to assess the participants' creative abilities and behavior. It was composed of the alternative uses task (AUT), the ICAA, a self-report of creative abilities, a scale of preferences in creativity between adequacy and originality, and a fluency task on six FGAT cues. They are described in detail in the Supplemental Methods.

Statistical Analysis

All analyses were performed using Matlab; MATLAB (2020). 9.9.0.1495850 (R2020b), Natick, Massachusetts: The MathWorks Inc.

FGAT Responses. The main behavioral measures in the FGAT task are the response time (pressing the space key to provide an answer), the typing speed (number of letters per second), and the associative frequency of the responses. This frequency was computed based on a French database called *Dictaverf* (http://dictaverf.nsu.ru/; Debrenne, 2011) built on spontaneous associations provided by at least 400 individuals in response to 1,081 words (each person saw 100 random words). Frequencies were log-transformed to take into account their skewed distribution toward 0. Cues varied in terms of steepness (the ratio between the associative frequency of the first and second free associates of a given cue word), which was a variable of interest. Subjects' ratings of their responses (adequacy, originality, and likeability) were also used as variables of interest.

Linear regressions were conducted at the subject level between normalized variables. Significance was tested at the group level using one sample, two-tailed t tests on coefficient estimates.

Likeability Ratings Relationship With Adequacy and Originality Ratings. In this analysis, we aimed at explaining how likeability ratings integrated adequacy and originality dimensions. We tested whether this integration was linear or not (with exponential terms or with the addition of interaction terms, or without) and whether adequacy and originality were in competition or not (one relative weight balancing adequacy and originality or two independent weights).

First, we fitted 12 different functions to likeability ratings capturing different types of relationships; for instance, linear of not linear between likeability (L) and adequacy (A), and originality (O):

- Linear models:

$$L_i = \beta A_i, \tag{1}$$

$$L_i = \alpha O_i + (1 - \alpha)A_i, \tag{2}$$

$$L_i = \alpha O_i + \beta A_i. \tag{3}$$

- Linear with interaction term models:

$$L_i = \alpha O_i + (1 - \alpha)A_i + \gamma O_i * A_i, \tag{4}$$

$$L_i = \alpha O_i + \beta A_i + \gamma O_i * A_i, \tag{5}$$

$$L_i = \gamma O_i * A_i. \tag{6}$$

- Nonlinear models (with the same nonlinearity on both dimensions):

$$L_i = (\alpha O_i^{\delta} + (1 - \alpha)A_i^{\delta})^{\frac{1}{\delta}} \text{ (CES)}, \tag{7}$$

$$L_i = (\alpha O_i^{\delta} + \beta A_i^{\delta})^{\frac{1}{\delta}}, \tag{8}$$

$$L_i = \alpha O_i^{\delta} + \beta A_i^{\delta}. \tag{9}$$

The nonlinear model (7) is also referred to as constant elasticity of substitution (CES; Andreoni & Miller, 2003).

- Nonlinear models (with different nonlinearity on both dimensions):

$$L_i = \beta A_i^{\delta}, \tag{10}$$

$$L_i = \alpha O_i^{\delta} + (1 - \alpha) A_i^{\varepsilon}, \tag{11}$$

$$L_i = \alpha O_i^{\delta} + \beta A_i^{\varepsilon}. \tag{12}$$

Greek letters correspond to free parameters estimated with the fitting procedure described below; i refers to a given cue–response association.

Then, we compared the performance of the 12 models to explain the relationship between likeability ratings and adequacy and originality ratings. Model fitting and comparison procedure is detailed in the General Procedure for Model Fitting and Comparison section.

Results

Sixty-nine subjects were included in the analyses (see the Participants section). The experiment consisted of several successive tasks (Figure 2; see the Experimental Design section): the Free Generation of Associate Task (FGAT), designed to investigate generative processes and creative abilities, a likeability rating task, a choice task, an originality, and adequacy rating task, and a battery of creativity assessment.

FGAT Behavior: Effect of Task Condition on Speed and Link With Likeability

In the First condition of the FGAT task, participants were asked to provide the first word that came to mind in response to a cue. In the Distant condition, they had to provide an original, unusual, but associated response to the same cues as in the First condition (see Figure 2 and the Free Generation of Associations Task section).

We investigated the quality and speed of responses in the FGAT task in the First and Distant conditions. The quality of responses was investigated using their associative frequency obtained from the French database of word associations *Dictaverf* (see the Statistical Analysis section) and using the ratings that participants provided in three rating tasks requiring them to judge how much they liked an idea (likeability of a response to the FGAT Distant condition, see the Rating Tasks section), how much original they found it (originality), and how appropriate (adequacy).

FGAT Responses: Associative Frequency. Consistent with the instructions of the FGAT conditions, we found that participants provided more frequent responses (i.e., more common responses to a given cue based on the French norms of word associations *Dictaverf*) in the First condition than in the Distant condition, $\log(\text{Frequency}_{\text{First}}) = -3.25 \pm 0.11$, $\log(\text{Frequency}_{\text{Distant}}) = -6.21 \pm 0.11$, $M \pm$ *standard error of the mean*, $t(68) = 18.93$, $p = 8.10^{-29}$. Then, we observed that

response time in the FGAT task decreased with the cue–response associative frequency, both in the First, $\beta = -0.34 \pm 0.02$, $t(68) = -15.92$, $p = 1.10^{-24}$, and Distant, $\beta = -0.10 \pm 0.02$, $t(68) = -6.27$, $p = 3.10^{-8}$, conditions, suggesting that it takes more time to provide a rare response compared to a common one (Supplemental Figure S1A). We also observed that the cue steepness (how strongly connected is the first associate of the cue, see the Statistical Analysis section) also significantly shortened response time for First responses but not significantly for Distant responses, $\beta_{\text{First}} = -0.13 \pm 0.02$, $t(68) = -8.5$, $p = 3.10^{-12}$; $\beta_{\text{Distant}} = -0.02 \pm 0.01$, $t(68) = -1.16$, $p = .25$, Supplemental Figure S1B.
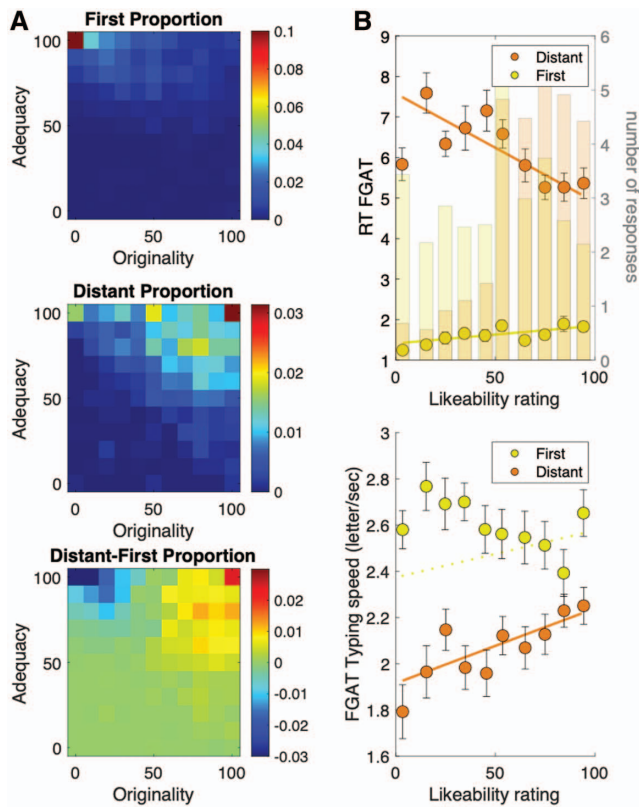
FGAT Responses: Adequacy and Originality. Using adequacy and originality ratings provided by the participants, we found that First responses were rated as more adequate than Distant responses, $\text{Adequacy}_{\text{First}} = 86.47 \pm 0.99$, $\text{Adequacy}_{\text{Distant}} = 77.24 \pm 1.23$, $t(68) = 9.29$, $p = 1.10^{-13}$, but Distant responses were rated as more original than First responses, $\text{Originality}_{\text{First}} = 33.80 \pm 1.74$, $\text{Originality}_{\text{Distant}} = 64.43 \pm 1.37$, $t(68) = -16.36$, $p = 3.10^{-25}$. Note that the difference in originality ratings (First vs. Distant responses) was greater than the difference in adequacy ratings, $t(68) = -13.87$, $p = 2.10^{-21}$, suggesting that Distant responses were found both adequate and original, that is, creative, while First responses were mainly appropriate (Figure 3A).

FGAT Responses: Likeability. Last, we considered that response time and typing speed could reflect an implicit valuation of responses (Niv, 2007). To test whether an implicit subjective valuation of responses happened during the FGAT creative condition (Distant), we investigated the link between response time, typing speed, and the likeability of their own FGAT responses (see the FGAT Responses section). We found that response time in the Distant condition decreased with likeability, $\beta_{\text{Distant}} = -0.15 \pm 0.02$, $t(68) = -7.25$, $p = 5.10^{-10}$, and that typing speed increased with it, $\beta_{\text{Distant}} = 0.08 \pm 0.02$, $t(68) = 3.88$, $p = 2.10^{-4}$. Participants were faster for providing Distant FGAT responses they liked the most. The pattern was different in the First condition, in which we observed a significant increase in response time with likeability, $\beta_{\text{First}} = 0.08 \pm 0.02$, $t(68) = 3.78$, $p = 3.10^{-4}$, and no significant effect of likeability on typing speed, $\beta_{\text{First}} = 0.009 \pm 0.02$, $t(68) = 0.36$, $p = .72$. The effects of likeability significantly differed at the group level between the First and Distant conditions; Distant vs. First effect of likeability on response time: $t(68) = -7.30$, $p = 4.10^{-10}$; on typing speed: $t(68) = 2.21$, $p = .03$, Figure 3B.

