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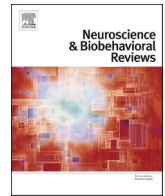
A neurocomputational model of creative processes

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A R T I C L E   I N F O

A B S T R A C T

Creativity is associated with finding novel, surprising, and useful solutions. We argue that creative cognitive processes, divergent thinking, abstraction, and improvisation are constructed on different novelty-based processes. The prefrontal cortex plays a role in creative ideation by providing a control mechanism. Moreover, thinking about novel solutions activates the distant or loosely connected neurons of a semantic network that involves the hippocampus. Novelty can also be interpreted as different combinations of earlier learned processes, such as the motor sequencing mechanism of the basal ganglia. In addition, the cerebellum is responsible for the precise control of movements, which is particularly important in improvisation. Our neurocomputational perspective is based on three creative processes centered on novelty seeking, subserved by the prefrontal cortex, hippocampus, cerebellum, basal ganglia, and dopamine. The algorithmic implementation of our model would enable us to describe commonalities and differences between these creative processes based on the proposed neural circuitry. Given that most previous studies have mainly provided theoretical and conceptual models of creativity, this article presents the first brain-inspired neural network model of creative cognition.

1. Introduction

Exploring whether someone is creative, besides how and why creativity happens, are fundamental crucial questions facing research on the neuroscience of creativity. Further questions include determining what happens in the brain when generating a creative idea and what cognitive elements contribute to driving creative thoughts. These core puzzles are of great interest to creativity researchers, especially neuroscientists.

Although it is widely accepted that creativity can be defined as developing novel and useful outputs (Loui et al., 2018), there are various meanings and no agreed-upon definitions of creative thought, rendering it an elusive concept. For example, Han et al. (2021) argued that creativity is strongly associated with novelty and surprise (which are related) and similar to the creative dimension of usefulness. Amabile (1983) suggested that novelty and appropriateness are the main criteria for accessing creative products, while Boden (2004) viewed creativity as the capability to develop an idea that is novel, surprising and valuable. Similarly, Sternberg and Lubart (1998) claimed that creativity is the

ability to construct something that has novelty and appropriateness. Accordingly, novelty and usefulness are essential elements of creativity.

Although creativity has been explored extensively in numerous studies, none of the existing neurocomputational models have attempted to integrate these existing experimental studies into a coherent framework. Therefore, this perspective article provides a unified neurocomputational model of creative processes and their neural substrates. We focused on certain kinds of creativity based on novelty but not usefulness it is difficult because is difficult to measure the latter. We overly focused on novelty aspects related to three types of creative thinking (divergent thinking (DT), abstraction, and improvisation) and their relevant neural structures.

Novelty refers to finding similarities among apparently dissimilar objects (through abstraction and generalization), connecting objects that seem unrelated, or newly integrating previously learned processes. A major complication in creativity research is the high degree of variability in the agreement on a unified definition (Bruner, 1962; Gero, 1996; Maher et al., 1996). For instance, while many researchers rely

only on two criteria (such as novelty and usefulness), others argue that these could be insufficient and must be augmented by a third criterion (i. e., surprise) to measure the unexpectedness of a novel design.

The use of novelty and usefulness as criteria is clouded by cultural differences. Simonton (2012) reported that creators in modern Europe tend to be biased toward novelty (Erez and Nouri, 2010; Simonton and Ting, 2010), whereas creative people in China are biased toward usefulness. Moreover, researchers such as Chiu and Shu (2012) and Zheng and Miller (2020) consider surprise to be a facet of novelty, while others (e.g., Boden, 2004; Simonton, 2012; Gero et al., 2019) have considered a surprise as distinct from novelty. Further, Chiu and Shu (2012) stated that novelty and usefulness are agreed-upon measures of creativity in science and engineering. They defined these terms as follows: (1) novelty relates to a creative idea when it involves a certain degree of newness, originality, or surprise (Torrance, 1974; Howard et al., 2008; Hubka and Eder, 1996; Shai et al., 2009; Wilson, 1953); and (2) usefulness requires creative ideas to contain a certain degree of value and appropriateness (Akin and Akin, 1998; Amabile, 1989; De Bono, 1992; Besemer and Treffinger, 1981; Howard et al., 2008; Shai et al., 2009). In addition, appropriateness could be defined as something that is scientifically correct (Amabile, 1989) or emphasized in the context of functionality, which is prevalent in the engineering literature (Dieter, 2000; Pahl and Beitz, 1996; Shah et al., 2000; Ullman, 2003). Similarly, Zhang and Miller (2020) refer to novelty as how unique or surprising an idea is without distinguishing between uniqueness and surprise.