Note that the link between likeability rating and response time or typing speed remains after removing confounding factors (adequacy and originality ratings, Supplemental Table S1).

Together, those findings suggest that likeability might have been cognitively processed during the FGAT task and influenced the behavior, particularly during the FGAT Distant condition, which is assumed to require an evaluation of the response before the participants typed their answers. As a

Figure 3
Behavioral Results of the Free Generation of Associations Task (FGAT)

Note. (A) Heat maps of First (top), Distant (middle), and Distant–First (bottom) proportions of responses per bin of adequacy and originality ratings. (B) Correlation between response time (top) and typing speed (bottom) in the FGAT task and likeability ratings of the FGAT responses for the First (yellow) and Distant (orange) conditions. Circles indicate binned data averaged across participants. Error bars are intersubject standard errors of the mean. Solid lines correspond to the averaged linear regression fit across participants, significant at the group level ($p < .05$). Dotted lines indicate that the regression fit is nonsignificant at the group level ($p > .05$). In B top, transparent bars correspond to the average number of responses per bin of likeability. RT = response time.

control analysis, we also found that likeability ratings drove choices (choice task, see Supplemental Results and Supplemental Figure S2), suggesting that likeability is relevant both in the FGAT Distant condition and in binary choices linked to creative response production. We next assessed how likeability ratings relied on adequacy and originality ratings.

Likeability Depends on Originality and Adequacy Ratings

To better understand how subjects built their subjective value and assigned a likeability rating to a cue–response association, we focused on the behavior measured during the rating tasks. In the rating tasks, participants judged a series of cue–response associations in terms of their likeability, adequacy, and originality (see Figure 2 and the Rating Tasks

section). Here, we explored the relationship between those three types of ratings.

We first observed that likeability increased with both originality and adequacy (Figure 4). Then, to precisely capture how adequacy and originality contributed to likeability judgments, we compared 12 different linear and nonlinear models (see the Likeability Ratings Relationship With Adequacy and Originality Ratings section). Among them, the CES model outperformed (Lopez-Persem et al., 2017) the alternatives (estimated model frequency: Ef = 0.36, exceedance probability: Xp = 0.87). CES combines originality and adequacy with a weighting parameter α and a convexity parameter δ into a subjective value (likeability rating; see equation in Figure 1 and fit in Figure 4). In our group of participants, we found that α was significantly lower than 0.5, indicating an average overweighting of adequacy compared to originality, $M \alpha = 0.43 \pm 0.03$, $t(68) = -2.37$, $p = .02$, one sample two-sided t test against 0.5. Additionally, δ was significantly lower than 1, indicating that a balanced equilibrium between adequacy and originality was on average preferred compared to an unbalanced equilibrium, such as associations with high adequacy and low originality, $M \delta = 0.62 \pm 0.11$, $t(68) = -3.46$, $p = 9.10^{-4}$, one sample two-sided t test against 1.

Individual Preferences and Responses Creativity

In the previous analyses, we found that the new ideas people like the most are produced the fastest. On the contrary, we found that infrequent ideas took more time to be provided. Unsurprisingly, when assessing the relationship between frequency of responses and likeability ratings of Distant responses in our group of participants, we found no significant effect at the group level; linear regression of likeability ratings against frequency at each individual level, one sample two-sided t test at the group level on the mean regression coefficient: $t(68) = 0.13$, $p = .89$, Supplemental Figure S3.

Nevertheless, in the previous analyses, we also found that preferences rely on a balance between adequacy and originality. We then checked the relationship between frequency and likeability of Distant responses by splitting our group of participants according to the value of the α parameter. Participants with $\alpha > 0.5$ (favoring originality in their likeability judgments) were pooled in Group 1 and participants with $\alpha < 0.5$ (favoring adequacy in their likeability judgment) in Group 2. We found that Group 1 preferred (rated likeability higher) more creative ideas, $t(28) = -2.70$, $p = .01$, Supplemental Figure S3, while Group 2 preferred less creative ideas, $t(39) = 2.60$, $p = .013$, Supplemental Figure S3. The difference of regression coefficient between groups was strong and significant; two-sample, one-sided t test: $t(67) = 4.23$, $p = 7.10^{-5}$. In other word, the link between likeability and creativity was positive only in participants who favored originality over adequacy.

Figure 4
Behavioral Results of the Rating Tasks: Building the Valuator Module
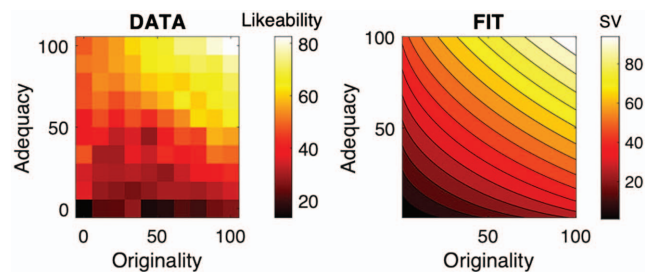
Note. Average likeability ratings (left) and fit (right) are shown as functions of adequacy and originality ratings. Black to hot colors indicate low to high values of likeability ratings (left) or fitted subjective value (SV, right). The value function used to fit the ratings was the CES utility function. CES = constant elasticity of substitution.

To go a step further, we tested whether ideas provided by Group 1 during FGAT Distant were overall less frequent than Distant ideas provided by Group 2. The comparison was significant, two-sample, one-sided t test: $t(67) = -1.812$, $p = .037$.

To summarize, individuals who favor originality in their likeability ratings prefer more creative ideas and provide more creative ideas compared to individuals who favor adequacy.

Discussion

The first aim of our study was to determine whether subjective valuation occurs during idea generation and define a valuator module from the decision-making tasks. Overall, these results indicate that subjective valuation occurs during idea generation, as we observed significant relationships between response speed and likeability ratings in the generation task, with preferred responses being provided faster. This result can be interpreted as a form of behavioral energization, which mechanisms need to be better understood. The choice task allowed us to verify that likeability was the most relevant dimension that participants used to choose between options, consistent with previous studies on value-based decision-making (Lopez-Persem et al., 2017, 2020).

The rating tasks have allowed us to characterize how likeability is built from the adequacy and originality of ideas. Overall, participants overweighted adequacy (weight parameter) and preferred responses with balanced originality and adequacy compared to unbalanced responses (convexity parameter). This result is in line with previous literature showing that originality tends to be openly or theoretically valorized but depreciated in practice (Blair & Mumford, 2007; Mueller et al., 2012). Nevertheless, it is essential to highlight here that participants overall take into account both dimensions, but vary in the way they do it: Some individuals favor high originality over high adequacy in their likeability

judgment (high α parameter), while others favor equilibrium between the two dimensions (δ lower than 1).

Importantly, we found that this equilibrium (through the α parameter) seems to be influential in participant's creativity: Participants overweighting originality in their preference provide less frequent ideas and thus more creative ideas.

The utility function fitting also constitutes the development of the valuator module in our general computational model, as the CES utility function, which builds a subjective value from adequacy and originality ratings.

In the next section, we will address the other aims of this study and develop a computational model that aims at disentangling how valuation differentially impacts exploration and selection processes underlying creative ideation. Two nonexclusive alternative hypotheses exist. Valuation either influences the exploration phase: navigating from one idea to another when searching for a creative idea is biased by preferences, or the selection phase: among the considered ideas, the one with the highest likeability is selected.

Computational Modeling of Empirical Data

Method

To develop our computational model, we focused on its three modules separately. The explorer module was developed using simulations with semantic networks, and the valuator and selector modules were developed using model fitting and model comparisons. Model simulations aim at generating surrogate data that are then analyzed and compared to human data. Model fitting aims at adjusting the parameters of equations at the individual level to match the data. Model comparison aims at determining which equation better matches the data (at the group level), once the parameters have been estimated.

We first explain below the model fitting and comparison procedures that we used. Then, we explain how we modeled the valuator (partially based on analyses conducted in the empirical study) for all participants.

Then, as the second aim of the present study was to identify whether likeability influences exploration or selection and to develop the full model, we explain how we simulated data from various versions of the explorer and how we developed the selection module.

Next, to address the third aim of this study, we combined the three modules to get a "full" model and generated surrogate data to compare the model behavior to participants' behavior.

Finally, to assess the relevance of model parameters to creative abilities (fourth aim), we conducted a canonical correlation analysis.

General Procedure for Model Fitting and Comparison

Every model/module was fitted at the individual level to ratings and choices using the Matlab variational Bayesian analysis toolbox (https://mbb-team.github.io/VBA-toolbox/), which implements variational Bayesian analysis under the

Laplace approximation (Daunizeau et al., 2009; Stephan et al., 2009). This iterative algorithm provides a free-energy approximation to the marginal likelihood or model evidence, which represents a natural trade-off between model accuracy (goodness of fit) and complexity (degrees of freedom; Friston et al., 2007; Penny, 2012). Additionally, the algorithm provides an estimate of the posterior density over the model-free parameters, starting with Gaussian priors. Individual log-model evidence was then taken to group-level random-effect Bayesian model selection (random-effect analysis Bayesian model selection) procedure (Rigoux et al., 2014; Stephan et al., 2009). Random-effect analysis Bayesian model selection provides an exceedance probability (Xp) that measures how likely it is that a given model (or family of models) is more frequently implemented, relative to all the others considered in the model space, in the population from which participants were drawn (Rigoux et al., 2014; Stephan et al., 2009).

We conducted the first model comparison to determine which variable (adequacy A, originality O, or likeability L) best explained choices (see Supplemental Methods, Relationship Between Choices and Ratings section). The second model comparison was performed to identify which utility function (valuator module) best explained how originality and adequacy were combined to compute likeability (see the Likeability Ratings Relationship With Adequacy and Originality Ratings section). The third one aimed at establishing relationships between adequacy and originality ratings and associative frequency of cues and responses (Methods Adequacy and Originality Ratings Relationship With Associative Frequency). The fourth one aimed at identifying the best possible input variable for the selector module (see the Decision Functions as the Selector Module section).

Valuator Module: Combining Likeability, Originality, and Adequacy of the Rating Tasks With Responses Associative Frequency

For all participants, the ratings were used to estimate the likeability of a given response to a cue from its adequacy and originality (see the Likeability Ratings Relationship With Adequacy and Originality Ratings section), themselves estimated from its associative frequency.

We investigated how adequacy and originality were linked to associative frequency F_{ci} between a cue (c) and a response (i). We tested for linear and nonlinear relationships between adequacy/originality and frequency using polynomial fits of second order. For each dimension X (A or O), we compared three models:

$$X_i = \mu_X^l \log(F_{ci}), \tag{13}$$

$$X_i = \mu_X^q \log(F_{ci})^2, \tag{14}$$

$$X_i = \mu_X^l \log(F_{ci}) + \mu_X^q \log(F_{ci})^2. \tag{15}$$

μ_X^l corresponds to the linear regression coefficient and μ_X^q to the quadratic regression coefficient.

Model Identification Group and Test Group

For the next analyses, we randomly split our group of participants into two subgroups, one group to develop the explorer and selector modules (two third of the group: 46 subjects) and one group to validate the full model (combination of the explorer, valuator, and selector modules) by comparing its behavioral prediction to the actual behavior of the participants (23 subjects).

Modeling the Explorer Module

We modeled the explorer module following a three-step procedure. First, we built semantic networks (for each cue) from a database available online to which we added the participant's responses. Then, we developed random walks that would wander into those networks according to different rules (biased by associative frequency or likeability, for instance). Finally, we compared the probabilities of those random walks to reach the First and Distant responses (nodes) of each participant for each cue during their trajectories in the semantic networks.

Construction of Semantic Networks. For each FGAT cue, we built a semantic network based on the Dictaverf database and the FGAT responses from the current data set. Each network corresponds to an unweighted and undirected graph (an edge linked two nodes if the frequency of association between them was higher than 0). See details in Supplemental Methods.

Random Walks Variants and Implementation. We used censored random walks that start at a given cue and walk within their associated network N. Censored random walks have the property of preventing return to previously visited nodes. In case of a dead end, the censored random walk starts over from the cue but does not go back to previously visited nodes. The five following variants of censored random walks were applied to the semantic networks to simulate potential paths.

- The random walk random was a censored random walk starting at the cue and with uniform distribution of probabilities of transition from the current node to each of its neighbors (excluding previously visited nodes).

- The random walk frequency (RWF) was a censored random walk biased by the associative frequency between nodes, where the probability of transition from one node to another one is defined as follows:

$$P_{ij}^F = \frac{F_{ij}}{\sum_j F_{ij}}, \qquad (16)$$

with P_{ij}^F the probability of transition to node j, F_{ij} the frequency of the association (in the C matrices described in the Supplemental Methods) with the current node i, and j all the other nodes linked to the current node n.

- Three additional censored random walks were run. They were biased by adequacy, originality, or likeability of association between nodes and cue, where the probability of transition from one node to another one is defined as follows:

$$P_{ij}^X = \frac{X_{cj}}{\sum_j X_{cj}}, \qquad (17)$$

with P_{ij}^X the probability of transition from node i to node j, X_{cj} the estimated adequacy, originality, or likeability of the node j with the cue node c, j are all the nodes linked to the current node i.

Estimated adequacy, originality, and likeability of all the network nodes (X_i) were computed based on the model comparison results performed in the first section (see the Valuator Module: Combining Likeability, Originality, and Adequacy of the Rating Tasks With Responses Associative Frequency section). The following equations were consequently used:

$$A_i = \mu_A \log(F_{ci}), \qquad (18)$$

$$O_i = \mu_O^l \log(F_{ci}) + \mu_O^q \log(F_{ci})^2, \qquad (19)$$

$$L_i = \left(\alpha O_i^\delta + (1 - \alpha)A_i^\delta\right)^{\frac{1}{\delta}}, \qquad (20)$$

with F_{ci} as the frequency of association between the node and the cue (and see Supplemental Methods).

The number of steps performed by each random walk was constant across cues and participants and was defined by the median fluency score among the group, that is, 18 steps, resulting in no more than 17 visited nodes.

Probability of Reaching First and Distant Responses for Each Participant and Cue. We computed the probability of reaching the First and Distant responses (targets T) from a starting node cue (c) for each type of random walk as follows:

$$P_{c,T} = \sum_{G=a}^{z} \prod_{\substack{i=c \\ i,j \in G}}^{j=T} P_{i,j}, \qquad (21)$$

with G representing all possible paths between c and T, ranging from the shortest one (a) to the longest one (z; limited to 18 steps), and i and j all pairs of nodes belonging to each path, linked by a transition probability $P_{i,j}$. In other words, it corresponds to the sum of the cumulative product of edge weights for all the possible paths between the cue and the target shorter than 18 steps.

Decision Functions as the Selector Module

Next, we intended to decipher the criteria determining the selection of a given response. We compared seven criteria: random values, node rank (first visited nodes have higher chances of being selected), estimated adequacy, estimated originality, interaction between estimated adequacy and originality, sum of estimated adequacy and originality, and estimated likeability.

For each subject and cue, we simulated RWF as described above and retained the paths that contained both the First and Distant response of the subject for further analyses (the number of excluded cues ranged between 0 and 31 trials over 62, $M = 9.04$ trials, exclusion mainly due to missing responses from participants either in the FGAT First or Distant condition).

Using the variational Bayesian analysis toolbox, we fitted the choices (response First or response Distant) that subjects made among the hypothetically visited nodes (obtained by RWF simulations) for each trial using the following *softmax* functions:

$$P(R_{i,t}^F) = \frac{e^{-X_{i,t}/\beta^F}}{\sum_{k=1}^{n} e^{(-X_{k,t}/\beta^F)}}, \qquad (22)$$

$$P(R_{i,t}^D) = \frac{e^{-(X_{i,t})/\beta^D}}{\sum_{k=1}^{n} e^{(-X_{k,t}/\beta^D)}}. \qquad (23)$$

P is the probability of node i being selected as a response (R) in the First (F) or Distant (D) conditions for a given cue, among all the possible nodes k belonging to the n options from the paths at trial t. X corresponds to the values within seven different possible inputs (criteria defined earlier). β^F and β^D are free parameters estimated per subject, corresponding to the temperature (choice stochasticity).

We then compared the seven models for the First and Distant response separately and reported the results of the model comparison in the results. Details of the input structure are in Supplemental Methods.

Cross-Validation of the Model: Comparing the Surrogate Data to Human Behavior

To simulate the behavior of the remaining 23 subjects, we combined all the previously described modules together.

Concretely, we applied RWF with 18 steps on the built networks (see the Construction of Semantic Networks section) and assigned values to each visited node according to each subject's valuator module parameters. The list of

visited nodes (candidate responses) for each cue and each subject was simulated without the constraint of containing participants' First and Distant responses. The selection was made using an *argmax* rule on adequacy (winning criteria for the selector module) for the First response and on likeability (winning criteria for the selector module) for the Distant response (as we do not have the selection temperature parameters β^F and β^D for those remaining subjects). We ran 100 simulations per individual following that procedure.

The rank in the path was used as a proxy for response time, and we analyzed surrogate data in the exact same way as subjects' behavior.

For statistical assessment, regression estimates of ranks against frequency, steepness, and estimated likeability were averaged across 100 simulations per individual, and significance was addressed at the group level (one representative simulation was used in Figure 5 and Supplemental Figure S6). For this analysis, the group frequency of response was computed instead of *Dictaverf* associative frequency to (a) avoid any confounds with the structure of the graph, built with *Dictaverf*, and (b) compare the distribution of frequencies relative to the group.

Canonical Correlation Between Creativity Scores, FGAT Task, and Model Parameters

To investigate the link between creative abilities and our task and model parameters, we extracted the individual task scores and model parameters and grouped them into the label "FGAT scores and parameters." We pooled the scores obtained from the battery of creativity test and labeled them "Battery scores." We conducted a canonical correlation between those two sets of variables and checked for significance of correlation between the computed canonical variables of each set. Note that a canonical correlation analysis can be compared to a principal component analysis, in the sense that common variance between two data sets is extracted into canonical variables (equivalent to principal components). Canonical variables extracted for each data set are ordered in terms of strength of correlations between the two data sets. Each variable within a data set has a loading coefficient that indicates its contribution to the canonical variable. Here, we extracted the coefficients of each variable on its respective canonical variable and reported them.

Results

Computational Modeling of the Valuator Module

The goal of our computational model is to explain and predict the behavior of participants in the FGAT, by modeling an explorer that generates a set of candidate ideas, a valuator that assigns a subjective value to each candidate idea, and a selector that selects a response based (or not) on this subjective value. Our computational model thus needed to be able to predict the likeability of any potential cue–response associations, including those that have not been rated by our participants (see the Valuator Module: Combining Likeability, Originality, and Adequacy of the Rating Tasks With Responses Associative Frequency section) and those that have not been expressed by participants during the FGAT Distant condition (hidden candidate ideas).

We found that adequacy and originality ratings could be correctly predicted by associative frequency (see Supplemental Results and Supplemental Figure S4). Adequacy ratings could be well fitted through a linear relation with frequency ($Ef_{lin} = 0.86$, $Xp_{lin} = 1$), and originality could be estimated through a mixture of linear and quadratic links with frequency. This result allows us to estimate the adequacy and originality of any cue–response association for a given participant.

Importantly, we explored the validity of the valuator module using estimated adequacy and originality. We estimated likeability from the estimated adequacy and originality, using the individual parameters of the CES function mentioned above. We found a strong relationship between estimated and real likeability judgments, $M\ r = 0.24 \pm 0.02$, $t(68) = 11.04$ $p = 8.10^{-17}$.