Boden (2004) debated that creativity is related to three types of surprise. The first involves unfamiliar assembly combinations of familiar ideas, such as poetic imagery, paintings, textile collages, and analogies. These novel mixtures can be generated either intentionally (deliberately) or automatically (spontaneously). The second type of surprise is developing an unexpected idea that may 'fit' into a style of thinking that the person had already. The third type is about astonishment, which could endanger other ideas that a person thought were equally impossible.

Although critics continually debate whether dissimilar ideas are rarely extraordinarily equivalent (e.g., Schmookler, 1966), genuine instances exist (Lamb and Easton, 1984; Simonton, 1979). An area for agreement is that an idea can only be considered creative if it can be credited with novelty and surprise. Moreover, special prominence makes surprise an essential component (e.g., Bowden and Jung-Beeman, 2003). To conclude, the most common statements entail a version of the two-criterion definition in which creativity requires novelty and usefulness (Mayer, 1999; Simonton, 1999; Sternberg and Lubart, 1999).

At the neural level, the prefrontal cortex (PFC) is considered the central brain region for several executive functions (EFs). Hence, it plays a vital role in creative ideation and problem-solving by providing a control mechanism (Cassotti et al., 2016; Diamond, 2013; Khalil et al., 2018b, 2019, 2020). Computationally, it has been proposed that the PFC provides control mechanisms through lifelong learning with transfer and savings through gating and memory, similar to "grow-when-required" algorithms (Tsuda et al., 2020). This learning rule refers to creating new schemas while preserving and utilizing old ones. Tsuda et al. (2020) suggested a computational framework model incorporating hierarchical gating to model the PFC's ability to flexibly encode and use multiple disparate schemas. This gating leads to transfer learning and robust memory saving, forming a more potent control mechanism. Thinking about novel solutions can also activate distant or loosely connected neurons in semantic networks involving the hippocampus (HPC). Intrinsically, novelty per se can integrate previous knowledge in a novel manner, such as motor plans in the basal ganglia (BG) (Chakravarthy and Moustafa, 2018; Mandali et al., 2015, 2018; Moustafa et al., 2014, 2018; Moustafa and Srinivasa Chakravarthy, 2018; Redgrave, 2007; Srinivasa Chakravarthy and Moustafa, 2018; Houk, 2007), which is essential in the motor sequencing process.

It is widely known that the cerebellum is essential in motor learning and control, particularly for the precise control of movements

(Desmurget and Grafton, 2000; Garrido et al., 2013; Kalveram et al., 2005; Kawato and Gomi, 1992; Moustafa et al., 2013; Sergio et al., 2005; Stroeve, 1997). The cerebellum uses signals from the surrounding brain regions to learn and process sensorimotor information (from the associative sensory cortex and the PFC). Hence, it regulates the initiation, intensity, and duration of motor acts in an anticipatory manner (Manto et al., 2012; Spencer et al., 2005). Apart from its role in motor timing and control, Sereno et al. (2020) highlighted that the surface area of the human cerebellar cortex is more tightly folded than the cerebral cortex and that the human cerebellum comprises almost 78% of the surface area of the neocortex. In addition to motor control, the cerebellum might also involve higher-order EFs. Although some studies on creativity have indicated that visual DT is associated with the cerebellum (Gao et al., 2017, 2020; Saggar et al., 2017), the mechanistic role of the cerebellum in visual DT remains unclear. More interestingly, recent evidence has suggested the existence of disynaptic pathways connecting the BG and cerebellum (Bostan et al., 2013).