This result is not only a critical validation of our model linking likeability, originality, and adequacy but also allows defining a set of parameters for each individual for the valuator module. Thanks to that set of parameters, we could significantly predict any cue–response association's originality, adequacy, and likeability ratings based on its objective associative frequency. Henceforth, in the subsequent analyses, likeability, adequacy, and originality estimated through that procedure will be referred to as the "estimated" variables.

In the next section, using computational modeling, we address the second aim of our study, which was to develop the explorer and the selector and determine which module the valuator drives the most.

Computational Modeling of the Exploration and Selection Modules

Model Description and Overall Strategy. As we do not have direct access to the candidate ideas that participants explored before selecting and producing their response to each cue during the FGAT task, we adopted a computational approach that uses random walk simulations ran on semantic networks (one per FGAT cue) to develop the explorer module. We built a model that coupled random walk simulations (explorer) to a valuation (valuator) and selection (selector) function (Figure 1). The model takes as input an FGAT cue and generates responses for the First and Distant conditions, allowing us to ultimately test how similar the predicted

Figure 5
Response Speed for the Participants and Surrogate Data of the Test Group (n = 23)
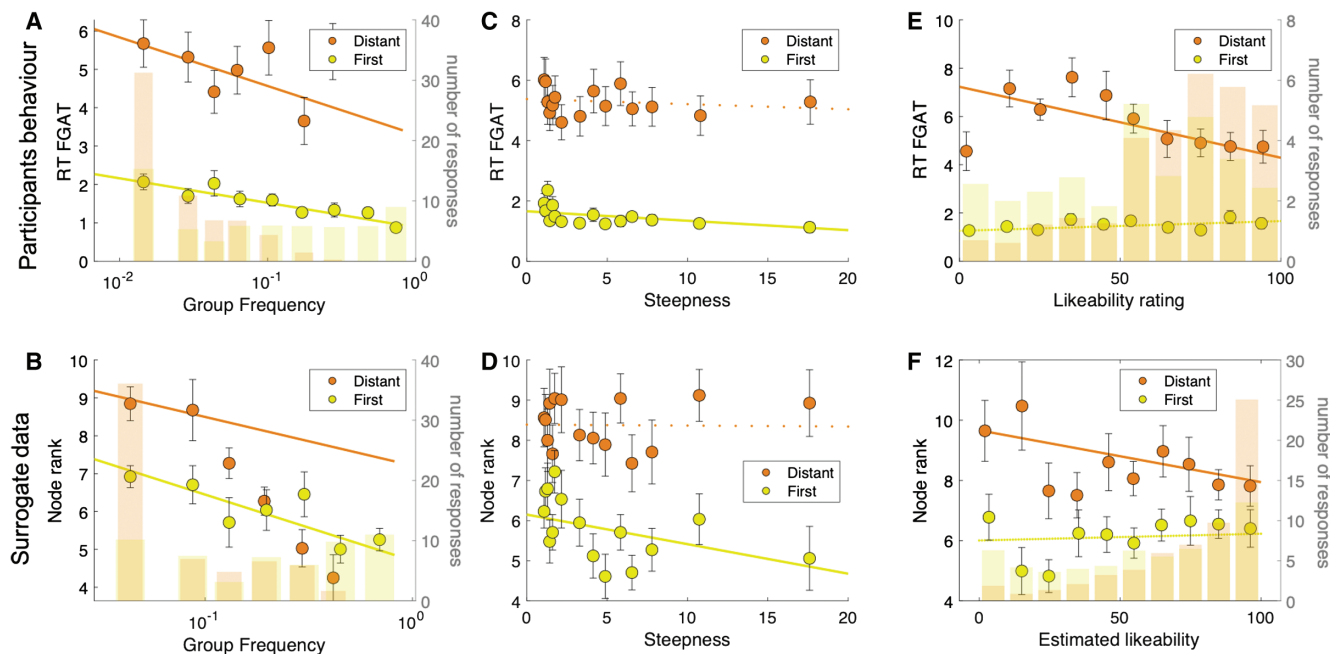
Note. (A, B) Correlation between response time RT (A) or node rank (B) in the FGAT task and the response frequency for the First (yellow) and Distant (orange) conditions. (C, D) Correlation between response time RT (C) or node rank (D) in the FGAT task and the cue steepness for the First (yellow) and Distant (orange) conditions. (E, F). Correlation between response time RT (E) or node rank (F) in the FGAT task and likeability ratings (E) or estimated likeability (F) of the FGAT responses for the First (yellow) and Distant (orange) conditions. Circles indicate binned data averaged across participants. Error bars are intersubject SEM. Solid lines correspond to the averaged linear regression fit across participants, significant at the group level ($p < .05$). Dotted lines indicate that the regression fit is nonsignificant at the group level ($p > .05$). In (A), (B), (E), and (F), transparent bars correspond to the average number of responses per bin of frequency (A, B) or likeability (E, D). Note that the surrogate data presented in the figure correspond to one simulation (among 100) that is representative of the statistics obtained over all simulations and reported in the text. RT = response time; FGAT = Free Generation of Associations Task; SEM = standard error of the mean.

responses from the model were to the real responses of the participants.

In the following analyses, we decompose the model into modules (random walks and selection functions) and investigate by which variable (estimated likeability, estimated originality, estimated adequacy, associative frequency, or mixtures) each module is more likely to be driven.

To assess the model's validity, we developed it, conducted the analyses on 46 subjects (two third of them), and then cross-validated the behavioral predictions on the 23 remaining participants.

Modeling the Explorer Module Using Random Walks on Semantic Networks. For each cue, we built a semantic network from the *Dictaverf* database that was enriched from both First and Distant FGAT responses from all participants (see the Construction of Semantic Networks section). Then, to investigate whether exploration could be driven by likeability, we compared five censored random walks, each with different transition probabilities between nodes (random, associative frequency, adequacy, originality, or likeability, see Random Walks Variants and Implementation section). For each random walk, subject, and cue, we computed the

random walk's probability of visiting the First and Distant responses nodes (Supplemental Figure S5A). We found that the frequency-driven random walk (RWF) had the highest chance of walking through the First (mean probability = 0.30 ± 0.01; all $p < 10^{-33}$) and Distant (mean probability = 0.05 ± 0.004; all $p < 10^{-4}$) responses. This result suggests that the explorer module may be driven by associative frequency between words in semantic memory. According to this result, we pursued the analyses and simulations with the RWF as an explorer module for both First and Distant responses.

Visited Nodes With the RWF as a Proxy for Candidate Responses. To define sets of candidate responses that will then be considered as options by the selector module, we simulated the RWF model for each subject and each cue over 18 steps (see the Probability of Reaching First and Distant Responses for Each Participant and Cue section). Each random walk produced a path: that is, a list of words (nodes) visited at each iteration. Each node is associated with a rank (position in the path), which will then be used as a proxy of response time. As a sanity check, we compared the list of words obtained from those random walks to the participants' responses to a fluency task on six FGAT cues (see Battery of Creativity Tests

section). We identified the common words between the model path and the fluency responses for each subject. Then, using a mixed-effect linear regression with participants and cues as random factors (applied to both intercept and slope), we regressed the node model rank against its corresponding fluency rank. We found a significant fixed effect of the fluency rank, $\beta = 0.12 \pm 0.03$, $t(649) = 3.35$, $p = 8.10^{-3}$, Supplemental Figure S6, suggesting that those simulations provide an adequate proxy for semantic memory exploration.

Together, results reported in the two last sections suggest that a censored random walk driven by the frequency of word associations provides a good approximation of semantic exploration during response generation in the FGAT task and that likeability has a negligible role during that phase. Hence, valuation does not seem to play a significant role in the explorer module.

Modeling the Selector Module as a Decision Function. We then explored the possible factors driving individual decisions to choose a given response (selector module) among the word nodes visited by the explorer module.

To investigate the selection of First and Distant responses among all nodes in each path, that is, on which dimension responses were likely to be selected, we compared seven choice models with different variables as input: random values, node rank (first visited nodes have higher chances of being selected), estimated adequacy, estimated originality, interaction between estimated adequacy and originality, sum of estimated adequacy and originality, and estimated likeability (see the Decision Functions as the Selector Module section). We found that estimated adequacy was the best criterion to explain the selection of First responses ($Ef_{adequacy} = 0.89$, $Xp_{adequacy} = 1$) and likeability was the best criterion to explain the selection of Distant responses ($Ef_{likeability} = 0.66$, $Xp_{likeability} = 0.99$; Supplemental Figure S5B). These results indicate that valuation (based on individual likeability) is needed to select a creative response in the creative condition of the FGAT (Distant).

Validity of the Full Model: Does It Predict Behavioral Responses in the Test Group?

The next analyses address our third aim to confront simulated and observed data. After having characterized the equations and individual parameters of the valuator on all participants using the rating tasks and of the explorer and selector modules on a subset of participants ($n_1 = 46$), we checked whether this model could generate surrogate data similar to the behavior of the remaining participants (test group, $n_2 = 23$). We simulated behavioral data and response time from the full model (explorer, valuator, selector), depicted in Figure 1 (see the Cross-Validation of the Model: Comparing the Surrogate Data to Human Behavior section).

We analyzed the behavior of the simulated data the same way we analyzed the behavior of the real human data of the test group. We found the same patterns at the group level (Figure 5, Supplemental Table S2 and Figure S6): (a) First responses were much more common than Distant responses (Figure 5A, B); (b) the rank in path decreased with the group frequency of responses, both for First and Distant responses (Figure 5A, B), confirming that it takes more time to provide a rare response compared to a common one; (c) ranks decreased with the cue steepness, both for First and Distant responses (Figure 5C, D); (d) ranks of the Distant responses decreased with estimated likeability. The effect was significant only for Distant responses, and the difference between regression estimates for First and Distant responses was significant (Figure 5E, F); (e) First responses were more appropriate than Distant responses, but Distant responses were more original than First responses. The difference in originality rating between the First and Distant responses was bigger than the difference in adequacy (Supplemental Figure S7).

Additionally, we checked whether the surrogate data generated by the model for each participant was relevant at the interindividual level. We estimated the selector parameters for the test group and conducted the analyses on all participants to increase statistical power. We found that the mean response time per participant across trials of the FGAT Distant condition was correlated with the mean rank of Distant responses across trials in the model exploration path ($r = 0.72$, $p = 1.10^{-4}$). Similarly, the mean associative frequency (*Dictaverf*) of participants' Distant responses was significantly correlated with the mean frequency of the model Distant responses ($r = 0.53$, $p = 9.10^{-3}$). These results mean that the model successfully predicted individual behavioral differences in the FGAT task.

Relevance of Model Parameters for Creative Abilities

Finally, to address our fourth aim and assess the relevance of the individual model parameters in relation to the FGAT task for creative abilities, we defined two sets of variables: FGAT parameters and scores reflecting the valuator, selector, and explorer individual characteristics, and Battery scores related to several aspects of creativity (see the Battery of Creativity Tests section and Supplemental Methods). We conducted a canonical correlation analysis between those two sets in all participants and found one canonical variable showing significant dependence between them ($r = 0.61$, $p = 0.0057$). When assessing which variables within each set had the highest coefficient to the canonical score, we found that the two likeability parameters (α and δ, from the valuator), the inverse temperature (choice stochasticity), from the choice task (β choice), and from the Distant response selection (β^D, from the selector; see Supplemental Results and Methods, Relationship Between Choices and Ratings section), and the First response associative frequencies were significantly

contributing to the FGAT canonical variable. Additionally, fluency score from the fluency task and from the AUT, creativity self-report, and PrefScore (self-report of preferences regarding ideas) significantly contributed to the Battery canonical variable. No significant contribution was observed from creative activities (C-Act) and achievements (C-Ach) in real-life scores (Supplemental Table S3, Figure 6). Overall, this significant canonical correlation indicates that measures of valuation and selection relate to creative behavior.

Discussion

Thanks to the computational modeling of empirical data, we addressed the second, third, and fourth aims of our study, which were (2) developing the explorer and selector modules and characterizing which module(s) relies on subjective valuation (explorer and/or selector); (3) simulating surrogate data from the full model composed of the three modules and comparing it to human behavior; and (4) assessing the relevance of the model parameters for creative abilities.

We have developed a computational model that includes three modules: an explorer, a valuator, and a selector. Through successive Bayesian model comparisons, we have found that the explorer is more likely to be driven by associative frequency of ideas than likeability of ideas, that the valuator integrates both adequacy and originality of ideas, and that the selector uses likeability to generate a final output for the creative idea generation. The model makes behavioral predictions that are accurate both at the group level (general relationship between response time and frequency of responses, for instance) and at the individual level (given a set of valuation parameters specific to an individual, it predicts whether this individual will be fast or slow to provide creative responses, for instance). Finally, the model parameters, together with the behavior in the FGAT, are predictive of creative abilities evaluated with a battery of creativity tests, suggesting that this model is relevant to creative abilities.

General Discussion

Using data from an empirical study combining creativity tasks and decision-making tasks, as well as computational modeling from those data, we provided empirical and computational evidence in favor of the involvement of subjective

Figure 6
Canonical Correlation Between the FGAT Parameters/Metrics and Creativity Tests Belonging to a Battery
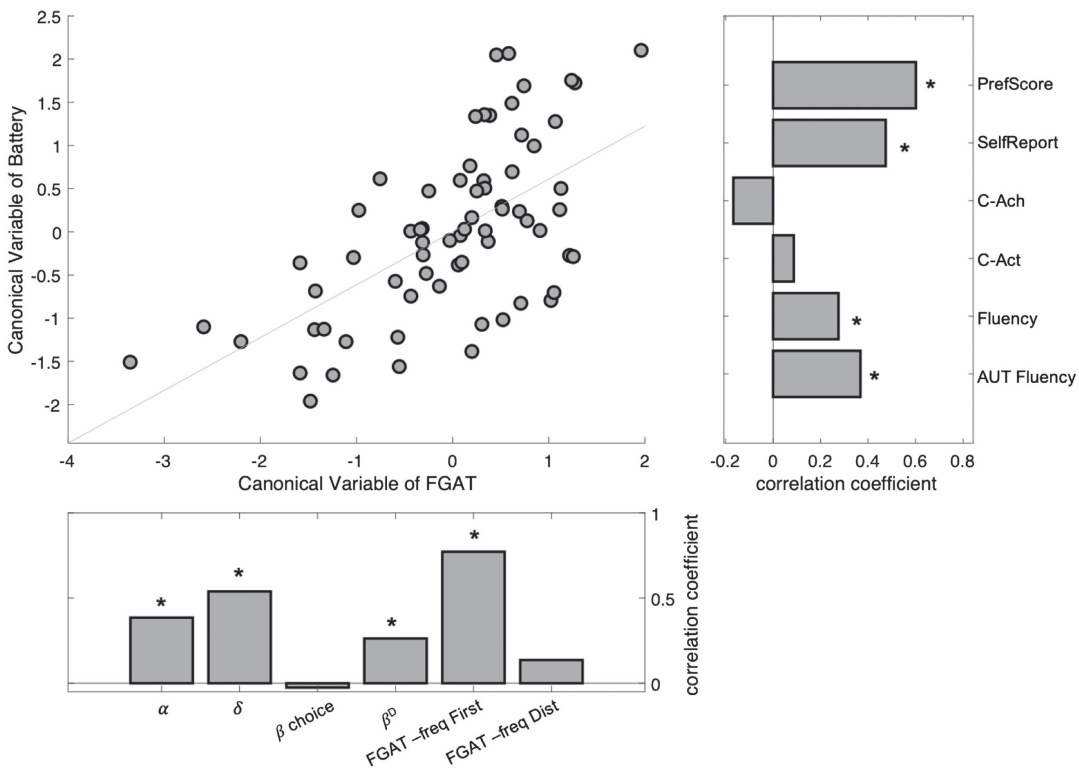
Note. Top left: Correlation between the first canonical variables of the battery of tests and the FGAT parameters/metrics. Each dot represents one participant. Top right: correlation coefficient between each battery test and the canonical variable of battery. Bottom left: correlation coefficient between each FGAT parameters/metrics and the canonical variable of FGAT. Asterisks indicate significance ($p > .05$). FGAT = Free Generation of Associations Task; C-Act = activities; C-Ach = creative achievements; AUT = alternative uses task.

valuation in creativity. We found that subjective value energizes the participants' behavior during idea generation and is driving the selection of ideas (more than the exploration of ideas).

Preferred Associations Are Produced Faster When Thinking Creatively

Using the FGAT task, previously associated with creative abilities (Bendetowicz et al., 2017), we found that Distant responses were overall more original and slower in response time than First responses. In addition, response time decreased with steepness (only for First) and cue–response associative frequency. Those results are in line with the notion that it takes time to provide an original and rare response (Beaty & Silvia, 2012; Christensen et al., 1957).

Critically, we identified that the likeability of Distant responses was negatively linked to response time and positively linked to typing speed. Interpretation of response time can be challenging as it could reflect the easiness of choice (Ratcliff & Rouder, 1998), the quantity of effort or control required for action (Botvinick et al., 2001), motivation (Niv, 2007), or confidence (Ratcliff & Starns, 2009). In any case, this result, surviving correction for potential confounding factors (see the FGAT Behavior: Effect of Task Condition on Speed and Link With Likeability section), represents evidence that subjective valuation of ideas occurs during a creative (hidden) choice. To our knowledge, this is the first time that such a result has been demonstrated. With our computational model, we attempt to provide an explanation of a potential underlying mechanism involving value-based idea selection.

Subjective Valuation of Ideas Drives the Selection of a Creative Response

The striking novelty our results reveal is the role of the valuator module coupled with the selector module in idea generation. These modules are directly inspired by the value-based decision-making field of research (Levy & Glimcher, 2012; Lopez-Persem et al., 2020). To make any kind of goal-directed choice, an agent needs to assign a subjective value to items or options at stake so that they can be compared and one can be selected (Rangel et al., 2008). Here, we hypothesized that providing a creative response involves such a goal-directed choice that would logically require the subjective valuation of candidate ideas. After finding a behavioral signature of subjective valuation in response time and typing speed, we have shown that likeability judgments best explained Distant response selection among a set of options. This pattern was similar to the behavior observed in the choice task, explicitly asking participants to choose the response they would have preferred to give in the FGAT Distant condition. Assessing valuation processes during creative thinking is highly relevant to understanding the role of motivation in creativity, as decision-making research

shows that valuation is closely related to motivation process, and it is assumed that subjective values energize behaviors (Pessiglione et al., 2007). Previous studies have highlighted the importance of motivation in creativity (Collins & Amabile, 1999; Fischer et al., 2019). However, those reports were mainly based on interindividual correlations, while our study brings new evidence for the role of motivation in creativity with a mechanistic approach. Our model adds to this literature by demonstrating novel, precise, and measurable mechanisms by which motivation may relate to creative thinking at the intraindividual level. Through computational modeling of the empirical data, we showed how subjective valuation drove idea selection. We did not find that subjective valuation drove exploration better than associative frequency. This negative result does not exclude a potential role of motivation in the exploration phase of idea generation. Future investigations using, for example, individual semantic networks will be invaluable to confirm or deny the role of motivation and value-based decision-making in the exploration phase, as suggested by other authors (Lin & Vartanian, 2018). In any case, our findings support the hypothesis that the BVS (sometimes called the reward system) is involved in creative thinking and pave the way to later investigate its neural response during experimental creativity tasks.