Besides the previously mentioned neural regions, the dispensable role of neuromodulators, particularly dopamine (DA), should not be ignored. Accumulation of evidence revealed functional differentiation between two neural circuits related to DA (striatal and prefrontal DA). More interestingly, it has been indicated that optimized levels of DA can benefit creative cognition by facilitating flexible processing and enabling persistence-driven persistence creativity (Boot et al., 2017). However, despite this insight into the critical role of DA neurotransmission in human creative thought and behavior (especially novelty seeking), the computational features of these relevant neural circuits remain sparse, particularly when the cerebellum is included.

Given these considerations, we propose a computational neural model for three fundamental dimensions of creativity: DT, abstraction, and improvisation-based novelty. The proposed model comprises five brain areas: PFC, the sensory associative cortex, HCP, BG, and cerebellum. These networks are modulated by DA, which can be segregated based on functional and structural organization into different pathways. Therefore, we argue that these brain regions represent key hubs for processing underlying creative cognition.

2. Divergent Thinking (DT), Convergent Thinking (CT), and Lateral Thinking (LT)

There are two common types of creative thinking: creative idea generation and creative problem solving. According to Guilford's structure of intellect model, researchers have identified these two critical cognitive processes as DT and convergent thinking (CT), respectively (Guilford, 1967). Researchers have identified DT as a dimension of creativity, which refers to searching for multiple solutions to a single open-ended problem (Beaty et al., 2016; Forthmann et al., 2019; Khalil et al., 2019, 2020; Schiavio and Benedek, 2020). For instance, we might think divergently when designing a novel product or writing an imaginary (i.e., fictional) story.

In contrast, we use CT for well-defined problems with unique correct solutions, such as spelling an unknown word or calculating company profits from the previous quarter. Consequently, CT has - been described as focused because it clarifies all available and relevant data into a single solution (Guilford, 1950). In other words, CT is related to finding conventional and "correct" ideas and solutions rather than original options (Runco and Acar, 2012). It is questionable whether DT and CT can occur simultaneously. Moneta (1994) postulated an optimal balance between these two modes of thinking. Similarly, Brophy (1998) argued that creative problem solving requires alternating from DT to CT at the right time; nevertheless, only a minority of people can do both with an adequate balance. Importantly, DT can be reliably tested with the alternate uses test (AUT; Guilford, 1967), which is among the most frequently used assessment methods and provides valuable information on creativity (Khalil et al., 2019, 2020). The AUT is a prominent DT task (though not the only one) through which creative new uses for everyday

objects can be found, such as bricks or car tires (Schiavio and Benedek, 2020). Other prevalent DT tasks require experimental participants to imagine the consequences of ultimate situations, propose product improvements, complete abstract figures, or produce creative metaphors and humorous puns (Schiavio and Benedek, 2020). Moreover, DT-related task performance is usually scored quantitatively and qualitatively (Schiavio and Benedek, 2020). Quantitative scoring measures the following indices: the total number of responses (fluency), the number of responses from different categories (flexibility), and the number of original ideas (originality) produced at a given time (Khalil et al., 2019, 2020; Schiavio and Benedek, 2020).

By comparison, creative quality is commonly evaluated by raters, tabulated norms, or statistical infrequency analysis (Barbot et al., 2019; Reiter-Palmon et al., 2019). Mednick (1962) proposed the remote associates test (RAT) for measuring CT, which relies on finding a word linked to unrelated words and multiple insight problems (Gilhooly and Murphy, 2005). For further information about the cognitive tests for measuring DT and CT, see Table 1 for creativity self-report and standardized performance measures in Boot et al. (2017).