Our study reveals some mechanisms about how individual preferences are built and used to make creative choices. We identified how originality and adequacy ratings were taken into account to build likeability and determined preference parameters (relative weight of originality and adequacy and convexity of preference) to predict the subjective likeability of any cue–response association. Subjective likeability relies on subjective adequacy and originality. The identified valuation function linking likeability with adequacy and originality, that is, the CES utility function, has been previously used to explain moral choices or economic choices (Andreoni & Miller, 2003; Armington, 1969; Lopez-Persem et al., 2017), making it an appropriate candidate for the valuator module of our model. Overall, these results indicate that likeability is a relevant measure of the individual values that participants attributed to their ideas and inform us on how it relies on the combination of originality and adequacy.

The second novelty of our study is to provide a valid full computational model composed of an explorer, a valuator, and a selector module. We characterized these modules and brought an unprecedented mechanistic understanding of creative idea generation. Moreover, this full model can generate surrogate data similar to real human behavior at the group and interindividual levels.

A Computational Model That Provides a Mechanistic Explanation of Idea Generation

The computational model presented in the present study is consistent with previous theoretical frameworks involving two

phases in creativity: exploration and evaluation/selection (Campbell, 1960; Kleinmintz et al., 2019; Lin & Vartanian, 2018; Mekern et al., 2019; Simonton, 1998; Sowden et al., 2015). The explorer module was developed using random walks, as it had been successfully done in previous studies to mimic semantic exploration (Austerweil et al., 2012; Kenett & Austerweil, 2016). Here, we found that the simulated semantic exploration was driven by associative frequency between words but was not biased by subjective judgments of likeability, adequacy, or originality. This result is consistent with the associative theory of creativity (Mednick, 1962), which assumes that creative search is facilitated by semantic memory structure, and with experimental studies linking creativity and semantic network structure (Benedek et al., 2020; Ovando-Tellez et al., 2022) or word associations (Marron et al., 2018). Indeed, the random walks that we compared could be combined into three groups: purely random, structure-driven (frequency-biased), and goal-directed (cue-related adequacy, originality, and likeability biased). We found that the structure-driven random walk outperformed the random and goal-directed random walks, providing further evidence that semantic search has a spontaneous, bottom-up component. Overall, our model is thus compatible with several theoretical accounts of creativity and extends them, for instance, in terms of phases (generation/evaluation decomposed into exploration, valuation, and selection), or in terms of associative theory (showing how spontaneous associations occur during the exploration phase).

Perspectives

Similar to a previous neurocomputational model of creative processes (Khalil & Moustafa, 2022), our computational model presents the advantage of mathematically formalizing what could be the cognitive operations implemented by the brain during a creative search. This is of importance, as it provides actual variables (such as the likeability of ideas at each trial) that can be related to neural activity and thus provide insight into the role of each brain region or network involved in the creative process. For instance, the DMN has been identified as a key network for creativity (Beaty et al., 2014), yet it is unclear which computations the different brain regions of this network implement. Our framework, which includes valuation processes, implies that the BVS represents the subjective value of ideas when searching for a creative idea, as this brain network has been found to automatically encode subjective values of any kind of item (Lopez-Persem et al., 2020). Although the BVS has not been frequently reported in previous studies, there is a substantial overlap between the DMN and the BVS, notably in the ventromedial prefrontal cortex and in the posterior cingulate cortex. It is possible that regions considered as belonging to the DMN in previous studies of creativity in fact pertain to the BVS (which deals with idea valuation), while the DMN regions

are involved in idea exploration. This hypothetical dissociation has to be directly tested in subsequent studies.

The BVS is also in a good position to interact with the other networks involved in creativity. When making a value-based choice, the BVS interacts with the executive and salience networks in different ways. First, the ECN, including the dorsolateral prefrontal cortex, is thought to regulate—through cognitive control—choices according to the context and goal of the agent (Domenech et al., 2018; Gläscher et al., 2012). For instance, when faced with a food choice between healthy and unhealthy items, the dorsolateral prefrontal cortex (dlPFC, hub of the ECN) has been found to upregulate the weight of the healthy item in the decision (Hare et al., 2009). In our framework, we could speculate that one function of the ECN could be to upregulate the weight of originality in the computation of likeability and favor more creative outputs and avoid obvious ideas. Second, the salience network, which includes the insula and dorsal anterior cingulate cortex (dACC), is known in the neuroscience of decision-making to integrate the decision value over time to trigger an action selection (Hunt et al., 2014). If the decision value is close to zero (difficult choice because the two options have close values), the dACC may recruit the dlPFC to exert some form of control over the choice (better estimating the value of items at stake, for instance; Shenhav et al., 2013). Interestingly, the salience network has been proposed to balance the relative involvement of the DMN and ECN in the generation and evaluation processes of creative thinking (Beaty et al., 2016). Some authors have also linked the salience network to a trade-off between exploration and exploitation strategies (Lin & Vartanian, 2018). Thus, the salience network could either play a role in the recruitment of the ECN to exert some control or to balance the need for exploration (knowledge exploration) and exploitation (maintaining the ongoing idea or strategy; Kolling et al., 2016). In any case, the value of ideas could be the key missing element in the current framework of creativity. If the value of the current idea is not high enough (low saliency), exploration should be pursued or reestimation of value can be performed. Otherwise, the current idea can be further exploited. Future studies will help to specify the role of the dACC and the salience network in creativity.

In future studies, we will assess the neural bases related to the tasks presented in the present study, and we will focus on the involvement of the BVS and salience network. Additionally, we will assess the generalization of the model with drawings (Barbot, 2018) and AUT (Guilford, 1967). Building networks that could be explored by random walks for those modalities will be challenging, but thanks to the development of various artificial neural networks, similarity matrices (and thus networks) of words (Word2Vec; Mikolov et al., 2013), concepts (Bidirectional Encoder Representations from Transformers; Devlin et al., 2019) or drawings (Siamese networks; Chicco, 2021) can be built.

Then, our model will require two inputs: the condition (First or Distant), mimicking the goal of the participant, stated in the instructions, and the domain (semantic, drawing, or object use). Our framework predicts that only the structure of networks modeling knowledge should differ between modalities, and that valuation and selection functions should be stable across domains.

Limitations

Some limitations of this study need to be acknowledged. First, the present study assesses creative cognition in the semantic domain. To fully validate our computational model and the core role of preference-based idea selection, it is necessary to apply similar analyses on other domains such as drawings or music. Second, to build our model, we made many assumptions, such as the structure of semantic networks, and each of them should be tested explicitly in future studies. Third, our main result concludes on the role of motivation and preferences in idea selection, but their role in the exploration process per se remains to be further understood.

Conclusion

The present study reveals the role of individual preferences and decision-making in creativity by decomposing and characterizing the exploration and evaluation/selection processes of idea generation. Our findings demonstrate that the exploration process relied on associative thinking, while the selection process depended on the valuation of ideas. We also show how preferences are formed by weighing the adequacy and originality of ideas. By assessing creativity at the group level, beyond the classical interindividual assessment of creative abilities, the present study paves the way to a new framework for creativity research and places creativity as a complex goal-directed behavior driven by reward signals. Future neuroimaging studies will examine the neural validity of our model.

References

Abbott, J. T., Austerweil, J. L., & Griffiths, T. L. (2015). Random walks on semantic networks can resemble optimal foraging. *Psychological Review*, 122(3), 558–569. https://doi.org/10.1037/a0038693

Aberg, K. C., Doell, K. C., & Schwartz, S. (2017). The "Creative Right Brain" revisited: Individual creativity and associative priming in the right hemisphere relate to hemispheric asymmetries in reward brain function. *Cerebral Cortex*, 27(10), 4946–4959. https://doi.org/10.1093/cercor/bhw288

Anderson, J. R. (1983). A spreading activation theory of memory. *Journal of Verbal Learning and Verbal Behavior*, 22(3), 261–295. https://doi.org/10.1016/S0022-5371(83)90201-3

Andreoni, J., & Miller, J. (2003). Giving according to GARP: An experimental test of the consistency of preferences for altruism. *Econometrica*, 70(2), 737–753. https://doi.org/10.1111/1468-0262.00302

Ang, Y.-S., Manohar, S., Plant, O., Kienast, A., Le Heron, C., Muhammed, K., Hu, M., & Husain, M. (2018). Dopamine modulates option generation for behavior. *Current Biology*, 28(10), 1561–1569.e3. https://doi.org/10.1016/j.cub.2018.03.069

Armington, P. S. (1969). A theory of demand for products distinguished by place of production. *Staff Papers—International Monetary Fund*, 16(1), 159–178. https://doi.org/10.2307/3866403

Austerweil, J., Abbott, J. T., & Griffiths, T. (2012). *Human memory search as a random walk in a semantic network* [Conference session]. NIPS'12: Proceedings of the 25th International Conference on Neural Information Processing Systems, Red Hook, New York, United States. https://proceedings.neurips.cc/paper/2012/hash/14d9e8007c9b41f57891c48e07c23f57-Abstract.html

Barbot, B. (2018). The dynamics of creative ideation: Introducing a new assessment paradigm. *Frontiers in Psychology*, 9, Article 2529. https://doi.org/10.3389/fpsyg.2018.02529

Beaty, R. E., Benedek, M., Silvia, P. J., & Schacter, D. L. (2016). Creative cognition and brain network dynamics. *Trends in Cognitive Sciences*, 20(2), 87–95. https://doi.org/10.1016/j.tics.2015.10.004

Beaty, R., & Silvia, P. (2012). Why do ideas get more creative across time? An executive interpretation of the serial order effect in divergent thinking tasks. *Psychology of Aesthetics, Creativity, and the Arts*, 6(4), 309–319. https://doi.org/10.1037/a0029171

Beaty, R. E., Benedek, M., Wilkins, R. W., Jauk, E., Fink, A., Silvia, P. J., Hodges, D. A., Koschutnig, K., & Neubauer, A. C. (2014). Creativity and the default network: A functional connectivity analysis of the creative brain at rest. *Neuropsychologia*, 64, 92–98. https://doi.org/10.1016/j.neuropsychologia.2014.09.019

Bendetowicz, D., Urbanski, M., Garcin, B., Foulon, C., Levy, R., Bréchemier, M.-L., Rosso, C., Thiebaut de Schotten, M., & Volle, E. (2017). Two critical brain networks for generation and combination of remote associations. *Brain: A Journal of Neurology*. Advance online publication. https://doi.org/10.1093/brain/awx294

Benedek, M., & Jauk, E. (2018). Spontaneous and controlled processes in creative cognition. In K. Christoff, & K. C. R. Fox (Eds.), *The oxford handbook of spontaneous thought* (pp. 285–298). Oxford Academic Press. https://doi.org/10.1093/oxfordhb/9780190464745.013.22

Benedek, M., Jurisch, J., Koschutnig, K., Fink, A., & Beaty, R. E. (2020). Elements of creative thought: Investigating the cognitive and neural correlates of association and bi-association processes. *NeuroImage*, 210, Article 116586. https://doi.org/10.1016/j.neuroimage.2020.116586

Benedek, M., Kenett, Y. N., Umdasch, K., Anaki, D., Faust, M., & Neubauer, A. C. (2017). How semantic memory structure and intelligence contribute to creative thought: A network science approach. *Thinking & Reasoning*, 23(2), 158–183. https://doi.org/10.1080/13546783.2016.1278034

Benedek, M., Könen, T., & Neubauer, A. C. (2012). Associative abilities underlying creativity. *Psychology of Aesthetics, Creativity, and the Arts*, 6(3), 273–281. https://doi.org/10.1037/a0027059

Bernard, M., Kenett, Y. N., Tellez, M. O., Benedek, M., & Volle, E. (2019). *Building individual semantic networks and exploring their relationships with creativity* [Conference session]. The 41st Annual Meeting of the Cognitive Science Society, Montreal, Canada.

Bieth, T., Kenett, Y., Ovando-Tellez, M., Lopez-Persem, A., Lacaux, C., Oudiette, D., & Volle, E. (2021). *Dynamic changes in semantic memory structure support successful problem-solving*. PsyArXiv. https://doi.org/10.31234/osf.io/38b4w

Blair, C. S., & Mumford, M. D. (2007). Errors in idea evaluation: Preference for the unoriginal? *The Journal of Creative Behavior*, 41(3), 197–222. https://doi.org/10.1002/j.2162-6057.2007.tb01288.x

Boot, N., Baas, M., van Gaal, S., Cools, R., & De Dreu, C. K. W. (2017). Creative cognition and dopaminergic modulation of fronto-striatal networks: Integrative review and research agenda. *Neuroscience and Biobehavioral Reviews*, 78, 13–23. https://doi.org/10.1016/j.neubiorev.2017.04.007

Botvinick, M. M., Braver, T. S., Barch, D. M., Carter, C. S., & Cohen, J. D. (2001). Conflict monitoring and cognitive control. *Psychological Review*, 108(3), 624–652. https://doi.org/10.1037/0033-295X.108.3.624

Campbell, D. T. (1960). Blind variation and selective retention in creative thought as in other knowledge processes. *Psychological Review*, *67*(6), 380–400. https://doi.org/10.1037/h0040373

Chermahini, S. A., & Hommel, B. (2010). The (b)link between creativity and dopamine: Spontaneous eye blink rates predict and dissociate divergent and convergent thinking. *Cognition*, *115*(3), 458–465. https://doi.org/10.1016/j.cognition.2010.03.007

Chicco, D. (2021). Siamese neural networks: An overview. In H. Cartwright (Ed.), *Artificial Neural Networks* (pp. 73–94). Springer US. https://doi.org/10.1007/978-1-0716-0826-5_3

Christensen, P. R., Guilford, J. P., & Wilson, R. C. (1957). Relations of creative responses to working time and instructions. *Journal of Experimental Psychology*, *53*(2), 82–88. https://doi.org/10.1037/h0045461

Collins, M. A., & Amabile, T. M. (1999). Motivation and creativity. In R. J. Sternberg (Ed.), *Handbook of creativity* (pp. 297–312). Cambridge University Press.

Daunizeau, J., Friston, K. J., & Kiebel, S. J. (2009). Variational Bayesian identification and prediction of stochastic nonlinear dynamic causal models. *Physica D. Nonlinear Phenomena*, *238*(21), 2089–2118. https://doi.org/10.1016/j.physd.2009.08.002

de Manzano, O., Cervenka, S., Karabanov, A., Farde, L., & Ullén, F. (2010). Thinking outside a less intact box: Thalamic dopamine D2 receptor densities are negatively related to psychometric creativity in healthy individuals. *PLOS ONE*, *5*(5), Article e10670. https://doi.org/10.1371/journal.pone.0010670

Debrenne, M. (2011). Le dictionnaire des associations verbales du français et ses applications [The dictionary of French verbal associations and its applications]. In *Variétés, variations et formes du français* (p. 366). Éditions de l'Ecole polytechnique.

Devlin, J., Chang, M.-W., Lee, K., & Toutanova, K. (2019). *BERT: Pre-training of deep bidirectional transformers for language understanding*. arXiv. http://arxiv.org/abs/1810.04805

Dietrich, A. (2004). The cognitive neuroscience of creativity. *Psychonomic Bulletin & Review*, *11*(6), 1011–1026. https://doi.org/10.3758/BF03196731

Domenech, P., Redouté, J., Koechlin, E., & Dreher, J.-C. (2018). The Neurocomputational architecture of value-based selection in the human brain. *Cerebral Cortex*, *28*(2), 585–601. https://doi.org/10.1093/cercor/bhw396

Donzallaz, M., Haaf, J. M., & Stevenson, C. (2021). *Creative or not? Hierarchical diffusion modeling of the creative evaluation process*. PsyArXiv. https://doi.org/10.31234/osf.io/5eryv

Ellamil, M., Dobson, C., Beeman, M., & Christoff, K. (2012). Evaluative and generative modes of thought during the creative process. *NeuroImage*, *59*(2), 1783–1794. https://doi.org/10.1016/j.neuroimage.2011.08.008

Fischer, C., Malycha, C. P., & Schafmann, E. (2019). The influence of intrinsic motivation and synergistic extrinsic motivators on creativity and innovation. *Frontiers in Psychology*, *10*, Article 137. https://doi.org/10.3389/fpsyg.2019.00137

Friston, K., Mattout, J., Trujillo-Barreto, N., Ashburner, J., & Penny, W. (2007). Variational free energy and the laplace approximation. *NeuroImage*, *34*(1), 220–234. https://doi.org/10.1016/j.neuroimage.2006.08.035

Gläscher, J., Adolphs, R., Damasio, H., Bechara, A., Rudrauf, D., Calamia, M., Paul, L. K., & Tranel, D. (2012). Lesion mapping of cognitive control and value-based decision making in the prefrontal cortex. *Proceedings of the National Academy of Sciences of the United States of America*, *109*(36), 14681–14686. https://doi.org/10.1073/pnas.1206608109

Guilford, J. P. (1967). Creativity: Yesterday, today and tomorrow. *The Journal of Creative Behavior*, *1*(1), 3–14. https://doi.org/10.1002/j.2162-6057.1967.tb00002.x

Guo, Y., Lin, S., Acar, S., Jin, S., Xu, X., Feng, Y., & Zeng, Y. (2022). Divergent thinking and evaluative skill: A meta-analysis. *The Journal of Creative Behavior*, *56*(3), 432–448. https://doi.org/10.1002/jocb.539

Hare, T. A., Camerer, C. F., & Rangel, A. (2009). Self-control in decision-making involves modulation of the vmPFC valuation system. *Science*, *324*(5927), 646–648. https://doi.org/10.1126/science.1168450

Huang, F., Fan, J., & Luo, J. (2015). The neural basis of novelty and appropriateness in processing of creative chunk decomposition. *NeuroImage*, *113*, 122–132. https://doi.org/10.1016/j.neuroimage.2015.03.030

Huang, F., Tang, S., Sun, P., & Luo, J. (2018). Neural correlates of novelty and appropriateness processing in externally induced constraint relaxation. *NeuroImage*, *172*, 381–389. https://doi.org/10.1016/j.neuroimage.2018.01.070

Hunt, L. T., Dolan, R. J., & Behrens, T. E. J. (2014). Hierarchical competitions subserving multi-attribute choice. *Nature Neuroscience*, *17*(11), 1613–1622. https://doi.org/10.1038/nn.3836

Jung, R. E., & Vartanian, O. (2018). *The Cambridge handbook of the neuroscience of creativity*. Cambridge University Press. https://doi.org/10.1017/9781316556238

Kenett, Y. N., Anaki, D., & Faust, M. (2014). Investigating the structure of semantic networks in low and high creative persons. *Frontiers in Human Neuroscience*, *8*, Article 407. https://doi.org/10.3389/fnhum.2014.00407

Kenett, Y. N., & Austerweil, J. L. (2016). *Examining search processes in low and high creative individuals with random walks* [Conference session]. 38th Annual Meeting of the Cognitive Science Society, Philadelphia, Pennsylvania, United States.