There is a question over whether DT and CT are the only players in creative thinking. De Bono (2010) claimed that random stimulation could prompt people to realize new patterns and restructure problems, thus engaging in lateral thinking (LT). However, there have been fewer experimental investigations into exposure to randomness as a formal aid in tasks related to LT (Matlhouse et al., 2022). Malthouse et al. (2022) showed that LT might be rarer than previously expected, and that if one decides to think outside the box, it might make sense to at least try to think nearby. Because there are no adequate neurobiological data about CT and LT neural substrates compared with DT, we mainly focus on DT rather than CT and LT in addition to reasons. First, there is substantial evidence that DT ability has a considerable function in diverse domain-specific forms of creativity (Schiavio and Benedek, 2020). It has been demonstrated that DT ability can predict the creativity of humor production and intelligence (Kellner and Benedek, 2017), mathematical creativity, mathematical competence (Schiavio and Van Der Schyff, 2018), narrative creativity, and story writing (Joy and Breed, 2012). Second, DT ability is also a predictor of creative lifetime achievements, as assessed by self-reporting across domains (Plucker, 1999; Jauk et al., 2014). Third, studies focusing on specific domains have reported that DT ability predicts levels of creative accomplishment in advertising (Agnoli et al., 2019) and jazz improvisation (Beaty et al., 2013). Previous studies have revealed a direct correlation between the default mode network (DMN) and DT (Bashwiner, 2018). This network is an assembly of brain regions that are mainly involved in self-generated thought and DT. Similarly, it has been suggested that brain regions related to the executive control network (ECN) and DMN are involved during musical improvisation. The ECN is typically involved in top-down control, whereas the DMN is mainly involved in self-generated thought, which can be either spontaneous (mind-wandering) or goal-directed (mental navigation) (Andrews-Hanna et al., 2014; Christoff et al., 2016; Schiavio & Benedek, 2020). Finally, levels of DT are higher in professional dancers compared to novices (Fink et al., 2009).

Therefore, we elaborate on DT in the following sections. In terms of brain structure and function, we argue that certain brain regions are involved in our neurocomputational model during DT: PFC, HPC, BG, and cerebellum and modulated by DA . (1) The PFC plays a role in creative ideation and problem solving by providing a control mechanism (Cassotti et al., 2016; Diamond, 2013; Khalil et al., 2018b, 2019, 2020; Kriete et al., 2013). (2) The HPC is necessary for the semantic network due to its functional role in generalization (Faghihi and Moustafa, 2015; Khalil et al., 2015; Moustafa et al., 2009, 2012, 2013). (3) The BG plays a significant role in novelty detection signals and sequential learning (Bellebaum et al., 2008; Héricé et al., 2016; Khalil et al., 2015; Kriete et al., 2013; Moustafa et al., 2014; Redgrave, 2007; Swain et al., 2011). (4) The cerebellum provides precise gain and timing control of movements (Bellebaum et al., 2008; Garrido et al., 2013; Ivry and Spencer,

Table 1
Description of the suggested neural substrates for novelty-based- types of creative thinking.

Neural Substrate	Function (s), Methods and Implementation	Learning Rules	References[1] [Experimental and Computational studies, or both]
Prefrontal cortex (PFC)	It serves several executive functions (EFs); hence, it relates to the executive control network (ECN), which promotes several dimensions of creative ideation and problem-solving dimensions by providing a control mechanism.	Lifelong learning with transfer and savings through gating and memory is similar to "grow-when-required" algorithms (Tsuda et al., 2020)	(Diamond, 2013; Cassotti et al., 2016; Kriete et al., 2013; Khalil et al., 2018b; Khalil et al., 2019, 2020)
Hippocampus (HPC)	It provides context encoding, pattern separation, and generalization. Its role in generalization is essential when forming a semantic network, which aids in DT and abstraction.	Memory encoding and Goal-directed behavior, with simplified learning rules based on Hebbian modification or error correction (Hasselmo, 2011)	(Faghihi and Moustafa, 2015; Khalil et al., 2015; Moustafa et al., 2009, 2012, 2013)
Basal Ganglia (BG)	It is involved in action selection (AS) and reinforcement learning (RL). Its functions in novelty detection are based on mismatched signals. The concept behind **the novelty detection signal** (Pimentel et al., 2014) relies on first recognizing whether an input is novel . If it is novel, it is encoded in new synapses, as in prior models (Héricé et al., 2016; Mandali et al., 2015; Moustafa et al., 2014). As a result, newly encoded data will not interfere with previously encoded data.	AS, thought selection (TS), sequencing, RL and principal components analysis (PCA; Houk, 2007).	(Bellebaum et al., 2008; Héricé et al., 2016; Khalil et al., 2015; Kriete et al., 2013; Moustafa et al., 2014; Redgrave, 2007; Swain et al., 2011)
Cerebellum	The primary neural circuitry of the cerebellum is homogeneous throughout the cerebellar cortex. Hence, a single computational mechanism would be valuable for simultaneous gain and timing control (Yamazaki and Nagao, 2012). It also plays a critical role in precise gain and timing control, intensifying motor acts to be finely tuned in a predictive	Prediction error (Wallman and Fuchs, 1998). Unified gain and timing control (Yamazaki and Nagao, 2012). Adaptable gain regulation (Garrido et al., 2013).	(Bellebaum et al., 2008;Garrido et al., 2013;Ivry and Spencer, 2004; Moustafa et al., 2013; Swain et al., 2011;Tseng et al., 2007;Wallman and Fuchs, 1998; Yamazaki and Nagao, 2012).