Khalil, R., & Moustafa, A. A. (2022). A neurocomputational model of creative processes. *Neuroscience and Biobehavioral Reviews*, *137*, Article 104656. https://doi.org/10.1016/j.neubiorev.2022.104656

Kleinmintz, O. M., Ivancovsky, T., & Shamay-Tsoory, S. G. (2019). The two-fold model of creativity: The neural underpinnings of the generation and evaluation of creative ideas. *Current Opinion in Behavioral Sciences*, *27*, 131–138. https://doi.org/10.1016/j.cobeha.2018.11.004

Kolling, N., Wittmann, M. K., Behrens, T. E. J., Boorman, E. D., Mars, R. B., & Rushworth, M. F. S. (2016). Value, search, persistence and model updating in anterior cingulate cortex. *Nature Neuroscience*, *19*(10), 1280–1285. https://doi.org/10.1038/nn.4382

Levy, D. J., & Glimcher, P. W. (2012). The root of all value: A neural common currency for choice. *Current Opinion in Neurobiology*, *22*(6), 1027–1038. https://doi.org/10.1016/j.conb.2012.06.001

Lin, H., & Vartanian, O. (2018). *A neuroeconomic framework for creative cognition*. bioRXiv. https://doi.org/10.1101/184754

Lopez-Persem, A. (2022, November 10). *CreHackModel*. https://doi.org/10.17605/OSF.IO/8GKNA

Lopez-Persem, A., Bastin, J., Petton, M., Abitbol, R., Lehongre, K., Adam, C., Navarro, V., Rheims, S., Kahane, P., Domenech, P., & Pessiglione, M. (2020). Four core properties of the human brain valuation system demonstrated in intracranial signals. *Nature Neuroscience*, *23*(5), 664–675. https://doi.org/10.1038/s41593-020-0615-9

Lopez-Persem, A., Domenech, P., & Pessiglione, M. (2016). How prior preferences determine decision-making frames and biases in the human brain. *ELife*, *5*, Article e20317. https://doi.org/10.7554/eLife.20317

Lopez-Persem, A., Rigoux, L., Bourgeois-Gironde, S., Daunizeau, J., & Pessiglione, M. (2017). Choose, rate or squeeze: Comparison of economic value functions elicited by different behavioral tasks. *PLOS Computational Biology*, *13*(11), Article e1005848. https://doi.org/10.1371/journal.pcbi.1005848

Luce, R. D. (1959). On the possible psychophysical laws. *Psychological Review*, *66*(2), 81–95. https://doi.org/10.1037/h0043178

Marron, T. R., Lerner, Y., Berant, E., Kinreich, S., Shapira-Lichter, I., Hendler, T., & Faust, M. (2018). Chain free association, creativity, and the default mode network. *Neuropsychologia*, *118*(A), 40–58. https://doi.org/10.1016/j.neuropsychologia.2018.03.018

Mayseless, N., Aharon-Peretz, J., & Shamay-Tsoory, S. (2014). Unleashing creativity: The role of left temporoparietal regions in evaluating and inhibiting the generation of creative ideas. *Neuropsychologia*, *64*, 157–168. https://doi.org/10.1016/j.neuropsychologia.2014.09.022

Mednick, S. A. (1962). The associative basis of the creative process. *Psychological Review*, 69(3), 220–232. https://doi.org/10.1037/h0048850

Mekern, V., Hommel, B., & Sjoerds, Z. (2019). Computational models of creativity: A review of single-process and multi-process recent approaches to demystify creative cognition. *Current Opinion in Behavioral Sciences*, 27, 47–54. https://doi.org/10.1016/j.cobeha.2018.09.008

Mikolov, T., Chen, K., Corrado, G., & Dean, J. (2013). *Efficient estimation of word representations in vector space*. arXiv. https://doi.org/10.48550/arXiv.1301.3781

Mueller, J. S., Melwani, S., & Goncalo, J. A. (2012). The bias against creativity: Why people desire but reject creative ideas. *Psychological Science*, 23(1), 13–17. https://doi.org/10.1177/0956797611421018

Niv, Y. (2007). Cost, benefit, tonic, phasic: What do response rates tell us about dopamine and motivation? *Annals of the New York Academy of Sciences*, 1104(1), 357–376. https://doi.org/10.1196/annals.1390.018

Ovando-Tellez, M., Benedek, M., Kenett, Y. N., Hills, T., Bouanane, S., Bernard, M., Belo, J., Bieth, T., & Volle, E. (2022). An investigation of the cognitive and neural correlates of semantic memory search related to creative ability. *Communications Biology*, 5(1), Article 604. https://doi.org/10.1038/s42003-022-03547-x

Penny, W. D. (2012). Comparing dynamic causal models using AIC, BIC and free energy. *NeuroImage*, 59(1), 319–330. https://doi.org/10.1016/j.neuroimage.2011.07.039

Pessiglione, M., Schmidt, L., Draganski, B., Kalisch, R., Lau, H., Dolan, R. J., & Frith, C. D. (2007). How the brain translates money into force: A neuroimaging study of subliminal motivation. *Science*, 316(5826), 904–906. https://doi.org/10.1126/science.1140459

Pessiglione, M., Vinckier, F., Bouret, S., Daunizeau, J., & Le Bouc, R. (2018). Why not try harder? Computational approach to motivation deficits in neuro-psychiatric diseases. *Brain: A Journal of Neurology*, 141(3), 629–650. https://doi.org/10.1093/brain/awx278

Prabhakaran, R., Green, A. E., & Gray, J. R. (2014). Thin slices of creativity: Using single-word utterances to assess creative cognition. *Behavior Research Methods*, 46(3), 641–659. https://doi.org/10.3758/s13428-013-0401-7

Rangel, A., Camerer, C., & Montague, P. R. (2008). A framework for studying the neurobiology of value-based decision making. *Nature Reviews Neuroscience*, 9(7), 545–556. https://doi.org/10.1038/nrn2357

Rataj, K., Nazareth, D. S., & van der Velde, F. (2018). Use a spoon as a spade? Changes in the upper and lower alpha bands in evaluating alternate object use. *Frontiers in Psychology*, 9, Article 1941. https://doi.org/10.3389/fpsyg.2018.01941

Ratcliff, R., & Rouder, J. N. (1998). Modeling response times for two-choice decisions. *Psychological Science*, 9(5), 347–356. https://doi.org/10.1111/1467-9280.00067

Ratcliff, R., & Starns, J. J. (2009). Modeling confidence and response time in recognition memory. *Psychological Review*, 116(1), 59–83. https://doi.org/10.1037/a0014086

Redish, A. D., Schultheiss, N. W., & Carter, E. C. (2016). The computational complexity of valuation and motivational forces in decision-making processes. *Current Topics in Behavioral Neurosciences*, 27, 313–333. https://doi.org/10.1007/7854_2015_375

Ren, J., Huang, F., Zhou, Y., Zhuang, L., Xu, J., Gao, C., Qin, S., & Luo, J. (2020). The function of the hippocampus and middle temporal gyrus in forming new associations and concepts during the processing of novelty and usefulness features in creative designs. *NeuroImage*, 214, Article 116751. https://doi.org/10.1016/j.neuroimage.2020.116751

Rigoux, L., Stephan, K. E., Friston, K. J., & Daunizeau, J. (2014). Bayesian model selection for group studies—Revisited. *NeuroImage*, 84, 971–985. https://doi.org/10.1016/j.neuroimage.2013.08.065

Rominger, C., Papousek, I., Perchtold, C. M., Benedek, M., Weiss, E. M., Weber, B., Schwerdtfeger, A. R., Eglmaier, M. T. W., & Fink, A. (2020). Functional coupling of brain networks during creative idea generation and elaboration in the figural domain. *NeuroImage*, 207, Article 116395. https://doi.org/10.1016/j.neuroimage.2019.116395

Runco, M. A., & Jaeger, G. J. (2012). The standard definition of creativity. *Creativity Research Journal*, 24(1), 92–96. https://doi.org/10.1080/10400419.2012.650092

Rushworth, M. F. S., & Behrens, T. E. J. (2008). Choice, uncertainty and value in prefrontal and cingulate cortex. *Nature Neuroscience*, 11(4), 389–397. https://doi.org/10.1038/nn2066

Samuelson, P. A. (1938). The numerical representation of ordered classifications and the concept of utility. *The Review of Economic Studies*, 6(1), 65–70. https://doi.org/10.2307/2967540

Shenhav, A., Botvinick, M. M., & Cohen, J. D. (2013). The expected value of control: An integrative theory of anterior cingulate cortex function. *Neuron*, 79(2), 217–240. https://doi.org/10.1016/j.neuron.2013.07.007

Shenhav, A., & Karmarkar, U. R. (2019). Dissociable components of the reward circuit are involved in appraisal versus choice. *Scientific Reports*, 9(1), Article 1958. https://doi.org/10.1038/s41598-019-38927-7

Simonton, D. K. (1998). Donald Campbell's Model of the creative process: Creativity as blind variation and selective retention. *The Journal of Creative Behavior*, 32(3), 153–158. https://doi.org/10.1002/j.2162-6057.1998.tb00812.x

Sowden, P. T., Pringle, A., & Gabora, L. (2015). The shifting sands of creative thinking: Connections to dual-process theory. *Thinking & Reasoning*, 21(1), 40–60. https://doi.org/10.1080/13546783.2014.885464

Stephan, K. E., Penny, W. D., Daunizeau, J., Moran, R. J., & Friston, K. J. (2009). Bayesian model selection for group studies. *NeuroImage*, 46(4), 1004–1017. https://doi.org/10.1016/j.neuroimage.2009.03.025

Takeuchi, H., Taki, Y., Sassa, Y., Hashizume, H., Sekiguchi, A., Fukushima, A., & Kawashima, R. (2010). Regional gray matter volume of dopaminergic system associate with creativity: Evidence from voxel-based morphometry. *NeuroImage*, 51(2), 578–585. https://doi.org/10.1016/j.neuroimage.2010.02.078

Tik, M., Sladky, R., Luft, C. D. B., Willinger, D., Hoffmann, A., Banissy, M. J., Bhattacharya, J., & Windischberger, C. (2018). Ultra-high-field fMRI insights on insight: Neural correlates of the Aha!-moment. *Human Brain Mapping*, 39(8), 3241–3252. https://doi.org/10.1002/hbm.24073

Von Winterfeldt, D., & Fischer, G. W. (1975). Multi-attribute utility theory: Models and assessment procedures. In D. Wendt, & C. Vlek (Eds.), *Utility, probability, and human decision making* (pp. 47–85). Springer.

Zemla, J. C., & Austerweil, J. L. (2017). *Modeling semantic fluency data as search on a semantic network* [Conference session]. CogSci 2017-Proceedings of the 39th Annual Meeting of the Cognitive Science Society: Computational Foundations of Cognition.