Table 1 (*continued*)

Neural Substrate	Function (s), Methods and Implementation	Learning Rules	References[1] [Experimental and Computational studies, or both]
	manner through cerebro-cerebellar loops. This allows forward controller operation, as it is part of adaptable gain regulation. It also represents the passage of time over a range of tens to hundreds of milliseconds, which is an essential function for organizing movements of different body parts into coordinated action.		

[1] We limit the citations here to core reviews and our previous studies to assist in building and designing our proposed neural network model. We apologize if the table does not include all relevant references.

2004; Moustafa et al., 2013; Swain et al., 2011; Tseng et al., 2007; Wallman and Fuchs, 1998; Yamazaki and Nagao, 2012), which is a particular requirement for musical creativity.

3. Abstraction

Abstraction is a basic construct in cognitive science that incorporates the following six senses (Barsalou, 2005): categorical knowledge, the behavioral ability to generalize across instances, summary representation, schematic representations, flexible representations, and abstract concepts (Barsalou, 2005). Although these senses illustrate how abstraction is a central construct in cognitive science, we highlight abstraction as the formation of symbol-like categories of objects. Abstract thinking is also related to finding the sameness and difference among stimuli and objects in the environment (Cope et al., 2018). Finding sameness across different objects supports generalization and creative processes, meaning abstraction may be related to DT. For instance, the sameness between a brick and a hammer (i.e., both are hard objects) suggests using a brick to hammer a nail.

At the neural level, abstract representations could be linked to the generalization function and novelty seeking of the HPC (Kaufman et al., 2011; Tateo, 2013; Horzyk, 2014), which could be linked to the neural network of the HCP as one of the neural hubs for novelty ideation. Although previous findings have highlighted the role of interactions between the HCP and the DA system in generalization, the mechanistic pathways concerning the role of DA in the modulation of generalization remain elusive (Kahnt and Tobler, 2016).

4. Improvisation

In music and sports, improvisation is related to the novel integration of existing motor plans, leading to novel products (Beaty, 2015; Leisman et al., 2014, 2016; Loui, 2018). In applications of real-time creativity (such as musical improvisation or sports creativity), the perception-action feedforward–feedback cycle should promote the generation of novel ideas. However, existing knowledge bases should also be considered, such as previously known melodic fragments or "licks" and chord progressions in musical improvisation (Loui, 2018). Therefore, the cerebellum could be one of the core areas involved in the improvisation process for evaluating incoming sensory input from the environment before the motor control action is sent to the body (Luque

et al., 2014). Furthermore, it is well-accepted that the BG has a profound role in novelty detection signaling and the novel sequencing of previously learned motor plans, meaning its role should not be ignored in improvisation.

We argue that improvisation is related to the PFC, HPC, BG, and cerebellum functions, and modulated by DA. The BG executes the novel sequencing of previously learned motor plans through novelty detection signaling, while the cerebellum formulates and maintains gain and timing information. This role implies that the cerebellar controller manages the sensory information to deliver the optimum motor commands to accomplish the desired movement, which is relevant to improvisation in music and sports. These functions are indispensable for talented musicians and athletes, allowing them to execute their best performances.

5. Designing a novel computational model of creative cognitive processes

The suggested neural substrates for novelty-based creative thinking are described in Table 1 and Fig. 1.

Fig. 1 illustrates the proposed neural network architecture and the relevant model functions based on previously suggested computational models for each brain area. The neural substrates include four brain areas modulated by the DA system and the sensory association cortex, which provides input. The four brain areas are the PFC, HCP, BG, and cerebellum, which are involved in providing control, memory encoding, and novelty detection, respectively. Pathways are represented by black arrows and modulated by DA signals (blue arrows).

The proposed neural network is modulated by DA, which can be segregated based on functional and structural organization into distinct pathways. This proposed computational model and its neural circuits account for three types of creativity: DT, abstraction, and improvisation. The next step is to conduct simulation studies of this hypothetical model at the algorithmic level based on the suggested neural circuits to validate experimental findings related to these different types of creativity.

As in prior models (Faghihi and Moustafa, 2015; Khalil et al., 2017, 2018a), the new model can use integrate and fire (IAF) neurons in simulation studies. Table 2 presents the parameters used in a simplified IAF neuron model, and Eq. 1. shows the IAF neuron model.

$$dV/dt = 1/\tau \quad (E\_L - V(t) + I(t)).dt \tag{1}$$

$$if \quad V(t) > V_{th} \quad spike = 1 \& V(t) = V_{reset}$$

The difference in the average firing rate of each pair of neurons in the layers is measured and shown by $\Delta_{(i,j)}$ (Eq. 2). The change in the synaptic weight of the pairs of neurons ($\Delta w_{(i,j)}$) is calculated as in Eq. 3.

$$\Delta_{(i,j)} = f_i^1 - f_j^2 \tag{2}$$

$$if: \quad f_i > f_j; \Delta w_{(i,j)} = \alpha^* \left(\frac{1 - e^{-\Delta_{(i,j)}}}{1 + e^{-\Delta_{(i,j)}}} \right) \quad \alpha \in [0 \quad , \quad 1] \tag{3}$$

$$if: \quad f_i < f_j; \Delta w_{(i,j)} = -\beta^* \left(\frac{1 - e^{-\Delta_{(i,j)}}}{1 + e^{-\Delta_{(i,j)}}} \right) \quad \beta \in [1, 10]$$

f_i : firing rate of the first layer.

f_j : firing rate of the second layer.

In this learning rule, parameters α and β will be checked to find their optimal values for performing DT, abstraction, and improvisation. All of our simulations can be applied to the University of California Irvine (UCI) sentence dataset, which has been used extensively in prior machine learning and neural network studies. Prospect research should first train the newly developed model to acquire a semantic network of several sentences to simulate DT. Here, we will test how the model can activate loosely connected nodes, as in the case of creative people. We can stimulate the formation of abstraction as symbol-like concepts based
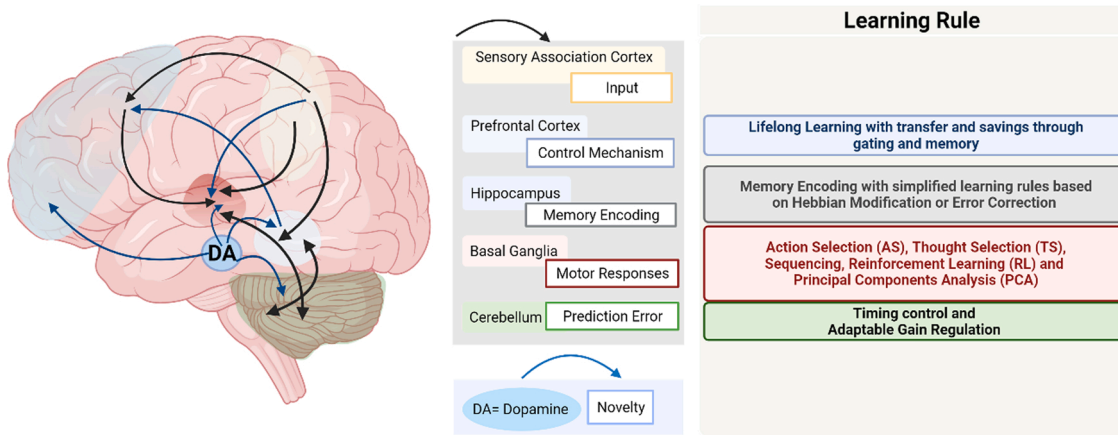
Fig. 1. Proposed neural network model architecture and learning rules to simulate creative processes based on novelty, including DT, abstraction, and improvisation.

Table 2
Description of IAF neuron parameters.

τ	membrane time constant (s)
E_L	resting potential (v)
V_{reset}	reset voltage
V_{th}	threshold voltage
V_0	initial membrane voltage
dt	time step (s)

on similar methods presented in Kriete et al. (2013). Importantly, using our proposed model will test how the formation of abstract concepts can aid generalization. Crucially, future work can simulate creative motor sequencing using the previous models of Moustafa (Chakravarthy and Moustafa, 2018; Moustafa and Gluck, 2011; Moustafa et al., 2013). In addition, we can simulate low vs. creativity states using our proposed model. One assumption that we can use is that the low creativity state corresponds to normal processes while increasing the parameter for DA value will increase novelty seeking in the high creativity state. Based on the same concept, this model can test the impact of increased DA levels on DT, abstraction, and improvisation for predicting and enhancing creativity.

6. Conclusion

We highlight the different creative cognitive processes (such as DT, abstraction, and improvisation), which are potentially based on rudimentary novelty-based processes. These cognitive processes underpin novelty recognition and novelty-seeking, modulated by DA and subserved by the PFC, HPC, cerebellum, and BG. These relevant brain regions could signify a network hub for novelty, representing the neural substrates for DT, abstraction, and improvisation. Evaluating this proposed computational model would require a comparison of model predictions and experimental findings. This comparison would describe the commonalities and differences between certain types of creativity based on their proposed neural circuitry, inspiring improved designs of neural circuits for creativity in health and disease.

One of the crucial implications of this review is the provision of a unified framework of seemingly disparate facets of creativity. This framework would benefit the application of creativity research both empirically (i.e., in terms of qualification and evaluation) and clinically (i.e., in terms of health and disease). Provision of such model would enable computational predictions of the underlying neural mechanisms related to creativity. Currently, this is one of the major complications in many research topics related to creativity, which is challenging to insufficient data. In this scope, more debate and discussion are required to bring these disparate areas of creativity closer together (Abraham,

2013).

Our proposed model implies that multiple distributed learning mechanisms are vital for explaining the complex properties of different creative processes. Consequently, how creativity in one domain may relate to creativity in other domains (even if only partially) and whether there are similar neural mechanisms could be questioned. This model is beneficial because it involves several neural circuits of different brain areas that are connected and serve each other. The relevant question here is whether the PFC, HPC, BG, and cerebellum are similarly connected at the same level of strength with the three kinds of creativity. For instance, narrative creativity (e.g., metaphors and creative word choices) relies on DT and the semantic network of the HPC. However, it is unclear whether the underlying neural mechanisms has the same strength and if the neural pathways of DT and abstraction are the same for improvisation, and how they are modulated by DA.

Lastly, previous studies have indicated a strong correlation between developing the drivers of creativity and several clinical illnesses, including depression, bipolar disorders, psychosis, Parkinson's disease, temporal lobe epilepsy, frontotemporal dementia, and autism spectrum disorders (Abraham et al., 2012; Carson, 2011; Flaherty, 2005, 2011; Khalil et al., 2019; Mula et al., 2016). Therefore, because our computational model would assist in providing a better understanding of the neural mechanisms in healthy conditions, this would facilitate the prediction of the underlying causes of illnesses where relevant brain areas are disturbed.

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